On Random Access Scheduling for Multimedia Traffic in Multi-hop Wireless Networks with Fading Channels

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***Abstract*—In this paper, we develop distributed random access scheduling schemes that exploit the time-varying nature of fading channels for multimedia traffic in multi-hop wireless networks. It should be noted that while centralized scheduling solutions can achieve optimal throughput under this setting, they incur high computational complexity and require centralized coordination requiring global channel information. The proposed solution not only achieves provable performance guarantees under a wide range of interference models, but also can be implemented in a distributed fashion using local information. To the best of our knowledge, this is the first distributed scheduling mechanism for fading channels that achieves provable performance guarantees. We show through simulations that the proposed schemes achieve better empirical performance than other known distributed scheduling schemes.**

***Index Terms*—Wireless scheduling, random access, distributed systems.**

I. Introduction

Link scheduling is a well-known and important problem in the design of multi-hop wireless networks. The wireless channel is inherently time-varying and transmissions between users can interfere with each other. Thus, in wireless systems, transmissions must be carefully scheduled (link scheduling) to maximize spatial reuse and opportunistically exploit favorable channel conditions. Efficient link scheduling thus becomes an important component of the overall problem of cross-layer design, which has gained much attention because of its notorious computational complexity. Recent work on cross-layer design has shown that using mathematical decomposition techniques [1]–[6], one can decompose the optimal cross-layer design problem into virtually separate components based on their functionalities, minimizing the amount of information needed to be shared among these components. Among these components, the optimal scheduling problem is often the most complex, and hence poses a major obstacle to practical implementation.

Although several throughput-optimal scheduling schemes for fading channels has been developed, these schemes have high computational complexity and require centralized coordination to collect global channel information [7]–[11]. Numerous efforts have been made to reduce the complexity and to facilitate decentralized implementation [6], [12]–[21]. However, most low-complexity scheduling schemes have been designed for networks with non-fading channels (e.g., see Section VI).

Since recent advances in communication technology enables wireless networks to exploit diversity from fading channels, low-complexity scheduling schemes that opportunistically utilize network resources and that can achieve performance gains from such diversity need to be developed. To this end, we develop random access based scheduling schemes that are provably efficient and amenable to distributed implementation. In the following, we first overview some of the research on the development of scheduling schemes for multi-hop wireless networks with non-fading channels, and discuss their limitations in the fading environment.

In their seminal work [22], Tassiulas and Ephremides showed how network components of different functionality interact to achieve the optimal throughput performance. They used the Maximum Weighted Scheduling (MWS) policy that maximizes the queue weighted rate sum by solving

$$\vec{r}(t) = \underset{\vec{r}\in\mathcal{F}}{\operatorname{argmax}} \sum_{l\in E} q_l(t) r_l,$$

where $\mathcal{F}$ denotes the set of all feasible schedules, $q_l(t)$ denotes the queue length of link l at time t, and $\vec{r} := \{r_l\}$ denotes the link rate vector of the feasible schedule. Note that the feasibility issue arises due to interference constraints between wireless links, i.e., two links that interfere with each other cannot transmit packets at the same time. Hence, a feasible schedule can be defined as a set of links that do not contain interfering links. Due to complex interference constraints, the set of feasible schedules is non-convex, and the above problem is in general an NP-Complete problem [23], resulting in a solution that requires high computational complexity.

A suboptimal scheduling called Greedy Maximal Scheduling (GMS) has been proposed to reduce the complexity [24]. It schedules links l in decreasing order of the queue weighted rate $q_l(t)r_l$ while conforming to the interference constraints. GMS guarantees a constant fraction of the optimal performance [24], [25], and empirically achieves the optimal performance under a variety of network settings [21]. However, it still requires organizing link activities in a *centralized* manner.

In multi-hop networks, it is often preferable to use low-complexity algorithms that are amenable to distributed implementation. In this direction, many algorithms have been proposed using a certain type of randomization techniques. Randomized Maximal Scheduling (RMS) is one of them. A feasible schedule is said to be *maximal* when no link can be added to it without violating interference constraints. RMS finds one of the maximal schedules at random. It achieves a fraction of the optimal throughput performance [6], [12], where the exact value depends on the underlying network graph. To achieve optimal performance in any network graph, a class of scheduling policies called Pick-and-Compare has been developed [13]–[16], [26]. A policy in this class picks a

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schedule at random, evaluates this and the current schedule by comparing their queue weighted rate sum, and chooses the one with the larger sum as the next schedule. One weakness of this approach is that the comparison process often needs network-wide computations, which incur high complexity. This problem has been solved by recently developed Carrier-Sensing-Multiple-Access (CSMA) based scheduling policies [17], [18], which simplify the comparison process by exploiting carrier-sensing. Although Pick-and-Compare and CSMA based approaches achieve optimal throughput performance for non-fading channels, they suffer from high complexity and/or high packet delays. Another class of distributed scheduling, called Queue-length based Random Access Scheduling policies, uses local message exchanges to resolve contention [19]–[21]. By adjusting each link's contention probability from the link's local queue information, it provides explicit tradeoffs between efficiency, complexity, and the contention period.

The above distributed solutions have been designed under the assumption of non-fading channels, i.e., each link has a constant transmission rate if there is no interfering transmission. Their extension to fading channel environment (with provable performance guarantees) is non-trivial, since the techniques often rely on long-term queue evolution, which ignore potential diversity gains that can be obtained by exploiting instantaneous link rate changes. While optimal solutions under fading channels have been developed [7], [9], [11], they require a centralized control entity with knowledge of global channel state, which is impractical for a large network. To the best of our knowledge, there is no distributed scheduling solution with provable performance guarantees in multi-hop wireless networks with fading channels.

In this paper, we develop a constant-time-complexity scheduling policy in multi-hop wireless networks with *fading channels*. Our solution is amenable to *distributed* implementation using only local information, and achieves a *provable performance guarantee* under a wide range of interference models. The paper is organized as follows. We first describe our network model in Section II. We show how previous randomized solutions can be inefficient in Section III. Next, we propose our solution and analyze its performance in Section IV, and discuss its complexity and limitation in Section V. After evaluating the performance of the proposed solution and other scheduling policies in Section VI, we conclude our paper in Section VII.

II. System Model

We consider a network graph $G(V,E)$ where V denotes the set of static nodes and E denotes the set of unidirectional links. We assume a time-slotted system, where each time slot consists of a contention period of M mini-slots and a transmission period for actual packet transmission as shown in Fig. 1. In each time slot, links participate in the contention process during the contention period to obtain the "right" to transmit data packets during the transmission period. Each link *contend*, and *attempts* broadcasting a control message (e.g., transmitting an RTS) at a mini-slot within the contention period in a probabilistic manner, where the attempt probability

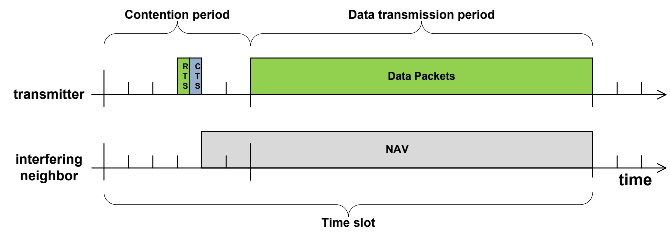

Fig. 1. Time frame structure and typical behavior of links. A time slot consists of a contention period with M mini-slots, and a transmission period for data packet transmissions. In each time slot, links attempt to transmit a control message such as a Request-To-Send (RTS) during the contention period. Those links that are successful are notified by the use of another control message like Clear-To-Send (CTS), and these successful links transmit data packets during the transmission period. Neighboring links whose (either) end node overhears the control messages do not attempt for the rest of the contention period, and wait for the next time slot, e.g., by setting Network Allocation Vector (NAV).

can be a function of network status. The link that makes a successful attempt (e.g., receiving a CTS) transmits data packets during the transmission period.

