A Greedy Link Scheduler for Wireless Networks with Fading Channels

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Abstract—We consider the problem of link scheduling for wireless networks with fading channels, where the link rates are varying with time. Due to the high computational complexity of the throughput optimal scheduler, we provide a low complexity greedy link scheduler GFS, with provable performance guarantees. We show that the performance of our greedy scheduler can be analyzed using the Local Pooling Factor (LPF) of a network graph, which has been previously used to characterize the stability of the Greedy Maximal Scheduling (GMS) policy for networks with static channels. We conjecture that the performance of GFS is a lower bound on the performance of GMS for wireless networks with fading channels.

I. INTRODUCTION

The link scheduling problem for wireless networks has received considerable attention in the recent past. In a wireless network with shared spectrum, interference from neighboring nodes prevents all nodes in the network from transmitting simultaneously at full interference free rate. A link scheduler chooses a set of links to deactivate at every time instant to eliminate their interference on other links and only active links transmit data. An important performance objective of a scheduler is throughput optimality, i.e., for any given network, the scheduler should keep all the queues in the network stable for the largest set of arrival rates that are stabilizable for that network.

For wireless networks in which a set of link activation vectors are defined according to a general binary interference model, the Maxweight policy or the dynamic back-pressure policy is known to be throughput optimal [1]. Maxweight type policies have also been shown to be throughput optimal for wireless networks with fading channels, where the link rates vary over time [2, 4]. However, the Maxweight policy suffers from high computational complexity (NP-hard in many cases, including k-hop interference models, k>1) [5], and has therefore motivated the study of schedulers that have low complexity, are amenable to distributed implementation and also offer provable performance guarantees. Examples of such schedulers include Greedy Maximal Scheduling (GMS) [8] and Maximal Scheduling [10], which have been widely studied for wireless networks with static channels.

There has been a number of studies that analyze the performance of GMS as a function of the network topology. The main parameter of focus has been efficiency, which is defined as the largest fraction of the network capacity region guaranteed to be stable under GMS. In [8], efficiency has been evaluated as a function of the local pooling factor of a network graph (LPF), which depends on the network topology and interference constraints. Later, using the LPF, GMS has been shown to be throughput optimal for a wide class of network graphs under the node exclusive interference model [6, 9].

The performance analysis of the aforementioned low complexity schedulers does not however, carry over to the scenario with fading, in which link rates are time-varying. For instance, unlike a static network, one cannot conclude in a network with time-varying links that satisfying local pooling under GMS implies throughput optimality. It is only known that in the case of the node-exclusive interference model, GMS can achieve at least half the network stability region. Thus, it is of interest to investigate if for networks with time varying link rates, GMS performs as well as it does in networks with fixed link rates.

In this paper, we develop a greedy link scheduler, GFS, for wireless networks with fading channels, which, although not throughput optimal, has low computational complexity and offers provably good performance guarantees. We show that the performance of our greedy scheduler can be related to the LPF of a network graph. We then conjecture that the performance of GFS is a lower bound on the performance of GMS for wireless networks with time-varying link rates.

II. SYSTEM MODEL

We consider a wireless network modeled as a graph $G = (\mathcal{V}, \mathcal{E})$ with edges representing links. We assume a single hop traffic model where each edge represents a source-destination pair. Time is divided into slots and packets arrive at the source node following an i.i.d. process with a finite mean at the start of each time slot. Let $A_l(t)$ denote the number of packets arriving during time slot $t$. $A_l(t)$ has a mean $\lambda_l$. The vector of channel states across all links in the network is assumed to be fixed over the duration of a time slot but changing after every time slot. The set of channels in the network can assume a state $j \in \{1, \ldots, J\}$ according to stationary probability $\pi^j$. In each time slot $t$, the achievable rate of link $l \in \mathcal{E}$, denoted by $\rho_l(t)$, assumes value $\rho^j_l$ if the network is in fading state $j$ at time slot $t$. The expected rate of a link, denoted by $\overline{\rho}_l$ is given by $\overline{\rho}_l = \sum_{j=1}^{J} \pi^j \rho^j_l$. We assume a generalized binary interference model, in which each link $l$ is associated with an interference set, denoted by $I_l \subset \mathcal{E}$. Set $I_l$ consists of the set of links that cannot be active whenever link $l$ is active.
Let $r^\delta_j$ denote a $1 \times |\mathcal{E}|$ rate allocation vector for a network that is in channel state $j$, where $r^\delta_j$ is the rate allocated to link $i \in \mathcal{E}$. Any rate allocation vector $r^\delta$ must satisfy the following properties:

