Performance of Random Access Scheduling Schemes in Multi-Hop Wireless Networks

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Abstract—The scheduling problem in multi-hop wireless networks has been extensively investigated. Although throughput optimal scheduling solutions have been developed in the literature, they are unsuitable for multi-hop wireless systems because they are usually centralized and have very high complexity. In this paper, we develop a random-access based scheduling scheme that utilizes local information. The important features of this scheme include constant-time complexity, distributed operations, and a provable performance guarantee. Analytical results show that it guarantees a larger fraction of the optimal throughput performance than the state-of-the-art. Through simulations with both single-hop and multi-hop traffics, we observe that the scheme provides high throughput, close to that of a well-known highly efficient centralized greedy solution called the Greedy Maximal Scheduler.

Index Terms—Capacity region, communication systems, multi-hop wireless networks, random access scheduling, stability.

I. INTRODUCTION

In multi-hop wireless networks, the optimal solution that maximizes overall system performance can be decomposed into two components: congestion control and scheduling [1]–[5]. While the congestion control component can be optimally solved using techniques from convex programming, the scheduling problem cannot be easily solved as it is a complex non-convex optimization problem caused by the interplay between the link schedule and wireless interference.

Note that although optimal scheduling algorithms have been known, it is difficult to implement them in practice because they typically require centralized information and high computational complexity [2], [5]–[8].

Due to the enormous complexity of optimal scheduling algorithms (high-degree polynomial or NP-hard, depending on the interference scenario), simpler scheduling algorithms with provable performance guarantees have attracted significant attention [5], [7], [9]–[12]. In this paper, we focus on developing simple, provably efficient, scheduling solutions that can be implemented via a random-access based distributed scheduling scheme.

We consider a multi-hop wireless network with N nodes and L links. Let λI denote the offered load on link l, and let cI denote the capacity of link l when no other neighboring links are transmitting. The actual transmission rate of link l depends both on the capacity cI and on the interference from its neighboring links. We also define a load vector \( \bar{\lambda} = [\lambda_1, \lambda_2, \ldots, \lambda_L] \), and a capacity region as a set \( \mathcal{X} \). A scheduling policy is said to achieve the capacity region if it supports any \( \bar{\lambda} \) in the capacity region while keeping the queues of all links finite. A throughput-optimal scheduling policy is defined as the scheduling policy that achieves the largest capacity region. If a scheduling policy achieves a capacity region, the throughput-optimal scheduling policy can achieve the same capacity region. The capacity region achieved by the throughput-optimal scheduling policy is called as the optimal capacity region \( \Omega \). If a suboptimal scheduling policy can support \( \gamma \bar{\lambda} \) for all \( \bar{\lambda} \in \Omega \), it is said to have an efficiency ratio of \( \gamma \). Throughout the paper, we use the efficiency ratio as the performance metric of a scheduling policy.

Note that \( \Omega \) is the optimal capacity region of networks where traffic only traverses a single hop. In multi-hop networks, the load is generally distributed over multi-hop links over a routing path between sender and receiver. However, for multi-hop networks where certain routing and scheduling schemes are used, the sum of the loads at each link must be inside \( \Omega \). That is, the optimal capacity region of networks where the traffic only traverses a single hop is larger than the optimal capacity region of networks with multi-hop traffic.

The optimal scheduling policy [5] is to schedule links such that

\[
\bar{\rho} = \arg \max_{\rho \in Co(\mathcal{R})} \sum_{l=1}^{L} q_l r_l
\]

where \( \bar{\rho} \) is the vector of rate assignment, \( Co(\mathcal{R}) \) is the convex hull (i.e., time averaging) of the set of feasible schedule \( \mathcal{R} \), and \( q_l \) is the implicit price (i.e., queue length) of link \( l \).

We first examine the performance of scheduling policies under the so-called node-exclusive or primary interference model, and then extend our study to the two-hop interference model. The former is a good model for Bluetooth or FH-CDMA networks [5], [13], and the latter is often used for IEEE 802.11 DCF ( Distributed Coordination Function ) networks [7], [8].

Under the node-exclusive interference model, a node cannot simultaneously transmit or receive, and cannot simultaneously communicate with two or more nodes in the network. Let \( E(i) \) be the set of links connected to node \( i \). Under the constraints of
the model and the fact that the offered load cannot exceed the link capacity, the optimal capacity region $\Omega$ is bounded by

$$\Omega \subseteq \Psi$$

where

$$\Psi = \left\{ X \left| \sum_{l \in E(i)} \frac{\lambda_l}{c_l} \leq 1, \text{for all nodes } i \right. \right\}. \quad (2)$$

In this model, the optimal scheduling policy, i.e., Maximal Weighted Matching\(^1\) (MWM) has $O(N^3)$ complexity [14], where $N$ is the number of nodes, and is thus difficult to implement. A simpler suboptimal policy like Greedy Maximal Matching\(^2\) (GMM) [15] can be used at the expense of performance. It is known that the centralized GMM can support up to $(1/2)\bar{X}$ for any $X \in \Psi$ [6], which means that it has the efficiency ratio of at least 1/2 while its algorithmic complexity is $O(L \log L)$, where $L$ is the number of links. Since both MWM and GMM are centralized algorithms requiring global information, they are difficult to implement in multi-hop networks. Resource restrictions on computational complexity, radio power, and bandwidth demand a distributed algorithm using local information.

Recent studies [5]–[9] focus on distributed scheduling policies that have a provable efficiency ratio. However, most of these policies have a non-constant time requirement to compute a single schedule: the computation time increases with the network size. For instance, the maximal matching scheduling policy (MM), whose efficiency ratio is at least 1/2 [5], requires $O(\log^2 N)$ computations [16]. Lin and Rasool have recently proposed a constant-time scheduling policy that completes its scheduling after a fixed number of rounds [6]. This policy is proven to achieve an efficiency ratio up to 1/3. However, simulations demonstrate that there is often a significant performance gap between it and GMM.