Each link transmits packets over a time-varying channel. We assume that the channel state does not change during a time slot, and when the channel is in state s, each link l has a fixed rate r_l^s. Hence, a channel state s can be understood as a vector of link rates $\{r_l^s\}$. The channel state, and thus the link rate, changes across time. We assume that the channel states have a stationary distribution with a finite number of states. The assumption is quite general accommodating a large class of fading channels, and allows link rates to change with a large variation and to be correlated with each other. Let $\mathcal{S}$ denote the set of all the channel states, and let $\{\pi^s\}$ denote the distribution satisfying $\sum_{s\in\mathcal{S}} \pi^s = 1$. We denote the average rate of link l by $\mu_l := \sum_{s\in\mathcal{S}} \pi^s r_l^s$, and the second moment by $\sigma_l := \sum_{s\in\mathcal{S}} \pi^s (r_l^s)^2$. We assume that each link does not have knowledge on channel state distribution, but it knows the first and second moments of the link rate with accuracy by a long-term observation. We also assume that the channel information can be exchanged between connected nodes using a separate control channel[1] in a smaller time scale than that for data transmission.

We describe wireless interference constraints by a matrix $[C_{ij}]$, where $C_{ij} = 1$ if two links i, j interfere with each other and $C_{ij} = 0$ otherwise. No two links that interfere with each other can transmit at the same time. We assume that the matrix is symmetric, i.e., $C_{ij} = 1$ if and only if $C_{ji} = 1$. This matrix interference model is very general and embraces a variety of interference models studied in the literature. For example, we can consider the K-hop interference model[2] that is often used to model Bluetooth networks (with $K = 1$) and IEEE 802.11

[1]The information can be also embedded in the data channel, in which case, there will performance degradation from additional overhead. To reduce the overhead in practice, one may use delayed information under slow fading environment. The impact of such delayed information is an interesting open problem and requires further research.

[2]Under the K-hop interference model, no two links within K-hop distance can transmit at the same time.

DCF networks (with $K = 2$) [27] as special cases.

Let N_l denote the set of links that interfere with link l, and let N_l^+ denote the union of N_l and $\{l\}$. The interference degree Δ_l of link l is defined as the largest number of links in N_l that can transmit simultaneously, i.e.,

$$\Delta_l := \max |X_l|,$$

where X_l is a subset of N_l such that $C_{ij} = 0$ for all $i, j \in X_l$, and $|\cdot|$ denotes cardinality of the set. Also, we define the maximum interference degree

$$\Delta := \max_{l \in E} \Delta_l. \tag{1}$$

Let $A_l(t)$ denote the number of packet arrivals at link l at time slot t. We assume that the arrival processes are i.i.d satisfying $\mathbb{E}[A_l(t)] = \lambda_l$ and are bounded by $A_l(t) \leq A_{\text{max}}$. We also assume that there is a minimum required transmission rate λ_{min} for every link with positive traffic rate, i.e., $\lambda_l \geq \lambda_{\text{min}}$ for all $l \in E$. Many different types of multimedia service like Voice over IP or Video streaming feature their traffic with the minimum transmission rate. We denote the arrival rate vector by $\vec{\lambda} := [\lambda_l]$. Let $D_l(t)$ denote the number of packet departures at link l during time slot t, which is bounded by $D_l(t) \leq D_{\text{max}}$. Note that $D_l(t)$ depends both on the chosen schedule and on the channel state at time slot t. Let $Q_l(t)$ denote the queue length of link l. At time slot t, the queue length of link l evolves as

$$Q_l(t+1) = (Q_l(t) - D_l(t) + A_l(t))^+,$$

where $(a)^+ := \max\{a, 0\}$. We can describe the system as a Markov chain where a state is described by queue lengths and link channel states. The network is said to be *stable* if the underlying Markov chain is ergodic. The capacity region of a scheduling scheme is the set of arrival rate vectors $\vec{\lambda}$ for which the network is stable under the scheme. The optimal capacity region Λ is the largest capacity region among all scheduling algorithms. A scheduling scheme is *throughput-optimal* if it achieves Λ. A scheduling scheme is said to achieve an efficiency ratio $\gamma (\leq 1)$, if its capacity region is no smaller than γ fraction of Λ, i.e., the network is stable under the scheme for any $\gamma\vec{\lambda}$ if $\vec{\lambda} \in \Lambda$.

We first consider well-known distributed scheduling strategies that provide provable performance guarantees for networks with non-fading channels, and examine their efficiency ratio γ under a fading environment. Specifically, we show that serving a maximal schedule in each time slot is not sufficient to achieve high efficiency for networks with fading channels. Even typical maximal scheduling like RMS can achieve a very small efficiency ratio for certain network graphs, however, the centralized GMS still achieves good performance. We then propose low-complexity scheduling schemes that are not only efficient under fading environment but also amenable to distributed implementation with local information.

III. Performance of Maximal Scheduling

It is known that MaxWeight scheduling maximizes the queue weighted rate sum at each time slot, and is throughput optimal for networks with fading channels [9], [11]. However, it requires a centralized algorithm with high complexity. It is NP-Complete under the matrix interference models considered in this paper [27]. An efficient suboptimal solution Greedy Maximal Scheduling (GMS) has been developed to reduce the complexity. At each time slot, GMS finds a maximal schedule in decreasing order of queue weighted rate. It can be easily shown that GMS achieves an efficiency ratio no smaller than $\frac{1}{\Delta}$ under fading environment. Although GMS is a highly efficient scheduling scheme, it still requires global link ordering, which requires at least $O(|V|)$ complexity. Recent studies show that, if link rates are fixed, GMS can achieve throughput optimality for tree topologies under the K-hop interference model and has an efficiency ratio of $\gamma \geq \frac{1}{6}$ in unit-disk network graphs [25]. Randomized Maximal Scheduling (RMS) can reduce the complexity further to $O(\log |V|)$ by choosing a maximal schedule at random. It has been shown that RMS also achieves an efficiency ratio of $\frac{1}{\Delta}$ when the channel state is fixed. RMS has attracted attention for its provable efficiency and distributed nature [6], [12]. However, as we will show below, unlike GMS, RMS can achieve poor performance for certain network graphs under fading environment.

A distributed implementation of RMS can be described as follows. At each time slot, a link attempts transmission at a mini-slot in a probabilistic manner by broadcasting a small control message (e.g., see Fig. 1). If a neighboring link overhears the control message[3], the link gives up the time slot and does not attempt for the rest of mini-slots, which ensures that no two links that interfere with each other transmit data packets during the transmission period. However, due to the randomness, it is possible that two or more neighboring links attempt at the same time slot. In this case, it is said that a collision occurs and all the attempted links (and their interfering neighbors) give up the time slot. The links that attempt successfully without collision are notified by another control message, and transmit data packets during the transmission period. It has been known that if each link l attempts at each mini-slot with probability $\frac{1}{|N_l^+|}$ and the number of mini-slots is $O(\log |V|)$, then the resultant schedule is maximal with high probability [28]. However, the following proposition shows that the performance of RMS in networks with fading channels can be much poorer.