(a) $r^\delta_j > 0$ implies $r^\delta_j = 0$, for all $k \in \mathcal{I}_j$, where $k \neq l$.

(b) There exists no link $k \in \mathcal{E}$ such that $r^\delta_j \neq c_j^k$ and $k \notin \mathcal{I}_j$ for all $l$ satisfying $r^\delta_j > 0$. In other words there exists no link that does not interfere with any other active link and is yet not scheduled.

Let $\mathcal{R}^\delta_j$ denote the set of all feasible rate allocation vectors for a wireless network graph when the network is in channel state $j$. Similarly, $\mathcal{R}^\delta_{\mathcal{L}}$ is the set of all feasible rate allocation vectors on the subgraph $\mathcal{L} \subset \mathcal{G}$. The stability region of the network $\Lambda$ is then given by the interior of the set $\Lambda = \{ \bar{\lambda} : \bar{\lambda} \preceq \bar{\phi}, \text{ for some } \bar{\phi} = \sum_{j=1}^{\mathcal{J}} \pi^j \psi^j \}, \psi^j \in Co(\mathcal{R}^\delta_j)$, with $Co(\mathcal{R}^\delta_j)$ representing the convex hull of the set $\mathcal{R}^\delta_j$, and $\preceq$ denoting component-wise inequality.

Fig. 1 shows an example of a simple two link network with two fading states, with the associated network stability region under a node-exclusive interference model. Figs. 1(a) and Figs. 1(b) illustrate the achievable rate regions in state 1 and in state 2 respectively. The network stability region $\Lambda$ is shown in Fig. 1(c).

In related work, [2] considered a queueing model analogous to a cellular network with $N$ links, where the network channel state followed an irreducible discrete time Markov chain with a finite state space. It was shown that the policy which selects the queue with the highest weight.

$$\max_{l=1,\ldots,N} q^\delta_l(t) + c_l(t)$$

in each time slot, where $q_l$ is the queue size for link $l$ was throughput optimal for this network. In [3], it was shown that a Maxweight-type scheduling policy was throughput optimal for power allocation in wireless networks with time varying channels. Similarly, [4] also showed throughput optimality of a class of Maxweight type policies for wireless networks with fading channels.

Before we describe our greedy scheduler, we discuss the performance of non-opportunistic schedulers in the following section. In particular, we focus on a scheduler that utilizes only the mean link rates, instead of instantaneous link rates. For this scheduler, we illustrate that when arrivals are correlated with channel states, the non-opportunistic policy can potentially drive links that are experiencing poor channel states, leading to a loss in throughput.

A. Performance of Non-opportunistic Schedulers

We show that a scheduler that utilizes the mean link rates, instead of instantaneous link rates could perform arbitrarily worse in certain cases. To illustrate this, we consider the two link network graph shown in Fig. 1. In this example, each link $l$ has one queue $Q_l$, into which packets arrive according to an IID process. Suppose that the rates of the two links in each of the channel states are given by $c_1^1 = 1, c_2^1 = \epsilon$, and $c_1^2 = \epsilon, c_2^2 = 1$ respectively. Also, let $\pi^1$ be the probability with which the network assumes channel state 2, and $\pi^2$ be the probability for network channel state 2. In each time slot, the greedy non-opportunistic scheduler that we consider serves the queue which maximizes the quantity $Q_l(t) \bar{c}_l$. We will now construct an arrival traffic for this network under which the queues for both links grow unbounded under the non-opportunistic scheduling scheme.