Another class of distributed scheduling schemes called Pick-and-Compare have recently been developed [3], [10], [11] to achieve 100% throughput. Their centralized version was first proposed in [17]. At each scheduling decision, these schemes compare the matching served in the previous schedule with a new matching, which is randomly chosen. Between two matchings, the matching with the larger queue weighted rate sum is served as the next schedule. Since the scheduling solutions of this class keep improving their schedules, they eventually achieve the optimal capacity region. However, they usually require high computational complexity and/or long convergence time [18], rendering them impractical.

Under the two-hop interference model, finding the optimal scheduling policy is NP-hard [19]. Recent studies [7], [8], [12] have developed distributed scheduling solutions, but they also require non-constant time to compute a schedule. The goal of this paper is to develop an efficient distributed constant-time scheduling scheme that outperforms the state-of-the-art.

\(^1\)MWM solves (1) using exhaustive search.

\(^2\)GMM chooses the largest $\tau_{ij}$ first. At each schedule, it includes link $l$ that has the largest $\tau_{ij}$ and excludes links within $l$’s interference range. For the remaining (neither included nor excluded) links, it repeats the include–exclude procedure until no link remains.

The paper is organized as follows. We begin with the description of our system model and overview previous constant-time scheduling policies in Section II. Motivated by these, we develop a new scheduling policy and analyze it in Section III. The proposed policy is extended to the two-hop interference model in Section IV. We evaluate several policies with single-hop and multi-hop flows under both node-exclusive and two-hop interference model in Section V. We conclude the paper in Section VII.

II. SYSTEM MODEL

In multi-hop wireless networks with $N$ nodes and $L$ links, a link $l$ consists of two nodes $s(l)$ and $r(l)$. Let $E(i)$ denote the set of links connected to node $i$, and $N(l)$ denote the set of neighboring links sharing a common node with link $l$, that is, $N(l) = E(s(l)) \cup E(r(l)) \setminus \{l\}$. In addition, let $N(l)^+ \subset N(l)^+ \subset N(l)^+$ denote the number of links in $N(l)$ and $N(l)^+$, respectively.

We assume that all links are synchronized and start a frame at the same time. Each frame consists of a contention period of $M$ slots and a transmission period for actual packet transmission. We reserve the term slot to indicate a unit time in the contention period. Each link can contend in a frame or remain idle, skipping to the next frame. If a link participates in contention in a frame, it attempts transmission at a slot in a probabilistic manner.

We consider two interference models in this paper: the node-exclusive and the two-hop interference model. The node-exclusive interference model does not allow any two links sharing a common node to transmit at the same time. If this happens, a collision is said to occur and the frame is discarded. The two-hop interference model does not allow any two-hop neighboring links to transmit at the same time. We begin with the node-exclusive interference model due to its simplicity, and extend our analysis to the two-hop interference model.

A. Policy $P$

We refer to the constant-time distributed scheduling scheme proposed in [6] as policy $P$. This policy is proven to have an efficiency ratio of at least $1/3 - 1/M$. Under policy $P$, each link $l$ contends in a frame with a probability $x_l$, which is given by

$$x_l = \frac{Q_l/c_l}{\max_k \left( \sum_{k \in E(s(k))} Q_k/c_k, \sum_{k \in E(r(k))} Q_k/c_k \right)} \quad (3)$$

where $Q_l$ is the queue length of link $l$ and $c_l$ is the number of packets can be transmitted in a frame time. Let $\mathcal{E}$ denote the vector $[x_1 c_1, x_2 c_2, \ldots, x_L c_L]$. Once a link decides to contend in a frame, it randomly picks a slot and attempts transmission at the slot if no neighboring link is already transmitting. In case that more than two neighboring links attempt transmission at the same slot, a collision occurs and the frame is discarded. Since the conditional probability of successful transmission provided a link $l$ attempts is at least $1/3 - 1/M$, the successful transmission probability $P_S^l$ can be written as

$$P_S^l \geq x_l \left( \frac{1}{3} - \frac{1}{M} \right). \quad (4)$$
We use the following lemma [6] to estimate the efficiency ratio of a scheduling policy.

**Lemma 1:** If a scheduling policy satisfies $P^l_S \geq x_l \cdot \gamma$ for all $l \in L$ and a constant $\gamma \in [0, 1]$, then the system is stable under the scheduling policy for all $\gamma \in \eta \Psi$.

See the Appendix for the proof.

From Lemma 1 and (4), we obtain

$$\gamma_p \geq \frac{1}{3} - \frac{1}{M}. \quad (5)$$

### B. An Equivalent Modification

Now, let us consider a policy $\hat{P}$ which results in an equivalent bound on the efficiency ratio of $P$. This policy will be used to obtain more efficient scheduling policies.

**Policy $\hat{P}$:** All links contend in every frame and attempt transmission at each slot with probability $x_l/M$ if no neighboring link is already transmitting.

The difference from policy $P$ is that links under policy $\hat{P}$ contend in every frame and attempt transmission at each slot with probability $x_l/M$. In contrast, links under policy $P$ contend with probability $x_l$ and attempt transmission at a randomly chosen slot among $M$ slots.

**Proposition 2:** The efficiency ratio $\gamma_p$ is no less than $1/3 - 1/M$.

**Proof:** Let $P^l_S[m]$ denote the successful transmission probability of link $l$ at time slot $m$. $P^l_S[0]$ is the product of link $l$’s attempt probability and the probability that neighboring links will not attempt transmission at the first slot, that is,

$$P^l_S[0] = \frac{x_l}{M} \cdot \prod_{k \in N(l)} \left(1 - \frac{x_k}{M}\right).$$

At $m = 1$, $P^l_S[1]$ is the product of the probability that no link in $N(l)^+$ attempts transmission at $m = 0$, the attempt probability of link $l$ at $m = 1$, and the probability that other neighbors $k \in N(l)$ do not attempt transmission at $m = 1$. This will be the same as $P^l_S[0]$ with the additional product of “non-attempt probabilities” of all links in $N(l)^+$ at $m = 0$, that is,

$$P^l_S[1] = \frac{x_l}{M} \cdot \prod_{k \in N(l)} \left(1 - \frac{x_k}{M}\right) \cdot \left[\prod_{k \in N(l)^+} \left(1 - \frac{x_k}{M}\right)\right].$$