Proposition 1: Randomized Maximal Scheduling (RMS) can achieve a fraction of the optimal throughput that is no greater than $\frac{1}{|E|}$.

Proof: We consider a star topology as shown in Fig. 2 where $|E|$ links share a node. Under the 1-hop interference model, only one link can transmit at a time slot (i.e., $\Delta = 1$ from (1)). We assume on-off channels. Each channel is in "on" state with probability ϵ, independent across links and time, and can transmit data at rate c if there is no simultaneous transmission. If a channel is in "off" state, it cannot make successful transmissions even without interference.

Suppose that all the links initially have a large enough queue length, and have the same arrival rate. Clearly, the maximum achievable arrival rate is equal to $\frac{1-(1-\epsilon)^{|E|}}{|E|} \cdot [c, c, \ldots, c] \approx$

[3]We say that a link overhears a message, if either end node of the link overhears the message.

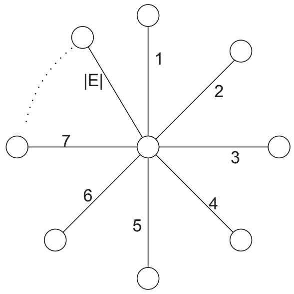

Fig. 2. Star topology with $|E|$ links, where links are an on-off channel with 'on' probability ϵ. Only one link can be active at a time slot, which means that the maximum interference degree $\Delta = 1$. In this network graph, typical maximal scheduling, e.g., Randomized Maximal Scheduling (RMS) achieves an efficiency ratio no greater than $\frac{1}{|E|}$. On the other hand, the schemes that will be proposed in Section IV achieve an efficiency ratio that does not depend on the network size.

$[\epsilon c, \epsilon c, \ldots, \epsilon c]$ for $\epsilon \ll 1$, since the probability that no link is in "on" state is $(1-\epsilon)^{|E|}$ and links are symmetric. RMS will choose a link at random regardless of the channel state, and its service rate of each link can be obtained as $\mathbb{E}[D_l(t)] = \frac{\epsilon c}{|E|}$. Therefore, RMS achieves an efficiency ratio γ no greater than $\frac{1}{|E|}$, which can be very small by increasing the number of links $|E|$. ■

Note that in the above example, the maximum interference degree Δ remains 1 regardless of network size $|E|$. Hence, in these network settings, the centralized GMS is optimal since it achieves the efficiency ratio of $\frac{1}{\Delta} = 1$. In the next section, we propose a random access scheduling scheme that not only achieves an efficiency ratio that does not depend on the network topology, but is also amenable to distributed implementation.

IV. Distributed Random Access Scheduling with Fading Channels

In this section, we propose a random access scheduling scheme that accounts for time-varying link rates due to fading, and show that the scheme achieves a provable efficiency ratio through rigorous analysis. The overall operation of the proposed scheme is similar to random access algorithms in [19]–[21]. Each link attempts transmission at each mini-slot with a certain probability p_l^s. A link's attempt can be overheard by its neighboring links, and those overheard links will not be scheduled for the time slot and will stop attempting for the rest of mini-slots. A collision may occur due to simultaneous attempts, in which case the links that cause the collision (and their interfering neighbors) cannot be scheduled for the time slot. The detailed operation can be described as in Algorithm 1. In this general random access algorithm, the attempt probability p_l^s is a key element that determines the performance of the scheduling scheme. In the following, we show how the random access algorithm can achieve good performance by appropriately choosing the attempt probabilities.

Algorithm 1 Generic random access scheduling with the attempt probability p_l^s.

At each time slot, each link does the following procedure.

```
sched ← 0
for each contention mini-slot do
  if sched = 0 then
    attempt transmission with probability p_l^s
    if attempt at this mini-slot then
      sched ← 1
    end if
    if overhear neighbors' transmission then
      \* override in case of collision *\
      sched ← (−1)
    end if
  end if
end for
if sched = 1 then
  transmit data packets during the transmission period
end if
```

We assume that each link l has accurate information about instantaneous link rate $r_l^s(t)$, queue length $Q_l(t)$, average link rate μ_l, and second moment σ_l. Let $x_l^s(t)$ be

$$x_l^s(t) = \frac{\frac{Q_l(t)}{\sigma_l}\frac{r_l^s(t)}{\mu_l}}{\max_{k\in N_l^+}\sum_{j\in N_k^+}\frac{Q_j(t)}{\sigma_j}\frac{r_j^s(t)}{\mu_j}}. \tag{2}$$

We also assume that link l can collect necessary information for calculating $x_l^s(t)$ by exchanging control messages locally with its interfering neighbors in N_l^+ through control channels. In case that the communication range is shorter than the interference range, multi-hop relay would be required to exchange the information. We further discuss the complexity involved in the message exchanges in Section V. Note that $\sum_{k\in N_l^+} x_k^s(t) \leq 1$ for all links $l \in E$. The random access scheduling scheme illustrated in Algorithm 1 operates with

$$p_l^s(t) = \frac{\sqrt{M}-1}{M}x_l^s(t). \tag{3}$$

The following lemmas will be used to analyze the performance of the proposed scheduling scheme.

Lemma 2: At each time slot with channel state s, if the random access scheduling shown in Algorithm 1 sets the attempt probability of each link l as (2) and (3), then the successful transmission probability $P_l(t,s)$ of link l is no smaller than $\beta x_l^s(t)$, where $\beta = 1 - \frac{2}{\sqrt{M}}$.

Proof: We follow the line of analysis in [19], [21]. We first let $p_l^s(t) = \frac{\alpha}{M}x_l^s(t)$ where the positive constant $\alpha < M$ will be determined later. Then the probability of successful transmission can be written as

$$\begin{aligned}P_l(t,s) &= \sum_{m=0}^{M-1}\left(p_l^s \cdot \prod_{k\in N_l}(1-p_k^s)\cdot \prod_{k\in N_l^+}(1-p_k^s)^m\right)\\ &= \sum_{m=1}^{M}\left(\frac{\frac{\alpha}{M}x_l^s}{1-\frac{\alpha}{M}x_l^s}\cdot \prod_{k\in N_l^+}\left(1-\frac{\alpha}{M}x_k^s\right)^m\right)\\ &\geq \frac{\alpha}{M}x_l^s\sum_{m=1}^{M}\left(1-\frac{\alpha}{M}\sum_{k\in N_l^+}x_k^s\right)^m\\ &= \frac{\alpha}{M}x_l^s\left(\sum_{m=0}^{M}\left(1-\frac{\alpha}{M}\sum_{k\in N_l^+}x_k^s\right)^m-1\right)\\ &\geq \frac{\alpha}{M}x_l^s\left(\frac{M}{\alpha\sum_{k\in N_l^+}x_k^s+1}-1\right).\end{aligned}$$

The last inequality comes from

$$\frac{1-\left(1-\frac{\alpha}{M}\sum_{k\in N_l^+}x_k^s\right)^{M+1}}{1-\left(1-\frac{\alpha}{M}\sum_{k\in N_l^+}x_k^s\right)} \geq \frac{M}{\alpha\sum_{k\in N_l^+}x_k^s+1},$$

for $\left(\frac{\alpha}{M}\sum_{k\in N_l^+}x_k^s\right) < 1$ [21]. Now we set $\alpha=\sqrt{M}-1$. From $\sum_{k\in N_l^+}x_k^s \leq 1$, we can obtain that

$$P_l(t,s) \geq \frac{\alpha}{M}x_l^s\left(\frac{M}{\alpha+1}-1\right) \geq x_l^s\left(1-\frac{2}{\sqrt{M}}\right). \quad (4)$$