Let the initial queue lengths be $Q_1(0) = Q_2(0) = 0$. At the beginning of each time slot, packets arrive according to the following statistics:

(i) If the network channel state is 1, then with probability $1 - \delta$, for an arbitrary channel state $\delta > 0$, $\epsilon$ packets arrive into the queue $Q_1$, and none into $Q_2$; With probability $\delta, C/\epsilon_1 + \epsilon$ packets arrive into the queue of link 1, and $C/\epsilon_2$ packets arrive into the queue of link 2 respectively. $C$ is a fixed positive quantity.

(ii) If the network channel state is 2, then with probability $1 - \delta, \epsilon$ packets arrive into the queue $Q_2$, and none into $Q_1$; With probability $\delta, C/\epsilon_1$ packets arrive into the queue of link 1, and $C/\epsilon_2 + \epsilon$ packets arrive into the queue of link 2 respectively.

Under this arrival statistic, we show that the end of each time slot, the length of each queue either remains unchanged or increases by a fixed quantity $C/\epsilon_2$. At the beginning of the first time slot, all queues are assumed to be empty. The non-opportunistic scheduler then serves the queue with the highest weight, i.e., the queue into which $\epsilon$ or $C/\epsilon_1 + \epsilon$ packets have arrived. At the end of each time slot, the queue lengths remain unchanged with probability $1 - \delta$, or increase by a fixed quantity $C/\epsilon_2$ with probability $\delta$. Moreover, the queue lengths are also equal at the end of each time slot and of the form $kC$, where $k$ is a nonnegative integer. Since the queue length process is non-decreasing, and the event that the queue length increases by a fixed positive quantity occurs infinitely often, the network is unstable under the greedy non-opportunistic scheduler. The arrival rate vector of our proposed arrival traffic is determined as $\bar{\lambda} = \pi^1(1 - \delta)\epsilon [0, 0] + \pi^1\delta [C/\epsilon_1 - C/\epsilon_2] + \pi^2(1 - \delta)\epsilon [0, \epsilon] + \pi^2\delta [C/\epsilon_1 - C/\epsilon_2]$, which simplifies to $\bar{\lambda} = \epsilon \left[ \pi^1 \pi^2 + \delta \left( \frac{C(\pi^1 + \pi^2)}{\epsilon_1} - \epsilon \frac{\pi^1}{\epsilon_2} \right) \right]$. Thus, when $\epsilon$ is small, the greedy non-opportunistic scheduler is unable to support arrival rates that are within a fraction of the stability region. Note that in the above example, the arrival process is correlated with the network channel state process.

III. A Greedy Scheduler for Networks with Fading Channels (GFS)

The greedy scheduler that we propose is similar to GMS except that it requires each link to have a virtual queue corresponding to every channel state of the network, i.e., each link has a set of $J$ virtual queues. In each time slot, packets arriving into a link $l$ are placed into one of the $J$ queues. In practice, each link could maintain only one real first-in-first-out queue, into which packets arrive and depart, and counters for the virtual queues which keep track of the number of packets in the virtual queue. The GFS scheduler would use the values of the counters to make the scheduling decision. Using such counters, also known as shadow queues have been effective
in reducing queueing complexity and delay \[15\]. Let \(Q_l^j\) be the virtual queue of link \(l\) corresponding to fading state \(j\) and \(q_l^j(t)\) denote its size at time \(t\). Let \(Q_l\) denote the real FIFO queue of link \(l\). We now describe our greedy scheduler:

1. At the beginning of time slot \(t\), packet arrivals \(A_l(t - 1)\) are placed in queue \(Q_l^j\) with probability \(\frac{c_l^j}{C_l}\).
2. In time slot \(t\), let the network be in fading state \(j\). GFS observes only the queues corresponding to fading state \(j\), in order to select the rate allocation vector. The scheduler first selects the link with highest weight \(m = \text{argmax}_{l \in G} q_l^j c_l^j\), removes all links in \(Z_m\) from the set of potential links to be scheduled at time \(t\), and repeats the process until there are no more non-interfering links that remain to be selected.