Similarly, $P^l_S[m]$ can be written as

$$P^l_S[m] = \frac{x_l}{M} \cdot \prod_{k \in N(l)} \left(1 - \frac{x_k}{M}\right) \cdot \left[\prod_{k \in N(l)^+} \left(1 - \frac{x_k}{M}\right)\right]^m.$$

Using $(1/1 - x_l/M) \geq 1$ and $(1 - x_k(1/M))^{m+1} \geq (1 - x_k(M + 1/M))$, we obtain

$$P^l_S[m] \geq \frac{x_l}{M} \cdot \prod_{k \in N(l)^+} \left(1 - \frac{x_k^{m+1}}{M}\right). \quad (7)$$

Since (7) is exactly the same equation as in [6], we apply the same analysis for obtaining the successful transmission probability $P^l_S$, i.e.,

$$P^l_S = \sum_{m=0}^{M-2} P^l_S[m] \geq \sum_{m=0}^{M-1} \left[\frac{x_l}{M} \cdot \prod_{k \in N(l)^+} \left(1 - \frac{x_k^{m+1}}{M}\right)\right].$$

$$= \sum_{m=0}^{M-1} \left[\frac{x_l}{M} \cdot \prod_{k \in N(l)^+} \left(1 - \frac{x_k^{m+1}}{M}\right)\right] - \frac{x_l}{M}.$$

Comparing with $\prod_{k \in N(l)^+} (1 - x_k u)$, which is a monotonic decreasing function of $u \in [0, 1]$, the summation is bounded by the following integral:

$$P^l_S \geq x_l \int_{0}^{1} \prod_{k \in N(l)^+} (1 - x_k u) du - \frac{x_l}{M}.$$

We also apply the following inequality, which can be validated by comparing the derivatives:

$$\prod_{k \in N(l)^+} (1 - x_k u) \geq (1 - u)^{H_l},$$

where $H_l = \sum_{k \in N(l)^+} x_k$, we obtain

$$P^l_S \geq x_l \int_{0}^{1} (1 - u)^{H_l} du - \frac{x_l}{M} \geq x_l \left(\frac{1}{H_l + 1} - \frac{1}{M}\right).$$

From (3),

$$H_l = \sum_{k \in N(l)^+} x_k \leq \sum_{k \in E(\alpha(l))} x_k + \sum_{k \in E(\gamma(l))} x_k \leq 2. \quad (8)$$

Hence, we obtain

$$P^l_S \geq x_l \left(\frac{1}{3} - \frac{1}{M}\right).$$

Then, from Lemma 1, we obtain

$$\gamma_p \geq \frac{1}{3} - \frac{1}{M}.$$ \quad (9)

### III. CONTROLLING THE ATTEMPT PROBABILITY

We propose an enhanced scheduling policy whose complexity is not affected by the link degree (like policies $P$ and $\hat{P}$) and which also achieves an efficiency ratio of $1/2$ for large $M$.

**Policy $V$:** Policy $V$ is identical to policy $\hat{P}$, except that each link attempts transmission with probability of $\alpha(x_l/M)$ instead of $x_l/M$, where

$$\alpha = \sqrt{M - 1} / 2.$$
The detailed algorithm is illustrated in Algorithm 1.

**Algorithm 1 Policy $V$**

At each frame, each link does the following procedure.

1: $sched \leftarrow 0$
2: for each contention slot do
3:  if $sched = 0$ then
4:    attempt transmission with probability $x_l(\sqrt{M} - 1/2M)$
5:  if attempt at this slot then
6:    $sched \leftarrow 1$
7:  end if
8:  if overhear neighbors’ transmission then
9:    $sched \leftarrow (-1)$
10: end if
11: end if
12: end for
13: if $sched = 1$ then
14:  transmit data packets during the transmission period
15: end if

Letting $G_l(\alpha, M) = (1 - (\alpha H_l/M))$, the inequality can be rewritten as

$$ P_S^k \geq \alpha \frac{x_l}{M} \sum_{m=0}^{M-1} G_l(\alpha, M)^{m+1} $$

$$ = \frac{x_l}{M} \sum_{m=0}^{M} G_l(\alpha, M)^{m} - 1 $$

$$ = \frac{x_l}{M} \left( \frac{1 - G_l(\alpha, M)^{M+1}}{1 - G_l(\alpha, M)} - 1 \right) $$

$$ \geq \frac{x_l}{M} \left( \frac{M}{\alpha H_l + 1} - 1 \right) . \tag{11} $$

For the last inequality in (11), we need to prove that

$$ \frac{1 - (1 - \alpha H_l/M)^{M+1}}{1 - (1 - \alpha H_l/M)^{M+1}} \geq \frac{M}{\alpha H_l + 1}. $$

Multiplying $\alpha H_l/M$ on both sides and rearranging the equations, we obtain the following equivalent inequality:

$$ \left( 1 - \frac{\alpha H_l}{M} \right)^{M+1} \leq \frac{1}{\alpha H_l + 1}. \tag{12} $$

The following provides the details to show the inequality (12). Defining a function $F(z)$ with $0 < z < M$ as

$$ F(z) = (z + 1) \left( 1 - \frac{z}{M} \right)^{M+1} $$

and differentiating it by $z$, we obtain

$$ \frac{dF(z)}{dz} = - \left( 1 - \frac{z}{M} \right)^{M} \left( z + 2 \frac{z}{M} + 1 \right). $$

Since $(dF(z)/dz) < 0$ for $z \in (0, M)$ and $F(0) = 1$, we have $F(z) \leq 1$ for all feasible $z$. After replacing $z$ with $\alpha H_l$, we obtain inequality (12).

Now, from (8) and (11), we obtain

$$ P_S^k \geq x_l \left( \frac{\alpha}{2 \alpha + 1} - \frac{\alpha}{M} \right). $$

Since this inequality holds for an arbitrary $\alpha \in (0, (M/2))$, we can maximize the lower bound by differentiating it by $\alpha$.

$$ P_S^k \geq x_l \left( \frac{\sqrt{M} - 1}{2M} \right) $$

$$ \geq x_l \left( \frac{1}{2} - \frac{1}{\sqrt{M}} \right) . \tag{13} $$

when

$$ \alpha = \frac{\sqrt{M} - 1}{2}. \tag{14} $$

Since $\alpha = (\sqrt{M} - 1/2)$, we confirm that $\alpha \in (0, (M/2))$ for any integer $M > 1$. From Lemma 1 and (13), the efficiency ratio $\gamma_V$ is bounded by $1/2 - 1/\sqrt{M}$. 