■

Lemma 3: The following function $f_{k,i}(\{r_l^s\})$ defined in the neighborhood of link k and link $i\in N_k^+$ is jointly convex:

$$f_{k,i}(\{r_l^s\}) := \frac{(\frac{Q_k}{\sigma_k}\frac{r_k^s}{\mu_k})^2\cdot\frac{\mu_k}{Q_k}}{\frac{Q_k}{\sigma_k}\frac{r_k^s}{\mu_k}+\sum_{j\in N_i^+\backslash\{k\}}\frac{Q_j}{\sigma_j}\frac{r_j^s}{\mu_j}}.$$

Proof: Let $g(u,v)$ denote the perspective of a convex function $c\cdot u^2$, where c is a constant, i.e., $g(u,v):=\frac{c\cdot u^2}{v}$. Then, $g(u,v)$ is convex [29]. Let $u=x$ and $v=x+\sum_j y_j$. Then function $f(x,\vec{y}):=g(x,x+\sum_j y_j)$ is also convex since the mapping is linear [29]. Now we can obtain the lemma by another linear mapping as

$$\begin{aligned}x &\leftarrow \tfrac{Q_k}{\sigma_k}\tfrac{r_k^s}{\mu_k},\\ y_j &\leftarrow \tfrac{Q_j}{\sigma_j}\tfrac{r_j^s}{\mu_j},\ \forall j\in N_i^+\backslash\{k\},\\ c &\leftarrow \tfrac{\mu_k}{Q_k}.\end{aligned}$$

■

Using Lemmas 2 and 3, we now characterize the efficiency ratio γ of the scheduling scheme using a Lyapunov technique. We define the Lyapunov function as

$$V(t) := \max_{l\in E}\sum_{k\in N_l^+}\frac{Q_k(t)}{\kappa\sigma_k}, \quad (5)$$

where[4] $\kappa := \min_{l\in E}\frac{\mu_l}{\sigma_l}$. Note that although κ represents global information, it is used for analysis purpose only and not used for computing the attempt probability. We will show that whenever the arrival rate is within a certain fraction of the optimal capacity region, $V(t)$ has a negative drift, which implies that the system is stable.

[4]Letting $r_{\max} := \max r_l^s$, the value of κ is bounded by $\kappa = \min\frac{\mathbb{E}[r_l^s]}{\mathbb{E}[(r_l^s)^2]} = \min\frac{\mathbb{E}[r_l^s/r_{\max}]}{\mathbb{E}[(r_l^s/r_{\max})^2]}\frac{1}{r_{\max}} \geq \frac{1}{r_{\max}}$ from $\frac{r_l^s}{r_{\max}} \leq 1$.

Lemma 4: For any $\epsilon > 0$ and a constant $C_1 > 0$, there exists $\bar{V} > 0$ such that, for any link l and any $\eta\in[0,1]$ satisfying

$$\sum_{k\in N_l^+}\frac{Q_k(t)}{\kappa\sigma_k} \geq \eta(V(t)-C_1), \quad (6)$$

$V(t)\geq\bar{V}$ implies that

$$\sum_{k\in N_l^+}\frac{\mathbb{E}[D_k(t)\mid Q(t)]}{\kappa\sigma_k} \geq \eta\beta(1-\epsilon), \quad (7)$$

under the proposed scheduling scheme (i.e., Algorithm 1 with (3)).

Proof: We consider a link l that satisfies (6). From Lemma 2, we can obtain a lower bound on the total number of successfully transmitted packets for links $k\in N_l^+$ as

$$\begin{aligned}\sum_{k\in N_l^+}\frac{\mathbb{E}[D_k(t)\mid Q(t)]}{\kappa\sigma_k} &= \sum_s \pi^s\sum_{k\in N_l^+}\frac{P_k(t,s)r_k^s}{\kappa\sigma_k}\\ &\geq \sum_s \pi^s\frac{\beta}{\kappa}\sum_{k\in N_l^+}\frac{\frac{Q_k}{\sigma_k}\frac{r_k^s}{\mu_k}}{\max_{i\in N_k^+}\sum_{j\in N_i^+}\frac{Q_j}{\sigma_j}\frac{r_j^s}{\mu_j}}\cdot\frac{r_k^s}{\sigma_k}.\end{aligned} \quad (8)$$

Let $u(k) := \operatorname{argmax}_{i\in N_k^+}\sum_{j\in N_i^+}\frac{Q_j}{\sigma_j}\frac{r_j^s}{\mu_j}$. Then we have that

$$\begin{aligned}\sum_{k\in N_l^+}\frac{\mathbb{E}[D_k(t)\mid Q(t)]}{\kappa\sigma_k} &\geq \frac{\beta}{\kappa}\sum_{k\in N_l^+}\sum_s\pi^s\frac{(\frac{Q_k}{\sigma_k}\frac{r_k^s}{\mu_k})^2\cdot\frac{\mu_k}{Q_k}}{\sum_{j\in N_{u(k)}^+}\frac{Q_j}{\sigma_j}\frac{r_j^s}{\mu_j}}\\ &\geq \frac{\beta}{\kappa}\sum_{k\in N_l^+}\frac{\frac{Q_k}{\sigma_k}\frac{\mu_k}{\sigma_k}}{\sum_{j\in N_{u(k)}^+}\frac{Q_j}{\sigma_j}}\\ &\geq \beta\sum_{k\in N_l^+}\frac{\frac{Q_k}{\sigma_k}}{\sum_{j\in N_{u(k)}^+}\frac{Q_j}{\sigma_j}}\\ &\geq \beta\frac{\sum_{k\in N_l^+}\frac{Q_k}{\sigma_k}}{\kappa V(t)}\\ &\geq \beta\frac{\eta(V(t)-C_1)}{V(t)}\\ &= \eta\beta\left(1-\frac{C_1}{V(t)}\right).\end{aligned} \quad (9)$$

- We can obtain the first inequality by rearranging (8).
- By applying Lemma 3 and and Jensen's inequality on $\{r_k^s\}$, we can obtain the second inequality.
- The third inequality comes from the definition of $\kappa := \min_{e\in E}\frac{\mu_e}{\sigma_e}$.
- The fourth inequality comes from the fact that $\kappa V(t) \geq \sum_{k\in N_e^+}\frac{Q_k(t)}{\sigma_k}$ for all links e.
- The fifth inequality holds from the choice of link l, i.e., from (6).

Hence, we obtain the result with $\bar{V}\geq\frac{C_1}{\epsilon}$. ■

Recall that $\Delta := \max_{l\in E}\Delta_l$ is the largest interference degree in the graph, and $\lambda_{\min}$ denotes the minimum required transmission rate for any link with positive traffic rate. From Lemma 4, we can obtain the following lemma.

Lemma 5: For any $\delta > 0$ and any $\epsilon > 0$, there exist a positive integer T and a constant $\bar{V}$, such that if $V(t) \geq \bar{V}$ and $\vec{\lambda}\sqrt{1+4\epsilon} \in \sqrt{\frac{\kappa\beta\lambda_{\min}}{\Delta}}\Lambda$, then we have

$$\text{Prob}\left\{\sum_{k\in N_l^+}\frac{Q_k(t+T)}{\kappa\sigma_k} \leq V(t) - T\beta\epsilon\right\} \geq 1-\delta, \quad (10)$$

for all links $l \in E$.