At the end of this procedure GFS selects a rate allocation vector that belongs to \(R^j\), when the network channel state is \(j\). Note that the GFS policy becomes identical to GMS in the case of networks with static link rates. Also, the application of the GFS policy on the queues corresponding to fading state \(j\), requires the knowledge of the network fading state at every node in the network. The departure process for the virtual queues can now be described as follows: For any link \(l\), \[\min(p_l(t), Q_l^j(t))\] packets depart from virtual queue \(q_l^j\), while \[\min(p_l(t), Q_l(t))\] packets depart from the real FIFO queue \(Q_l\).

### A. Performance Analysis of GFS

We now give the main result of this paper, which uses the LPF of a network graph to evaluate the stability region achievable using GFS. Before we state our result, we define the following static wireless network: given any wireless network graph \(G = (V, E)\) with time varying link rates, we associate with \(G\) a static wireless network \(\hat{G} = (V, \hat{E})\), whose link rates are fixed at \(c_l, \forall l\). Let \(\hat{R}\) denote the set of all feasible rate allocation vectors for the network graph \(\hat{G}\). We also define \(\mathcal{G}^j = (V, \mathcal{E})\) to be a static network whose link rates are fixed at \(c_l^j, \forall l, j = 1, \ldots, J\). Finally, let \(\Lambda\) and \(\Delta\) denote the network stability regions of the networks \(G\) and \(\hat{G}\) respectively.

**Definition 1.** Let \(L\) be any subgraph of \(\hat{G}\). Then \(\hat{L}\) satisfies \(\sigma\)-local pooling if, for any given pair \(\hat{\mu}, \hat{\nu}\), where \(\hat{\mu}\) and \(\hat{\nu}\) are convex combinations of the rate vectors in \(\hat{R}_{\hat{L}}\), we have \(\sigma\hat{\mu} \neq \hat{\nu}\).

The LPF \(\sigma^\ast\), for the network is then defined as:

\[
\sigma^\ast = \sup \left\{ \sigma \mid \forall \mathcal{L} \subset \hat{G}, \hat{L} \text{ satisfies } \sigma\text{-local pooling} \right\}.
\]

The LPF of a network graph depends only on the topology of the network graph and therefore is identical for \(\hat{G}\) and \(\mathcal{G}^j, j \in \{1, \ldots, J\}\).

**Theorem 1.** Let \(\sigma^\ast\) be the LPF of a network \(\hat{G}\). Then, the network \(\hat{G}\) is stable under the GFS policy for all arrival rate vectors \(\hat{\lambda}\) satisfying \(\hat{\lambda} \in \sigma^\ast \Lambda\), where \(\Lambda\) is the stability region of the corresponding network graph \(G\).

Theorem 1 provides performance guarantees for our scheduling policy for any wireless network in terms of the stability region of an associated identical static network whose link rates are fixed at their expected rates. Note that an LPF of 1 implies that the associated greedy policy can guarantee stability for any arrival rate in \(\Lambda\). Examples of network graphs which have LPF \(= 1\) include tree network graphs under the \(k\)-hop interference model for \(k \geq 1\). In [6], all network graphs with LPF \(= 1\) under the node-exclusive interference model are identified.

We prove Theorem 1 by first establishing the stability of the virtual queues. We then provide Lemma 3 to establish stability of the real FIFO queues as well.

**Proof:** We consider the fluid limit model of the system.

Let \(A_l^j(t)\) denote the cumulative arrival process into queue \(q_l^j\) and \(S_l^j(t)\) denote the cumulative service process for \(Q_l^j\) until time slot \(t\). For the arrival and service processes, we use \(A_l^j(t) = A_l(t), \forall l \in E\).