Proposition 3: The efficiency ratio $\gamma_V$ of policy $V$ is bounded by

$$ \gamma_V \geq \frac{1}{2} - \frac{1}{\sqrt{M}}. \tag{10} $$

Proof: We begin with the analysis of policy $\hat{P}$ except using attempting probability $\alpha(\xi_t/M)$ instead of $\xi_t/M$. We assume that $\alpha$ is an arbitrary real number in $(0, (M/2))$. We will later confirm that the $\alpha$ obtained to guarantee the efficiency ratio in the proposition will lie in $(0, (M/2))$.

From (6), the successful transmission probability of link $l$ can be written as

$$ P_S^k \geq \sum_{m=0}^{M-1} \frac{\alpha x_l/M}{1 - \alpha x_l/M} \left[ \prod_{k \in N(l)^+} \left( 1 - \frac{x_k}{M} \right) \right]^{m+1} $$

$$ \geq \sum_{m=0}^{M-1} \frac{x_l}{M} \left[ \prod_{k \in N(l)^+} \left( 1 - \frac{x_k}{M} \right) \right]^{m+1} $$

because $\alpha(x_l/M) \leq 1$. Letting $H_l = \sum_{k \in N(l)^+} x_k$, we have

$$ \prod_{k \in N(l)^+} \left( 1 - \frac{x_k}{M} \right) \geq 1 - \frac{\alpha H_l}{M}. $$

Note that $(1 - (\alpha H_l/M)) \geq 0$ from (8) and $\alpha \in (0, (M/2))$. 

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Remarks: Essentially, policy $V$ achieves the performance improvement over policy $P$ by controlling the attempt probability through the parameter $\alpha$. However, the control cannot be implemented in the framework of policy $P$. In policy $P$, each link contends within a frame with a probability $x_t$, and links participating in the contention choose a slot with probability $1/M$. To use the framework of policy $P$, each link has to contend with probability $\alpha x_t$ or contending links should pick a slot with probability $\alpha/M$. The former method is not possible because $\alpha x_t$ can be larger than 1, which is meaningless. The latter method cannot accomplish an efficiency ratio of (10) either because it reduces the probability of successful transmission by restricting the number of slots to $M/\alpha$ rather than $M$.

Another difference between the policies is in the distribution of the attempt probability. We clarify the difference by comparing their attempt probability and corresponding conditional attempt probability, which is defined as the attempt probability of a link at slot $m$ given that there is no attempt in its neighborhood up to $m - 1$ slots. Note that policy $P$ has a uniform distribution of the attempt probability over slots as shown in Fig. 1(a). This is equivalent to an exponentially increasing distribution of the conditional attempt probability as shown in Fig. 1(b). Hence, in the later part of the contention period, links attempt with a high probability, which often leads to a collision. For example, at the very last slot, if there are more than two links that are eligible for an attempt, they will attempt with probability 1 resulting in a collision. On the other hand, policy $V$ has a uniform distribution of the conditional attempt probability as shown in Fig. 2(b) and thus the collision rates are controlled at the same level over all contention slots. Note that the corresponding attempt probability is geometrically distributed as shown in Fig. 2(a). This implies that in practical implementation, it does not need to generate a random number at every slot. Instead, at the beginning of a frame, it randomly picks a slot with the geometric distribution. Note that there is a non-zero probability that a link does not attempt transmission within each frame.

In summary, Policy $P$ makes a two-level decision using a uniform attempt probability. The two-level decision prevents it from scaling the attempt probability. Policy $\hat{P}$ differs from Policy $P$ in that it has a uniform “conditional” attempt probability. Policy $V$ differs from Policy $\hat{P}$ by scaling the conditional attempt probability using $\alpha$, which enables it to achieve a higher probability of successful transmission.

We now extend our analysis to include the overhead caused by the contention period. Since each slot takes time, increasing $M$ to infinity is not realistic. Let $s$ denote the fraction of time of a single contention slot compared to the whole frame, that is, $sM$ is the total contention period when the frame time is 1. Given $s$, we optimize $M$. Note that the choice of $s$ does not affect the successful transmission probability $P^*_S$. Therefore, (13) and (14) still hold to bound the optimal performance. However, since the actual transmission rate is reduced from $q_1P^*_S$ to $q_1(1-sM)P^*_S$, the effective successful transmission probability can be represented as

$$\text{effective } P^*_S \geq a_1 \left(\frac{1}{2} - \frac{1}{\sqrt{M}}\right)(1-sM).$$

Then, the cost-deducted efficiency ratio $\gamma^*_V$ will be

$$\gamma^*_V \geq \left(\frac{1}{2} - \frac{1}{\sqrt{M}}\right)(1-sM) \geq \frac{1}{2} \cdot \frac{(\sqrt{M} - 2)^2}{\sqrt{M}(\sqrt{M} - 1)}. \quad (15)$$

The last inequality is obtained by differentiating by $M$, and the equality holds when $sM = \frac{1}{\sqrt{M} - 1}$. \quad (16)

The lower bound of (15) still converges to 1/2 as $M$ increases to infinity, i.e., as $s$ decreases to 0. We denote the number of slots satisfying (16) by $M^*$.

IV. TWO-HOP INTERFERENCE MODEL

The node-exclusive interference model is simple and is a good representation of Bluetooth and FH-CDMA networks. However, the two-hop interference model is more appropriate in characterizing the IEEE 802.11 DCF networks. It is known

Fig. 1. Attempt probability of policy $P$ over contention slots. (a) Attempt probability. (b) Conditional attempt probability.

Fig. 2. Attempt probability of policy $V$ over contention slots. (a) Attempt probability. (b) Conditional attempt probability.
that policy $P$ can be extended to the two-hop interference model [6].