Proof: Overall, our proof follows the line of analysis in [20]. However, there are technical difficulties in taking into account the time-varying link rates.

Since the arrivals and services are both bounded from the above, there exists a constant C_0 such that for all links l and time t,

$$\left|\sum_{k\in N_l^+}\frac{Q_k(t+1)}{\kappa\sigma_k} - \sum_{k\in N_l^+}\frac{Q_k(t)}{\kappa\sigma_k}\right| \leq \beta C_0. \quad (11)$$

Therefore, if $\sum_{k\in N_l^+}\frac{Q_k(t)}{\kappa\sigma_k} \leq V(t) - T\beta(C_0+\epsilon)$, then we have $\sum_{k\in N_l^+}\frac{Q_k(t+T)}{\kappa\sigma_k} \leq V(t) - T\beta\epsilon$.

For the case that $\sum_{k\in N_l^+}\frac{Q_k(t)}{\kappa\sigma_k} \geq V(t) - T\beta(C_0+\epsilon)$, we can obtain from (11) that for all $\tau \in [t+1, t+T]$,

$$\begin{aligned}\sum_{k\in N_l^+}\frac{Q_k(\tau)}{\kappa\sigma_k} &\geq V(t) - T\beta(C_0+\epsilon) - \beta C_0(\tau - t)\\ &\geq (V(\tau) - \beta C_0(\tau-t)) - T\beta(C_0+\epsilon) - \beta C_0(\tau-t)\\ &\geq V(\tau) - T\beta(3C_0+\epsilon).\end{aligned} \quad (12)$$

We now apply Lemma 4 with $\eta = 1$ and $C_1 = T\beta(C_0+\epsilon)$, and can find $\bar{V}$ such that

$$\sum_{k\in N_l^+}\frac{\mathbb{E}[D_k(\tau) \mid Q(t)]}{\kappa\sigma_k} \geq \beta(1-\epsilon), \quad (13)$$

for all $\tau \in [t+1, t+T]$. Note that the conditional expectation is with respect to $Q(t)$ from (12). Let

$$Y_l := \sum_{\tau=t+1}^{t+T}\sum_{k\in N_l^+}\frac{D_k(\tau)}{\kappa\sigma_k}.$$

From Chernoff bounds, we can show that there exists a constant t_1 such that

$$\text{Prob}\left\{Y_l \leq T\beta(1-2\epsilon)\right\} \leq e^{-Tt_1}. \quad (14)$$

Now, we bound aggregate arrivals for $[t+1, t+T]$, which can be shown using Jensen's inequality as follows. For a link l, let

$$Z_l := \sum_{k\in N_l^+}\sum_{\tau=t+1}^{t+T}\frac{A_k(\tau)}{\kappa\sigma_k}.$$

From $\lambda\sqrt{1+4\epsilon} \in \sqrt{\frac{\kappa\beta\lambda_{\min}}{\Delta}}\Lambda$, there exists a service vector $\{\phi_k^s\}$ such that $[\sum_s \pi^s\phi_k^s] \in \Lambda$ and $\lambda_k\sqrt{1+4\epsilon} \leq \sqrt{\frac{\kappa\beta\lambda_{\min}}{\Delta}}\sum_s \pi^s\phi_k^s$ for all $k \in E$. Also, the vector $\{\phi_k^s\}$ should satisfy that $\sum_{k\in N_l^+}\left(\frac{\phi_k^s}{r_k^s}\right)^2 \leq \Delta$ for all $s \in \mathcal{S}$, since at most Δ links in interfering neighborhood can transmit simultaneously at any time. (Note that $\sum_{k\in N_l^+}\frac{\phi_k^s}{r_k^s} \leq \Delta$ and $\phi_k^s \leq r_k^s$ in any case.) Then from Jensen's inequality[5], we will have

$$\begin{aligned}\Delta &\geq \sum_s \pi^s \sum_{k\in N_l^+}\left(\frac{\phi_k^s}{r_k^s}\right)^2\\ &\geq \sum_{k\in N_l^+}\frac{(\sum_s \pi^s\phi_k^s)^2}{\sum_s \pi^s (r_k^s)^2}\\ &> \frac{\Delta}{\kappa\beta\lambda_{\min}}\sum_{k\in N_l^+}\frac{\lambda_k^2}{\sigma_k}(1+4\epsilon).\end{aligned} \quad (15)$$

Thus, we have that

$$\sum_{k\in N_l^+}\frac{\lambda_k}{\kappa\sigma_k} \leq \sum_{k\in N_l^+}\frac{\lambda_k^2}{\kappa\sigma_k\lambda_{\min}} < \frac{\beta}{1+4\epsilon}, \quad (16)$$

and thus, we obtain that $\mathbb{E}[Z_l] < \frac{T\beta}{1+4\epsilon}$. Using Chernoff's bounds, there exists a constant t_0 such that[6]

$$\text{Prob}\left\{Z_l \geq T\beta(1-3\epsilon)\right\} \leq e^{-Tt_0}. \quad (17)$$

Combining (14) and (17), we can obtain that

$$\begin{aligned}&\text{Prob}\left\{\sum_{k\in N_l^+}\frac{Q_k(t+T)}{\kappa\sigma_k} \leq V(t) - T\beta\epsilon\right\}\\ &\qquad \geq \text{Prob}\{Z_l \leq Y_l - T\beta\epsilon\}\\ &\qquad \geq 1 - e^{-Tt_1} - e^{-Tt_0} \geq 1-\delta,\end{aligned}$$

by choosing a large enough T (and a large enough $\bar{V}$ accordingly). ■

The following is our main result.

Proposition 6: For any $\vec{\lambda}$ such that $\vec{\lambda}\sqrt{1+4\epsilon} \in \sqrt{\frac{\kappa\beta\lambda_{\min}}{\Delta}}\Lambda$ with some $\epsilon > 0$, the proposed scheduling scheme stabilizes the network system.

Proof: We consider the queue and channel states as a Markov chain and show that the Markov chain is positive recurrent, which means that the network system is stable.

From Lemma 5, for any $\delta > 0$, we can find a constant $\bar{V}$ and an integer T such that, if $V(t) \geq \bar{V}$,

$$\text{Prob}\{V(t+T) - V(t) \leq -T\beta\epsilon\} \geq 1 - |E|\delta. \quad (18)$$

Also, since the arrivals are bounded, there exists a constant C_0 such that $V(t+1) - V(t) \leq \beta C_0$. Then from (18), we can obtain that

$$\mathbb{E}[V(t+T) - V(t) \mid Q(t)] \leq -T\beta\epsilon(1-|E|\delta) + T\beta C_0|E|\delta.$$

Therefore, if $\delta \leq \frac{\epsilon}{2(C_0+\epsilon)|E|}$, we have that

$$\mathbb{E}[V(t+T) - V(t) \mid Q(t)] \leq -\frac{T\beta\epsilon}{2}, \quad (19)$$

[5]Note that $g(x,t) = tf(x/t)$ is convex when $f(x) = x^2$. Jensen's inequality has been applied to the function $g(x,t)$ with $x = \phi_k^s$ and $t = (r_k^s)^2$.

[6]We also use the boundedness condition of the arrival process.

for all $V(t) \geq \bar{V}$. In addition, since the queue and channel states compose a countable state space and the derivation of the Lyapunov function during T time slots is bounded, the Markov chain is positive recurrent by Foster's Theorem [30]. ∎

It is interesting to note that our algorithm achieves an efficiency ratio of $\sqrt{\frac{\kappa\lambda_{\min}}{\Delta}} = \sqrt{\frac{\lambda_{\min}}{\Delta\cdot\max\mu_l}}$ in networks with fixed link rates. Comparing with the performance bounds $\frac{1}{\Delta}$ of the previous known algorithms [20], our algorithm may improve the efficiency ratio[7] in a dense network with $\Delta > \frac{\max\mu_l}{\lambda_{\min}}$.