We now consider a sequence of scaled queueing systems \((q^{\ast}(\cdot), A^{\ast}(\cdot), S^{\ast}(\cdot))\), where we apply the scaling \(q^{\ast}(nt)/n, A^{\ast}(nt)/n, S^{\ast}(nt)/n, \forall \in E\) with the queue process satisfying \(\sum_{l \in E} q^{\ast}_{l}(0) = n\). Then, using the techniques to establish fluid limit in [13], one can show that a fluid limit exists almost surely, i.e., for almost all sample paths and for any positive \(n \to \infty\), there exists a subsequence \(n_k\) with \(n_k \to \infty\) such that following convergence holds uniformly over compact sets: For all \(l \in E, \frac{1}{n_k} A_l(t) \to \sum_{l \in E} A_l^{\ast}(nt)/n, \forall j \in E\). Let \(\tilde{S}^j\) denote the LPF of a network \(\hat{G}\) and \(\hat{G}^j\) are the fluid limits for the queue length processes and the service rate processes respectively. The fluid limit is absolutely continuous and hence the derivative of \(q_l^j(t)\) exists almost everywhere [13] satisfying:

\[
\frac{d}{dt} q_l^j(t) = \begin{cases} \pi c_l^j \lambda_l - q_l^j(t) & q_l^j(t) > 0 \\ 0 & \text{otherwise} \end{cases}
\]  

where \(\gamma_l^j(t) = \frac{d}{dt} q_l^j(t)\).

Consider the times \(t\) when the derivative \(\frac{d}{dt} q_l^j(t)\) exists for all \(l \in E, j = 1, \ldots, J\). Let \(L_0(t)\) denote the set of queues with the largest weight, i.e., \(L_0(t) = \text{argmax}_{Q_l \in \Psi} q_l^j(t) c_l^j\), where \(\Psi\) is the set of all queues in the network. Let \(L(t)\) denote the set of queues from \(L_0(t)\), which have the maximum derivative of the weights, i.e., \(L(t) = \text{argmax}_{Q_l \in L_0(t)} \frac{d}{dt} q_l^j(t) c_l^j\). The set \(L(t)\) can then be expressed as \(L(t) = \{Q_l : l \in E, Q_l^j \in L(t)\}, j = 1 \ldots J\).

Since \(q_l^j(t)\) is absolutely continuous, there exists a small \(\delta > 0\) such that in the interval \((t, t + \delta)\), the weight of queues in \(L(t)\) dominates the weight of other queues, whenever the network channel state is \(j\). Hence, GFS gives priority to queues belonging to \(L(t)\) in \((t, t + \delta)\). We now provide the following two lemmas to characterize the arrival rates and service rates for the queues in \(L(t)\). Let \(\tilde{E}_{L(t)} \subset \hat{G}^j\) denote the set of links whose queues are in \(L(t)\). Thus \(\tilde{R}_{L(t)}^j\) denotes the set of all feasible rate allocation vectors for the subgraph \(\tilde{G}_{L(t)}\). Let \(\tilde{\lambda}\) be the \(|E|\) dimensional arrival rate vector whose each
where $\vec{\mu}$ is omitted here. Consider all queues belonging to $\sum_c$ where $v$ vectors selected by GFS in network channel state projected on the set of links $\lambda_i$. The performance of GFS and GMS is plotted in Fig. 2b. Figure 2: A four-link network graph is shown in Fig. 2a and is a convex combination of the elements of $\sigma$.\footnote{The full proof is similar to that in \cite{2} and \cite{7} and is omitted here. Consider all queues belonging to $L(t)$.