**Policy Q**: Use the same framework as policy $P$, but each link contends with probability

$$\frac{Q_l / c_l}{\max_{k \in N(l)^+} \sum_{k \in N(l)^+} Q_h / c_h} \times \min \left( 1, \frac{A}{\max_{k \in N(l)^+} n_k^+} \right)$$

where $A$ is a positive number between 1 and $\hat{n} = \max_{k \in L} n_k^+$. The link that decided to contend randomly picks a slot and attempts transmission, as in policy $P$.

The extended policy $Q$ is proven to achieve an efficiency ratio of at least $(1/\hat{n} + 1) - (1/M)$.

In the two-hop interference model, the restriction on the capacity region is changed to

$$\psi' = \left\{ \lambda \mid \sum_{k \in N(l)^+} \frac{\lambda_k}{c_k} \leq 1, \text{ for all } l \right\}.$$  

Using similar techniques as in the node-exclusive interference model, it is proven in [6] that the optimal capacity region is within $[\bar{y}^*, \overline{\bar{y}}^*]$, where $\bar{y} \leq \overline{\bar{y}}^*$ and

$$y_l = \frac{Q_l / c_l}{\sum_{k \in N(l)^+} Q_h / c_h}.$$  

**Policy W**: Use the same framework as policy $V$, but each link now attempts transmission with probability of $\beta(y_l / M)$, where

$$\beta = \frac{\sqrt{M - 1}}{\hat{n}}.$$  

**Proposition 4**: The efficiency ratio of policy $W$ is bounded by

$$\gamma_w \geq \frac{2}{\hat{n}} \left( 1 - \frac{1}{\sqrt{M}} \right) - \frac{1}{2} - \frac{1}{\sqrt{M}}.$$  

Note that the bound also approaches $1/\hat{n}$, the performance bound of the centralized GMM scheme in the two-hop interference model [8].

**Proof**: Let $N_2(l)^+$ denote the set of two-hop neighbors of the link $l$ and link $l$ itself. Assuming that $\beta \in (0, (M/\hat{n}))$, the successful transmission probability is given as

$$P_s^I \geq \frac{\beta y_l}{M} \left( \sum_{m=0}^{M-1} \left( 1 - \frac{\beta}{M} \sum_{k \in N_2(l)^+} y_k \right)^m \right)^{m+1}.$$  

Letting $H'_I = \sum_{k \in N_2(l)^+} y_k$ and $G'_I(\beta, M) = (1 - (\beta H'_I / M))$, we can obtain

$$P_s^I \geq \frac{\beta y_l}{M} \left( 1 - \frac{1 - G'_I(\beta, M)^{M+1}}{1 - G'_I(\beta, M)} \right).$$  

For each link $l$, the sum of the attempt probability of links in $N_2(l)^+$ is bounded by

$$H'_I = \sum_{k \in N_2(l)^+} y_k \leq \sum_{k \in N_2(l)^+} \sum_{h \in N(k)^+} y_h \leq \sum_{k \in N(l)^+} 1 = n_l^+ \leq \hat{n}.$$  

Hence, along with $\beta \in (0, (M/\hat{n}))$, we have $(\beta H'_I / M) \leq 1$. From (12), (18), and (19), we obtain

$$P_s^I \geq \frac{\beta y_l}{M} \left( 1 - \frac{\beta}{\hat{n} + 1} \right).$$

Differentiating by $\beta$, we obtain the bound on the successful transmission probability to be

$$P_s^I \geq \gamma_w = \frac{2}{\hat{n}} \left( 1 - \frac{1}{\sqrt{M}} \right)$$

when

$$\beta = \frac{\sqrt{M - 1}}{\hat{n}}.$$  

Accounting for the overhead caused by the contention period, the same analysis as policy $V$ can be applied. Since the slot overhead $s$ does not affect the successful transmission probability but the actual transmission rate, we can obtain the effective successful transmission probability as

$$effective P_s^I \geq \gamma_w \left( 1 - sM \right).$$

Then, the cost-deduced efficiency ratio $\gamma_w$ is bounded as

$$\gamma_w \geq \frac{1}{\hat{n}} \cdot \frac{(\sqrt{M - 2})^2}{\sqrt{M} \sqrt{M - 1}}.$$  

when (16) is satisfied.

V. SIMULATION RESULTS

In this section, we evaluate scheduling policies through simulations. We first simulate with single-hop traffic in a grid topology. This simple scenario is aimed at clearly presenting and understanding the basic behavior of the various scheduling policies. We then show the effectiveness of our policies in a large random topology where nodes are randomly placed in space. Finally, we use multi-hop traffic in a random network topology to evaluate different scheduling policies including IEEE 802.11b DCF.
We first compare policies in a grid topology network assuming Poisson traffic arrivals. The grid network consists of 16 nodes and 24 links, as shown in Fig. 3. Each node is represented by a circle with a unique number and each link is illustrated by a dashed line with a label representing the link capacity. The solid line with arrows indicate single-hop poisson traffic with an identical unit rate (two solid lines for the rate of two units). We assume that all flows traverse a single hop. While all traffic streams have the same rate, the link capacities differ and flows are chosen to avoid uniform patterns. For comparison purposes, the simulation details are kept the same as in [6].

We use the performance of the centralized GMM as a reference value. We compare the performance of policies $P$ and $V$ for the node-exclusive interference model, and policies $Q$ and $W$ for the two-hop interference model.

Fig. 4 shows the performance of each policy in terms of the total queue lengths over the entire network. Note that MWM and GMM show the almost same performance. While GMM is proven to have the efficiency ratio of 1/2 in the worst case, its actual performance is much better and close to the optimal in most practical scenarios, where the worst case does not happen due to arbitrariness in the network topology and traffic patterns [20]. Hence, in the rest of the paper, we compare the performance of policies $P$, $Q$, $V$, and $W$ with GMM instead of the optimal MWM.

The performance of all the distributed policies shown in Fig. 4 has improved with a larger number of slots $M$. As the number of contention slots increases, queues remain stable for larger traffic loads, due to reduced collision. However, the performance of policies $P$ and $Q$ stops increasing beyond a certain threshold of traffic load, which is far away from that of GMM. In contrast, the performance of policies $V$ and $W$ keeps increasing and getting closer to that of GMM with increasing $M$. Note that the improvement in empirical results is more remarkable than in the analytical results. This is because the analytical results are about the worst case performance while the simulation results show average performance.