As an example, we analyze the performance of the proposed scheme for the previous scenario of the star networks shown in Section III. In this case, we have $\Delta = 1$, $\mu_l = \epsilon c$, $\sigma_l = \epsilon c^2$, and $\kappa = 1/c$. Assuming a sufficiently large number of contention mini-slots, we have $\beta \to 1$. From Proposition 6, we have that $\gamma \geq \sqrt{\frac{\lambda_{\min}}{c}}$. Note that unlike RMS in Proposition 1, the bound of the efficiency ratio no longer depends on the network topology. Instead, it depends on the minimum required transmission rate $\lambda_{\min}$ for non-zero traffic, which is a weakness of the solution and will be further discussed in the next section. In a certain network scenario, however, e.g., in a network with homogeneous multimedia traffic, where flows require certain minimum rate for service, like VoIP networks, the proposed solution can achieve high performance. The highest performance guarantee will be provided for uniform traffic. In the above example, when all links have an equal amount of packet arrivals, we can increase $\lambda_{\min}$ to the boundary of γ fraction of the capacity region, i.e., $\lambda_{\min} \approx \gamma\epsilon c$, since $[\epsilon c, \epsilon c, \ldots, \epsilon c]$ is the largest feasible arrival vector. Combining it with the previous inequality, we obtain that $\gamma \geq \epsilon$ regardless of the network size.

V. Discussion

Our design on the attempt probability can be considered as a generalization of the previous results in [19]–[21] to fading channels. In the previous works, the attempt probability is a function of link weights that are the queue length *divided by* the link rate. In our solution, we modify the link weight as the queue length *multiplied by* the link rate to take into account the channel fading. Our approach coincides with the insight of the well-known MaxWeight algorithm that finds a feasible schedule maximizing the queue weighted rate sum [22]. For the new attempt probability, we have developed novel analytical techniques to show scheduling efficiency of the proposed solution under fading channels, which are non-trivial extensions of the lines of the techniques in [19]–[21].

We have assumed that channel information of links within the interfering neighborhood is available at each link. However, in practice the information should be collected by exchanging control messages through separate control channels or embedded in data channels. Either in control channels or data channels, depending on the interference model, a link may directly communicate with a neighboring link or it may require multi-hop relays to disseminate the message in its interfering neighborhood. Hence, in case that the interference range is greater than the communication range, the solution will require additional complexity. For example, in a random network under the K-hop interference model, where nodes are randomly placed and any two links within K-hop distance cannot transmit simultaneously, it takes $O(\log^K |V|)$ time to finish the message exchanges between neighbors [28], where $|V|$ is the number of nodes.

Letting the set of neighborhood N_l denote 'one-step' interfering neighborhood of link l, our solution indeed requires 'two-step' neighborhood information at each link to calculate the attempt probability. This information can be collected by exchanging messages with one-step neighbors as follows. First, each link exchanges messages with its neighbors for $O(\log^K |V|)$ time, and collects its one-step neighborhood information that includes queue lengths, link rates, first and second moments of the link rates. Then, each link k can compute $\sum_{j\in N_k^+} \frac{Q_j(t)}{\sigma_j}\frac{r_j^s(t)}{\mu_j}$. During the next $O(\log^K |V|)$ time, each link exchanges this summation result with its one-step neighbors. Now each link l can obtain the necessary two-step neighborhood information to compute $\max_{k\in N_l^+} \sum_{j\in N_k^+} \frac{Q_j(t)}{\sigma_j}\frac{r_j^s(t)}{\mu_j}$, by choosing the maximum summation value transmitted during the second period. Hence, the complexity order of the message exchanges remains the same as collecting one-step neighborhood information.

Our analysis results suggest that the proposed solution achieves provable performance guarantee under fading channels, which, however, depends on the relative ratio $\kappa\lambda_{\min} = \frac{E[r_k^s/\lambda_{\min}]}{E[(r_k^s/\lambda_{\min})^2]}$ of the channel statistics. This is a weakness considering the previous results under non-fading channels [19]–[21], in particular when the minimum flow rate is small. This originates from our techniques where we have obtained the bound on the summation of the squared mean rates for the arrivals and the bound on the summation of the mean rate for the departures. The minimum flow rate has been introduced to compare the two values. Hence, if a link has small mean arrival rate, the difference will enlarge and the performance guarantee will decrease. This may imply that the worst-case performance can be obtained when a large number of links with small traffic interfere with each other. However, there are other constraints that are not directly used in our analytical bounds, such as $\sum_{k\in N_l^+} \frac{\phi_k^s}{r_k^s} \leq \Delta$ and $\lambda_k \leq E[\phi_k^s]$. We conjecture that these hidden constraints will prevent the system performance from approaching zero even when $\lambda_{min} \to 0$. We verify our conjecture through simulations.

VI. Simulation

In this section, we evaluate our proposed algorithm, and compare it with other scheduling schemes. We first show the performance of the proposed solution by examining its sensitivity to changes in the number of mini-slots M. Then we compare it with the centralized GMS and the state-of-the-art distributed scheduling schemes developed under the non-

[7] The capacity regions with and without fading channels will be different and vary depending on detailed channel characteristics. Hence, even if the proposed solution achieves higher efficiency ratio in a dense network with non-fading channels, its actual transmission rate may increase or decrease compared with the rate that it achieves under fading channels.

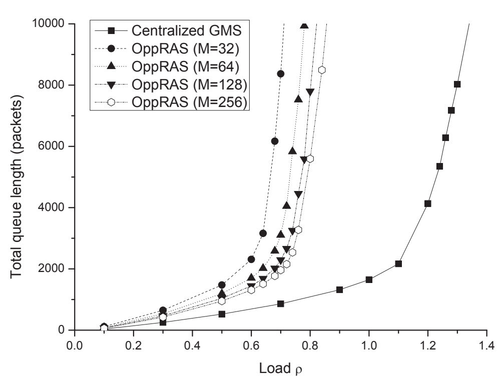

Fig. 3. Performance of the proposed solution under the 1-hop interference model as the number of mini-slots varies. It improves as the number of mini-slots increases.

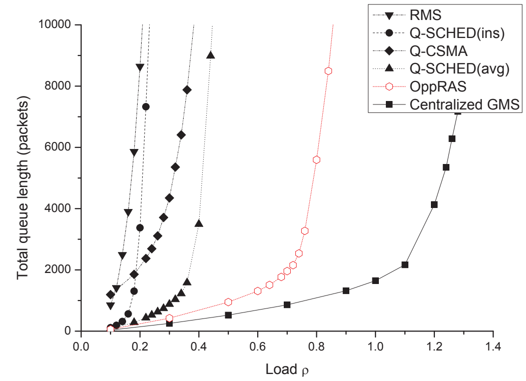

Fig. 4. Performance of scheduling schemes under the 1-hop interference model when $M = 256$.

fading environment. We also test the proposed solution for vulnerability to inaccurate measurement and low flow rates.