**Lemma 1.** Consider any fading state $j \in \{1, \ldots J\}$ such that $L_j(t) \neq 0$. If the arrival rate vector $\vec{\lambda}_j \in \sigma^{*} \Lambda$, then $\vec{\lambda}_j$ is the arrival rate into the queuing system in network state $\sum_c$, where $\vec{\mu}$ is a convex combination of the rate allocation vectors in $R_{L_j(t)}^j$.\footnote{Suppose at the beginning of time slot $t$, $t \geq 0$, we have $q_j(t) \leq \sum_{j=1}^J q_j(t) + B$, for all $l \in \mathcal{E}$. Let $j$ denote the network state in time slot $t$. Then, if $D_j(t)$ and $D_j(t)$ denote the packets departing in time slot $t$ from the real FIFO queue $q_j(t)$ and the virtual queue $q_j(t)$ respectively, the following must be true: If $D_j(t) > D_j(t)$, then in time slot $t+1$, we have $q_j(t+1) \leq \sum_{j=1}^J q_j(t+1)$, since both $q_j(t)$ and $\sum_{j=1}^J q_j(t)$ are incremented by the same number of arrivals $A_j(t)$. Similarly, if $D_j(t) > D_j(t)$, then it again implies that $q_j(t+1) \leq \sum_{j=1}^J q_j(t+1)$. Finally, if $D_j(t) < D_j(t)$, it implies that $q_j(t) < q_j(t)$, and consequently, $q_j(t)$ empties and $q_j(t+1) = A_j(t) \leq \sum_{j=1}^J q_j(t+1)$. Since $q_j(t) \leq \sum_{j=1}^J q_j(t)$ is satisfied at $t = 0$, we obtain the desired condition at any time $t$. $\blacksquare$

**Lemma 2.** Consider any fading state $j \in \{1, \ldots J\}$ such that $L_j(t) \neq 0$. Then the service rate vector $\vec{\gamma}_j(t)$, projected onto the links in $\mathcal{E}_{L_j(t)}$, can be expressed as $\vec{\gamma}_j|_{\mathcal{E}_{L_j(t)}} = \pi^j \vec{\nu}$, where $\vec{\nu}$ is a convex combination of the rate allocation vectors in $R_{L_j(t)}^j$.\footnote{In this section we simulate the performance of GFS for the four link network graph shown in Fig. 2a. Each link independently assumes one of four different states in each time slot, where the link states correspond to rates 1, 2, 3 and 4 units per time slot. The probability distribution of the link states are independent and non-identical across links, with the average link rates being $\tau_1 = 2.7$, $\tau_2 = 2.1$, $\tau_3 = 2.8$, and $\tau_4 = 3.1$ respectively. In Fig. 2b, we plot the total queue sizes as we incrementally increase the arrival rate into all links. The plots show that GFS is able to sustain a load of at least 1 unit per link. Since the network in Fig. 2a has LPF value of 1, GFS can stabilize the region $\Lambda$. GFS therefore guarantees a per-link symmetric rate of at least 1, since the arrival rate $[1 \ 1 \ 1 \ 1]$ lies inside $\Lambda$. While the performance of GMS is better than we consider all queues belonging to $\sum_c$, where $\vec{\mu}$ is a convex combination of the rate allocation vectors in $R_{L_j(t)}^j$. From Lemma 1 and Lemma 2 the arrival rate $\vec{\lambda}_j|_{\mathcal{E}_{L_j(t)}}$ as well as the service rate $\vec{\gamma}_j|_{\mathcal{E}_{L_j(t)}}$ can be expressed in terms of the convex combinations of elements in $R_{L_j(t)}^j$.

**IV. Simulation**

[Note: The remaining text is not visible in the image.]
GFS in the plot of Fig. 2b, the current known performance guarantee of GMS is only half the network stability region $\Lambda$ under the one-hop interference model, which corresponds to a symmetric load of 0.5 per link. Based on simulations, we conjecture that the performance of GFS is a lower bound on the performance of Greedy Maximal Scheduling in time varying wireless networks. The performance guarantees for GFS thus motivates the analysis of GMS for time varying networks as our future work.

V. CONCLUSION

We develop a greedy scheduler, GFS, for wireless networks with time varying channel states and provide provable performance guarantees for this scheduler. Our greedy scheduler, though suboptimal, has low computational complexity and performs better than non-opportunistic schedulers that do not exploit instantaneous channel state information. The performance guarantees, along with simulations, also paint an optimistic picture of the performance of GMS in wireless networks with fading channels, and we conjecture the stability region guaranteed under GFS for any wireless network to be a lower bound on the stability region of GMS.

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