In the following experiments, we compare the performance of policies $V$ and $W$ accounting for the overhead of the contention period. Fig. 5(a) and (b) show that the performance of policies $V$ and $W$, respectively, can be degraded over a certain threshold.
of \( M \) due to excessive overhead of the contention period. It is observed in our simulations that the capacity region increases until \( M = 128 \) for policy \( V \) (\( M = 512 \) for policy \( W \)) but shrinks back with more slots. On the other hand, policies \( V \) and \( W \) with \( M^* \) achieve higher performance with smaller \( s \) as shown in Fig. 5(c) and (d), where \( M^* \) is the number of slots satisfying (16).

Next, we examine the sensitivity of the control parameters \( \alpha \) and \( \beta \). Since the bounds given in (10) and (17) are conservative in that they are based on the worst case analysis of the network topology and traffic patterns, the average performance will be much better in most network scenarios. We test the effect of non-optimal parameters on the performance of policies \( V \) and \( W \). We also denote \( \alpha_{\text{opt}} \) and \( \beta_{\text{opt}} \) to be the optimal parameter obtained from (14) and (21), respectively.

Simulations using the grid topology demonstrates that a few multiple of \( \alpha_{\text{opt}} \) (or \( \beta_{\text{opt}} \)) is acceptable and usually leads to a larger capacity region as shown in Fig. 6. Policy \( V \) with \( \alpha = 4 \alpha_{\text{opt}} \) (or policy \( W \) with \( \beta = 16 \beta_{\text{opt}} \)) keeps queues stable with a heavier load than the policy with \( \alpha = \alpha_{\text{opt}} \) (or \( \beta = \beta_{\text{opt}} \)). However, excessively large \( \alpha \) (or \( \beta \)) results in inefficiency due to high collision rate.

Fig. 7(a) and (b) illustrate the change of the performance bounds by varying \( \alpha \) and \( \beta \), respectively, for different values of \( M \). At each \( M \), the highest bound is achieved at \( \alpha_{\text{opt}} \) and \( \beta_{\text{opt}} \), which increases on the order of square root of \( M \). Using this, we can configure the scheduler with non-optimal \( \alpha \) and \( \beta \) parameters at the expense of the guaranteed bound. For instance, we can set \( \alpha = 8.08 \) to guarantee an efficiency ratio of 1/3 when \( M = 64 \), while policy \( V \) has an optimal performance bound of 0.3828 with \( \alpha_{\text{opt}} = 3.5 \).

The non-optimal settings of \( \alpha \) and \( \beta \) are useful because policies \( V \) and \( W \) with a little higher \( \alpha \) and \( \beta \) can often achieve higher performance than with \( \alpha_{\text{opt}} \) and \( \beta_{\text{opt}} \) as shown in Fig. 6. The reason for this is in that we estimate \( \alpha_{\text{opt}} \) and \( \beta_{\text{opt}} \) based on the worst case scenario. When a link \( l \) attempts in a slot \( m \), we implicitly assumed that all its neighbors may attempt in slot \( m \) too. However, in many cases, some of the neighbors, e.g., link \( k \), do not attempt because they have already overheard an attempt of their own neighbors (which is not a neighbor of link \( l \)) in a slot within \([0, m - 1]\). Then, since link \( k \) does not attempt, link \( l \) can achieve a higher probability of successful transmission with

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Fig. 5. Performance of policies \( V \) and \( W \) accounting for the contention overhead. (a) Policy \( V \) with a fixed \( s = 2^{-10} \); (b) policy \( W \) with a fixed \( s = 2^{-12} \); (c) policy \( V \) with \( M^* \); (d) policy \( W \) with \( M^* \).
a higher attempt probability. Note that this scenario more likely occurs when links have more neighbors, i.e., as the network has a larger node-degree. For this reason, we use non-optimal setting in the following simulations under a large random network topology.

We next simulate scheduling policies in a large random network topology. The topology is generated by randomly locating 200 nodes on a $1 \times 1$ square space. A link is established between nodes if their distance is less than 0.1. A total of 570 links are established. Each link can transmit packets during a frame time, where $C_l$ is a randomly chosen integer within $[5, 10]$. All generated traffic traverses a single link. The packet arrivals of each flow follow a Poisson distribution with $\lambda_t$ (packets per frame), where $\lambda_t$ is randomly chosen between 0 (with probability 0.2), 1 (with probability 0.6), and 2 (with probability 0.2). The number of contention slots $M$ of random access scheduling policies is set to 128 for the node-exclusive interference model and to 1024 for the two-hop interference model.

The simulation results presented in Fig. 8 clearly show that policies $V$ and $W$ outperform policies $P$ and $Q$, respectively, as in the grid topology. Note that policy $W$ with $\beta = \beta_{opt}$ shows almost the same performance as policy $Q$ while policy $W$ with $\beta = 4\beta_{opt}$ achieves better performance. The reason for achieving better performance with non-optimal parameters has already been explained. However, it is an interesting question as to why the gap is so large for the random network topology under the two-hop interference model, and how to set non-optimal parameters in practice. The first question can be answered by the fact that the number of neighbors significantly increases in the random network topology under two-hop interference model. Comparing with the node degree of 4 in the grid topology in Fig. 3, the maximum node degree of the random network graph is 13. Moreover, the number of neighbors of a link under the two-hop interference model is at most as large as the square of the number of neighbors under the node-exclusive interference model. This implies that the worst case scenario is much less likely in the random topology under the two-hop interference model, and a higher attempt probability will improve the performance in many cases.

Note that the performance can also be improved by increasing $M$ further. However, the contention slots are not free, as shown in Fig. 5, and in practice should have some upper bound $\frac{M}{\lambda} \gg 1$. 
If policy $W$ with $\beta = \beta_{\text{opt}}$ and $M = \bar{M}$ has unsatisfactory performance, the non-optimal $\beta$ is recommended. Let $\beta = c\beta_{\text{opt}}$ where $c \geq 1$ is a constant. Setting $c$ satisfying $c \ll \sqrt{\bar{M}}$, the decrease of the guaranteed performance bound will be negligible.