We simulate single-hop traffic in a random topology, where 80 nodes are placed uniformly at random on a 1x1 area. A link is connected between any two nodes if their distance is less than 0.18. In our simulations, total 260 links are established, and the maximum link degree is 20, which implies the maximum interference degree Δ is no greater than 20 under the 2-hop interference model. (Note that $\Delta = 2$ under the 1-hop interference model; see the footnote in Section II for the definition of the K-hop interference model.). At each link l, the mean link rate μ_l is chosen uniformly at random between 5 and 10 packets per time slot. At each time slot t, each link has actual link rate $r_l^s(t)$ as one of the following four values $\mu_l/4$, $\mu_l/2$, μ_l, and $3\mu_l$ with probability 0.4, 0.2, 0.2, and 0.2, respectively, and changes its rate independently across time slots. (Thus, $\sigma_l = 2.075\mu_l$ and $\kappa = 2.075$.) We generate packet arrivals at each link following a Poisson process, where the mean arrival rate is chosen at random between 0, ρ, and 2ρ, where ρ is a traffic control parameter. Packets immediately leave the system after being served at a link (i.e., single-hop traffic). In our simulation, we measure the total number of packets in the network after 5000 time slots. We conduct 10 simulation runs for the same mean rate, and average the results. As we increase ρ, the arrival rate will approach the boundary of the capacity region, which results in a rapid increase of queue lengths. Although this is not an accurate method to calculate the throughput limits, it is reasonable in the sense that excessive queue lengths are not acceptable in many practical applications.

Fig. 3 shows that the performance of our proposed solution and GMS under the 1-hop model with different number of mini-slots. We use the performance of GMS as a reference since its empirical performance is very close to the optimal in many network settings [21]. The results show that, as the number of mini-slots M increases, the performance of the proposed solution (denoted by OppRAS) improves. However, substantial differences from the performance of centralized GMS are still observed and need to be narrowed in future work.

Next, we compare our solution with other scheduling schemes including GMS, RMS, and other random access scheduling schemes that are developed for fixed link rates, i.e., Q-CSMA [18] and Q-SCHED [20]. We briefly describe the algorithms of Q-CSMA and Q-SCHED:

- **Q-CSMA** has two levels of decision procedure. At each time slot, it first randomly chooses a decision schedule among the set of all feasible schedules. For each link in the decision schedule, if the link does not interfere with other links that are active in the previous time slot, Q-CSMA schedules the link in the next time slot with a certain probability. For all the other links that are not in the decision schedule, they inherit the scheduling decision at the previous time slot. It achieves the optimal throughput performance in the networks with fixed link rates, but usually has large queue lengths. We refer to [18] for the details.
- **Q-SCHED** uses the structure of Algorithm 1. The difference from our schemes is in setting the attempt probabilities p_l^s: at each time slot, each link l chooses its attempt mini-slot m with the distribution

$$\text{Prob}\{m \le z\} = 1 - \exp(-x_l \cdot z/M),$$
$$\text{where } x_l = \frac{\log M}{M} \cdot \frac{Q_l(t)/r_l^s(t)}{\sum_{k \in N_l^+} Q_k(t)/r_k^s(t)}.$$

  Note that the algorithm has only instantaneous link rates $r_l^s(t)$ to determine the attempt probabilities. Alternatively, one can replace $r_l^s(t)$ with mean rate μ_l. We denote them by Q-SCHED (inst) and Q-SCHED (avg), respectively.

Fig. 4 illustrates the results when the number of mini-slots M is 256 (under the 1-hop interference model). It is clear that our proposed algorithm outperforms other distributed scheduling schemes RMS, Q-CSMA and Q-SCHED, and achieves high throughput performance by exploiting wireless diversity from time-varying link rates. Under the 2-hop interference model, we can observe similar results as shown in Fig. 5. The proposed scheme achieves the lowest queue lengths among all distributed algorithms.

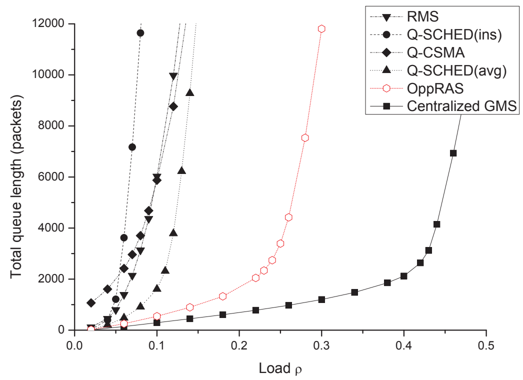

Fig. 5. Performance of scheduling schemes under the 2-hop interference model when $M = 256$.

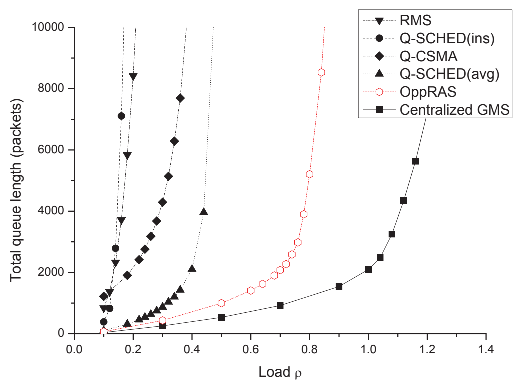

Fig. 6. Performance of scheduling schemes with different channel state distributions. Also, the algorithmic parameters are calculated from the measurements of instantaneous link rate. The results show that the performance gains of the proposed solution is retained under heterogeneous channel distributions and the measurement errors.

In the following experiment, we use three different channel state distributions under the 1-hop interference model. Among all the links, one third use the same distribution as before. Another one third have a larger variation, i.e., at each time slot, each link l in this group randomly chooses rate $\mu_l/10$, μ_l, and $6\mu_l$ with probability 0.5, 0.41, and 0.09, respectively. The last one third links have uniform distribution in $[0, 2\mu_l]$ at each time slot. Also, in this experiment, we assume that each link has no prior knowledge on channel statistics, but measures instantaneous link rate at each time slot. Each link l calculates average transmission rate μ_l and the second moment σ_l from the measurement history. The simulation results shown in Fig. 6 are similar to the previous ones, and demonstrate that the proposed solution performs well under a variety of fading channels and initial measurement errors on the moments μ_l and σ_l are negligible.

Finally, we show through simulations that the theoretical limitation provided in Proposition 6 may not exist in practice. To this end, we consider the same setting as in the first experiment, except that we randomly choose one-fifth links and reduce their mean arrival rates to $\frac{1}{10}$, i.e., for these links l, μ_l is chosen randomly within $[0.5, 1]$. We evaluate scheduling schemes under the previous traffic and under the new traffic with smaller minimum arrival rate, and compare their performance. Fig. 7 shows the results, where we mark simulations with the new traffic by (small). Even though the minimum arrival rate is now reduced to $\frac{1}{10}$, the empirical results show that the efficiency ratio, i.e., the performance ratio to the centralized GMS, remains unchanged. This indicates that the theoretical limitation may be a technical one that can be overcome, or the proposed solution usually achieves higher empirical performance than the worst-case performance that the analysis takes into account.

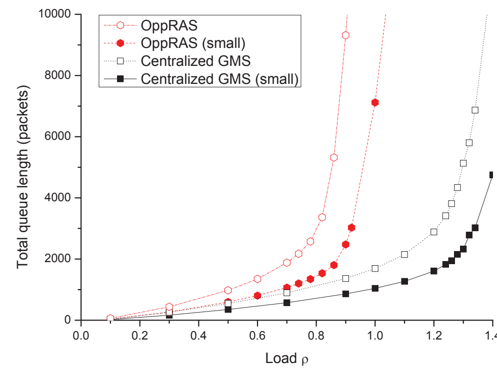

Fig. 7. Scheduling performance when the minimum mean arrival rate is small. Unlike the analytical results, in practice, the performance ratio of the proposed solution to GMS under the smaller minimum mean arrival rate, marked by (small), does not decrease.

VII. Conclusion

In cellular networks, it has been known that opportunistic scheduling can improve system performance by exploiting wireless diversity from fading channels. The idea can be extended to multi-hop networks, but the optimal solution requires a centralized control entity with global information of channel states, which is often unavailable in practical systems due to complexity and lack of scalability. In this paper, we develop distributed opportunistic scheduling schemes that are provably efficient under fading channels. The proposed random access algorithms can be implemented in a distributed manner with local information, and provide provable performance guarantees. Simulation results confirm the theoretical performance bounds and also show that the proposed schemes achieve higher empirical performance than other distributed scheduling schemes known in the literature.

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References

[1] R. L. Cruz and A. V. Santhanam, "Optimal Routing, Link Scheduling, and Power Control in Multi-hop Wireless Networks," in *IEEE INFOCOM*, April 2003.

[2] L. Georgiadis, M. J. Neely, and L. Tassiulas, "Resource Allocation and Cross-Layer Control in Wireless Networks," *Found. Trends Netw.*, vol. 1, no. 1, pp. 1–144, 2006.

[3] X. Lin, N. B. Shroff, and R. Srikant, "A Tutorial on Cross-Layer Optimization in Wireless Networks," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 8, August 2006.

[4] X. Wang and K. Kar, "Cross-layer Rate Control in Multi-hop Wireless Networks with Random Access," in *ACM MOBIHOC*, May 2005.

[5] M. J. Neely, E. Modiano, and C. E. Rohrs, "Power Allocation and Routing for Time-varying Wireless Networks," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 1, 2005.

[6] X. Lin and N. B. Shroff, "The Impact of Imperfect Scheduling on Cross-Layer Congestion Control in Wireless Networks," *IEEE/ACM Trans. Netw.*, vol. 14, no. 2, pp. 302–315, April 2006.

[7] L. Tassiulas, "Scheduling and Performance Limits of Networks with Constantly Changing Topology," *IEEE Trans. Inf. Theory*, vol. 43, no. 3, pp. 1067–1073, May 1997.

[8] M. Andrews, K. Kumaran, K. Ramanan, A. Stolyar, R. Vijaykumar, and P. Whiting, "CDMA Data QoS Scheduling on the Forward Link with Variable Channel Conditions," Bell Laboratories, Lucent Technologies, Tech. Rep., 2000.

[9] M. J. Neely, E. Modiano, and C. E. Rohrs, "Power Allocation and Routing in Multibeam Satellites with Time-varying Channels," *IEEE/ACM Trans. Netw.*, vol. 11, no. 1, pp. 138–152, 2003.

[10] S. Shakkottai, R. Srikant, and A. L. Stolyar, "Pathwise Optimality of the Exponential Scheduling Rule for Wireless Channels," *Advances in Applied Probability*, vol. 36, no. 4, pp. 1021–1045, December 2004. [Online]. Available: http://www.jstor.org/stable/4140388

[11] A. Eryilmaz, R. Srikant, and J. R. Perkins, "Stable Scheduling Policies for Fading Wireless Channels," *IEEE/ACM Trans. Netw.*, vol. 13, no. 2, pp. 411–424, 2005.

[12] X. Wu, R. Srikant, and J. R. Perkins, "Scheduling Efficiency of Distributed Greedy Scheduling Algorithms in Wireless Networks," *IEEE Trans. Mobile Computing*, vol. 6, no. 6, pp. 595–605, 2007.

[13] E. Modiano, D. Shah, and G. Zussman, "Maximizing Throughput in Wireless Networks via Gossiping," *Sigmetrics Performance Evaluation Review*, vol. 34, no. 1, pp. 27–38, 2006.

[14] Y. Yi and S. Shakkottai, "Learning Contention Patterns and Adapting to Load/Topology Changes in a MAC Scheduling Algorithm," in *IEEE WiMesh*, September 2006.

[15] S. Sanghavi, L. Bui, and R. Srikant, "Distributed Link Scheduling with Constant Overhead," in *ACM Sigmetrics*, June 2007, pp. 313–324.

[16] A. Eryilmaz, A. Ozdaglar, and E. Modiano, "Polynomial Complexity Algorithms for Full Utilization of Multi-hop Wireless Networks," in *IEEE INFOCOM*, May 2007.

[17] L. Jiang and J. Walrand, "A Distributed Algorithm for Optimal Throughput and Fairness in Wireless Networks with a General Interference Model," in *the 46th Annual Allerton Conference on Communications, Control, and Computing*, 2008.

[18] J. Ni and R. Srikant, "Distributed CSMA/CA Algorithms for Achieving Maximum Throughput in Wireless Networks," in *Information Theory and Applications Workshop*, 2009.

[19] X. Lin and S. Rasool, "Constant-Time Distributed Scheduling Policies for Ad Hoc Wireless Networks," *IEEE Trans. Autom. Control*, vol. 54, no. 2, pp. 231–242, Feburary 2009.

[20] A. Gupta, X. Lin, and R. Srikant, "Low-Complexity Distributed Scheduling Algorithms for Wireless Networks," in *IEEE INFOCOM*, May 2007, pp. 1631–1639.

[21] C. Joo and N. B. Shroff, "Performance of Random Access Scheduling Schemes in Multi-hop Wireless Networks," *IEEE/ACM Trans. Netw.*, vol. 17, no. 5, October 2009.

[22] L. Tassiulas and A. Ephremides, "Stability Properties of Constrained Queueing Systems and Scheduling Policies for Maximal Throughput in Multihop Radio Networks," *IEEE Trans. Autom. Control*, vol. 37, no. 12, pp. 1936–1948, December 1992.

[23] G. Sharma, R. R. Mazumdar, and N. B. Shroff, "Maximum Weighted Matching with Interference Constraints," in *IEEE International Workshop on Foundations and Algorithms For Wireless Networking*, March 2006.

[24] D. Avis, "A Survey of Heuristics for the Weighted Matching Problem," *Networks*, vol. 13, no. 4, pp. 475–493, 1983.

[25] C. Joo, X. Lin, and N. B. Shroff, "Understanding the Capacity Region of the Greedy Maximal Scheduling Algorithm in Multi-hop Wireless Networks," *IEEE/ACM Trans. Netw.*, vol. 17, no. 4, pp. 1132–1145, August 2009.

[26] L. Tassiulas, "Linear Complexity Algorithms for Maximum Throughput in Radio Networks and Input Queued Switches," in *IEEE INFOCOM*, April 1998, pp. 533–539.

[27] C. Joo, G. Sharma, N. B. Shroff, and R. R. Mazumdar, "On the Complexity of Scheduling in Wireless Networks," *EURASIP Journal of Wireless Communications and Networking*, October 2010.

[28] G. Sharma, C. Joo, N. B. Shroff, and R. R. Mazumdar, "Joint Congestion Control and Distributed Scheduling for Throughput Guarantees in Wireless Networks," *ACM Trans. Model. and Comput. Simul.*, vol. 21, no. 1, pp. 5:1–5:25, December 2010.

[29] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, 2004.

[30] F. G. Foster, "On the Stochastic Matrices Associated with Certain Queuing Processes," *The Annals of Mathematical Statistics*, vol. 24, no. 3, pp. 355–360, September 1953.

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