From (20), we obtain

$$\gamma_{w} \geq \frac{c\beta_{\text{opt}}}{c\beta_{\text{opt}} + 1} - \frac{c\beta_{\text{opt}}}{\bar{M}} \approx \frac{1}{\bar{n}} \left( 1 - \frac{c}{\sqrt{\bar{M}}} \right) \approx \frac{1}{\bar{n}} \left( 1 - \frac{1}{\sqrt{\bar{M}}} \right)$$

when $\bar{n} \gg 1$. In our simulations, we set $\bar{M} = 1024$ as the maximum number of contention slots used in the current IEEE 802.11b DCF technology, and set $c = 4$. With this setting, the performance guarantee decreases by 7.1% when $\bar{n} = 25$ ($= 2 \times (\text{max. node degree}) - 1$), but average performance gain is significant as shown in Fig. 8(b). Note that Fig. 6 can also be used as the guideline. Operators can set $c$ based on their own tolerance level on the guaranteed performance.

In the next experiments, we evaluate the performance of scheduling policies with multi-hop flows. We establish five multi-hop flows on a random network topology with 120 nodes. (Maximum node degree is 9 and more than 250 links are established.) The source and the destination of each flow are randomly chosen. Fig. 9(a) and (b) show the simulation results under the node-exclusive interference model and under the two-hop interference model, respectively. As in the previous simulations with single-hop flows, the performance of policy $V$ and $W$ are also close to that of the centralized GMM.

Finally, we compare policy $W$ with the existing IEEE 802.11b DCF using NS-2 simulator. Default settings are used with RTS/CTS enabled. The queue size (IFQ) at each node is
set to 100 packets. Physical link rate is set to 2 Mbps and the packet size is 1460 bytes. We randomly place 100 nodes in 1200 \times 1200 m space, and establish five multi-hop UDP flows, whose source and destination are chosen at random. DSDV routing protocol is used.

Policy W is implemented as an asynchronous algorithm by modifying IEEE 802.11b DCF accordingly. That is, it operates as IEEE 802.11b DCF except that i) the size of congestion window (CW) is fixed to 1024 without exponential backoff procedure, ii) at the beginning of a frame, each node can obtain the queue information of its neighbors, and iii) at each contention slot, a node attempts with probability of \( \beta(q_t/M) \) with \( \beta = 4/3M \). If a node did not attempt for all 1024 slots, the node updates the queue information of its neighbors and starts another frame, i.e., another contention period of 1024 slots. Note that in this asynchronous variation of policy W, when a node overhears its neighbor’s attempt (RTS or CTS), the node avoids a collision by freezing its contention during the transmission period instead of discarding the frame.

Fig. 10 shows the simulation results for 1000 seconds. It is clear that policy W significantly outperforms IEEE 802.11b DCF.

VI. DISCUSSION

We have focused on the throughput as a measure of performance of the scheduling schemes. However, there are also other important performance metrics such as delay and fairness that are beyond the scope of this paper. It should be noted though that our constant-time random access scheme empirically performs better than a class of scheduling schemes called Pick-and-Compare. Pick-and-Compare scheduling schemes in theory achieve the optimal capacity region [18]. At each time, they pick a schedule at random, compare it with previous schedule, and select the better one as next schedule. In this way they eventually find throughput-optimal schedule. However, since it takes long to find the schedule, they often have very poor delay performance, and significant loss of throughput because of the communication overhead. On the other hand, our random access scheduling schemes provide a suboptimal schedule by favoring links to serve that have longer queues. Since it chooses links based on the queue length, it is likely to achieve better delay performance. It is in general an open interesting question to study the precise delay performance of random access scheduling schemes.

Regarding the fairness issue, it might occur that under our queue-based scheduling scheme a link with very large queue length occupies the channel for a long time making others starve, which results in prevention of real-time applications from being served. However, we believe that the right way to handle this is not to make the scheduler fair, but rather to couple it with a congestion control element at the transport layer. That is, a flow whose path goes through a link with a large queue length should be controlled to reduce its rate so that other flows can share the network resources. The methodology for implementing congestion control and scheduling has been used extensively in the literature [1], [2], [4], [5], and we leave this as future work.

Another interesting problem in the case of multi-hop wireless scheduling is how to schedule links with time-varying wireless channels. Since recent wireless technology allows wireless links to adaptively change their rate based on received power level, interference, etc., considering time-varying links is of an important practical consideration. Under the time-varying rate assumption, our queue-based scheduling schemes may not provide the best solution, and an opportunistic scheduling mechanism may be needed to achieve higher throughput by serving links with higher rate. However, in order to achieve a larger capacity region, the queue length needs to be taken into account because it provides some information about the arrival rates. To this end, it is a very challenging and interesting problem of how to develop low-complexity scheduling schemes achieving high throughput performance under time-varying channel environments.

VII. CONCLUSION

For multi-hop wireless networks, a cross-layer approach with an appropriately chosen suboptimal scheduling component usually outperforms the layered approach [5]. However, it is important for the scheduling component to achieve a provable efficiency ratio in order to guarantee good performance. A higher efficiency ratio implies better performance.

In [6], a recent constant-time distributed scheduling policy has been developed and shown to have an efficiency ratio of \( 1/3 - 1/M \) for the node-exclusive interference model. This solution trades off complexity and performance. In addition, the bound is not a function of the network topology, i.e., the bound is not affected by the number of contending links \( \hat{n} \) in a local neighborhood. However, the policy still has a significantly lower bound than the 1/2 of the centralized GMM. The performance difference is also confirmed by empirical results.

In this paper, we propose a new constant-time distributed scheduling policy that not only retains the good features of the performance bound, i.e., the independence from the network topology, but also increases the lower bound on the efficiency ratio to \( 1/2 - 1/\sqrt{M} \) under the node-exclusive interference...
model. Its gain essentially comes from the control of links’ attempt probability separated from $M$ and the geometric distribution of the attempt over contention slots. Our policy is also extended to the two-hop interference model.

We evaluate several policies evaluated through extensive simulations using both grid topology and random topology. With single-hop flows, it is verified our policy outperforms the state-of-the-art scheduling policy, and actually achieves a capacity region comparable to the centralized GMM. Even after accounting the loss due to overhead of the contention period, we still find an optimal contention window size that achieves good performance, and show that the policy achieves better capacity as the cost of a unit slot decreases.

We note that as the local neighborhood of the network expands, the worst case scenario occurs less likely and that in practice non-optimal (from a worst case performance bound point of view) parameters can be set to improve average performance. The effectiveness of the non-optimal settings are confirmed by simulations with a large random topology under the two-hop interference model.

The performance of distributed scheduling policies with multi-hop flows is also evaluated including the IEEE 802.11b DCF, and the results show that our policy outperforms this and other distributed solutions.

APPENDIX

A. Proof of Lemma 1

Following the technique of [6], we define length and normalization of a vector. Note that given queue length, the successful transmission probability is bounded by $P_S \geq x_i \cdot \eta$. Using this, we show that the service rate of each link is no smaller than the normalized queue length. Since it holds for all links, we can find a Lyapunov function that has a negative drift if the offered load is strictly inside $\Psi$, where $\Psi = \{ \sum_{k \in E(i)} (\lambda_i/c_i) \leq 1, \text{for all nodes } i \}$. This implies that the system is stable under the offered load.

We first define the length of a vector $\mathbf{z}$ as

$$
\| \mathbf{z} \| = \inf \{ k | k \geq 0, k \mathbf{z} \in \Psi \}.
$$

Note that for two vectors $\mathbf{z}, \mathbf{b}$ and a non-negative constant $c$, the length satisfies $|\| \mathbf{z} + \mathbf{b} \| | \leq |\| \mathbf{z} \| | + |\| \mathbf{b} \| |$ and $|\| c \mathbf{z} \| | = c |\| \mathbf{z} \| |$. We also define the normalized vector as

$$
\tilde{\mathbf{z}} = \frac{\mathbf{z}}{\| \mathbf{z} \|}.
$$

Let $\tilde{Q}(t)$ denote the normalized vector of the queue length $Q(t)$. From (24), it is clear that $\| \tilde{Q}(t) \| = 1$ if $\tilde{Q}(t) \neq 0$. Then, since $\tilde{Q}(t)$ is on the boundary of $\Psi$, it has to satisfy

$$
\sum_{i \in E(i)} \frac{Q_i(t)}{c_i} \| \tilde{Q}(t) \| \leq 1, \text{for all nodes } i,
$$

from the definition of $\Psi$. After rearranging the inequality, we obtain

$$
\frac{1}{\| \tilde{Q}(t) \|} \leq \sum_{i \in E(i)} \frac{Q_i(t)}{c_i}, \text{for all nodes } i
$$

$$
\leq \frac{1}{\max_i \sum_{i \in E(i)} \frac{Q_i(t)}{c_i}}.
$$

From (3), it follows

$$
x_i(t)c_i \geq \frac{Q_i(t)}{\| \tilde{Q}(t) \|} = Q_i(t), \text{ for all links } i
$$

Now, we define the fluid model as in [21]. Let $A_l(t)$ and $D_l(t)$ denote the number of arrivals and departures, respectively. We extend them to real $t$ by $A_l(t) = A_l(\lfloor t \rfloor)$ and $D_l(t) := D_l(\lfloor t \rfloor)$, where $\lfloor t \rfloor$ is the largest integer no greater than $t$. The queue length $Q_l(t)$ is also extended using linear interpolation between $\lfloor t \rfloor$ and $\lfloor t + 1 \rfloor$. Then, from [21], there exist limits $\eta_l(t)$ and $\pi_l(t)$ for all $l$ such that $\eta_l(t)$ is absolutely continuous on $t$, and

$$
\frac{1}{r} \int_0^t A_l(s)ds \to \lambda_l t,
$$

$$
\frac{1}{r} \int_0^t D_l(s)ds \to \int_0^t \pi_l(s)ds,
$$

$$
\frac{1}{r} Q_l(\eta_l) \to \eta_l(t),
$$

as $r \to \infty$, and they also satisfy

$$
\eta_l(t) \geq 0,
$$

$$
\frac{d}{dt} \eta_l(t) = \begin{cases}
\lambda_l - \pi_l(t), & \text{if } \lambda_l - \pi_l(t) \geq 0 \text{ or } \eta_l(t) > 0, \\
0, & \text{otherwise},
\end{cases}
$$

$$
\pi_l(t) = P_l^L(t) c_l \geq \eta_l \pi_l(t) c_l \geq \eta_l \eta_l(t).
$$

The last inequality comes from the fluid limit version of (25), which is valid because (25) holds for all $t$.

We define the Lyapunov function as follows:

$$
V(\tilde{q}(t)) := \| \tilde{q}(t) \|.
$$

Since $\tilde{q}(t)$ is continuous, for any $\tilde{q}(t) \neq 0$, there exists a small $\delta t > 0$ such that for all $l$, $\eta_l(t) - \pi_l(t) \delta t \geq 0$ for $[t, t + \delta t]$. For such $\tilde{q}(t) \neq 0$ and $\delta t$, we have

$$
V(\tilde{q}(t + \delta t)) \leq \| \tilde{q}(t) + \delta t \| + \| \tilde{q}(t) \| + o(\delta t)
$$

$$
\leq \| \tilde{q}(t) \| + \| \tilde{q}(t) \| \delta t + \| \tilde{q}(t) \| + \| \tilde{q}(t) \| \delta t + o(\delta t)
$$

Hence, if $\tilde{q}(t)$ is strictly inside $\Psi$, we obtain

$$
\frac{d}{dt} V(\tilde{q}(t)) \leq \| \tilde{q}(t) \| + \| \tilde{q}(t) \| \delta t + o(\delta t)
$$

where $(d^+/d^+ f)(t) := \lim \sup_{\tau \to 0} (f(t+\tau)-f(t)/\tau)$. Hence, if $\tilde{q}(t) \neq 0$, the Lyapunov function has a negative drift. Then the
system is stable in the fluid limit model, and hence, from [21], the original system is also stable.

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