Distributed SINR based Scheduling Algorithm for **Multi-hop Wireless Networks**

Jiho Ryu[†], Changhee Joo[‡], Ted "Taekyoung" Kwon[†], Ness B. Shroff^{††}, Yanghee Choi[†] †School of Computer Science and Engineering Seoul National University, Korea {jihoryu, tkkwon, yhchoi}@snu.ac.kr

Department of EECE Korea University of Technology and Education cjoo@kut.ac.kr

††Departments of ECE and CSE The Ohio State University Columbus, OH 43210, USA shroff@ece.osu.edu

ABSTRACT

The problem of developing high-performance distributed scheduling algorithms for multi-hop wireless networks has seen enormous interest in recent years. The problem is especially challenging when studied under a physical interference model, which requires the SINR at the receiver to be above a certain threshold for decoding success. Under such an SINR model, transmission failure may be caused by interference due to simultaneous transmissions from far away nodes, which exacerbates the difficulty in developing a distributed algorithm. In this paper, we propose a scheduling algorithm that exploits carrier sensing and show that the algorithm is not only amenable to distributed implementation, but also results in throughput optimality. Our algorithm has a feature called the "dual-state" approach, which separates the transmission schedules from the system state and can be shown to improve delay performance.

Categories and Subject Descriptors

H.1.1 [Models and Principles]: Systems and Information Theory

General Terms

Algorithms

Keywords

Wireless scheduling, SINR, CSMA/CA, Discrete Time Markov

INTRODUCTION 1.

It is widely accepted that link scheduling (or media access control) is the bottleneck in throughput performance in wireless multi-hop networks. Over the past couple of decades, many scheduling algorithms have been studied to achieve high throughput performance with low complexity. Scheduling in wireless multi-hop networks refers to how to coordinate link activity (i.e. packet transmission) at a given

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MSWiM'10, October 17–21, 2010, Bodrum, Turkey. Copyright 2010 ACM 978-1-4503-0274-6/10/10 ...\$10.00. moment in order to achieve high throughput, low delay, fairness, and so on. In wireless environments, simultaneous links activations interfere with each other, which becomes a major challenge to develop efficient scheduling schemes. Also, practical implementation of wireless multi-hop networks often require that a scheduling algorithm be performed in a distributed fashion, which makes the scheduling problem even more challenging. Overall, there are many choices in designing a scheduling scheme such as degree of time complexity, interference model, operations (centralized or distributed), message-passing overhead, time granularity of media access (continuous or time-slotted), and so forth.

The problem of achieving throughput optimality in wireless networks has been well known for many years. For example, the celebrated Max-Weight Scheduling (MWS) [1] algorithm achieves throughput optimality at the cost of very high time-complexity. In a time slotted system, the MWS algorithm picks, at each time slot, the set of non-conflicting links whose queue-weighted rate sum is the largest. In general, finding such a set of max-weighted non-conflicting links is NP-hard and requires with centralized implementation. Many sub-optimal (and hence more practical) solutions have been proposed over the past several years mostly aiming to reduce this algorithmic complexity. For example, the Greedy Maximal Scheduling (GMS) [2, 3, 4, 5] is a well known suboptimal solution, which can achieve a constant-factor approximation of the optimal throughput of MWS. It picks links in decreasing order of the queue length without violating underlying the interference constraints. GMS [6] can operate in a distributed fashion but only at the expense of increased complexity due to the requirement that links be globally ordered. To address the difficulty of global ordering, Local Greedy Scheduling (LGS) [7] has been proposed suggesting that local ordering might be sufficient to achieve high performance in practice. Empirical results show that LGS provides good throughput and delay performance at a lower complexity, compared to those of GMS. However, although LGS requires only local message exchange for the queue length information of neighboring links, it shall suffer from high message-passing overhead, especially when the number of local neighbors are large.

Given the large scale deployment of IEEE 802.11, Carrier Sensing Multiple Access/Collision Avoidance (CSMA/CA) based scheduling algorithms [8, 9, 10, 11] have been developed and shown to achieve optimal throughput while retaining the key CSMA/CA feature of IEEE 802.11 networks. In particular, the Q-CSMA scheme [10] takes a discrete time approach that is similar to the IEEE 802.11 time-slotted protocol and can be modeled as a Discrete Time Markov Chain (DTMC) with the product form stationary distribution. Q-CSMA determines a transmission schedule by combining active links in the previous time slot and a set of potential candidate links that satisfy the interference constraint in a probabilistic manner. This probability is an increasing function of queue length so that a link with a longer queue has a higher probability to be activated (or to transmit its packet). Even though Q-CSMA can achieve optimal throughput, its delay performance can be poor, especially under heavy load.

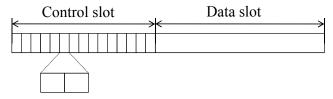
Note that all of the above scheduling schemes are developed on the basis of "somewhat theoretical" graph-based interference models. In a graph-based model, there is a binary interference relation for every pair of links. That is, whether two links can be active simultaneously does not depend on the activity of other links. The graph-based model approximates the signal-to-interference-noise-ratio (SINR) by simplifying wireless interference. However, in practice, the interference constraints are more complex due to the accumulating property of interfering signals. In [12],D. Qian et al. have taken into account the accumulated interference of Multi-Input Multi-Output (MIMO) links. To take practical interference constraints into consideration, we employ the more realistic SINR model.

In this paper, we propose a Distributed SINR-based Scheduling algorithm (DSS) for practical solutions in wireless multihop networks. Unlike prior scheduling schemes that are based on graph interference models, we consider a complex and realistic wireless interference relationship among multiple links by adopting the SINR interference model. Taking a CSMA approach in a time-slotted system, we show that DSS has a stationary distribution of link schedules in a product form, and can thus achieve optimal throughput performance. Further, we improve the delay performance of this new CSMA scheduling scheme by introducing a dual-state approach, which separates the transmission schedules from the system state.

The rest of this paper is organized as follows. We first give our system model in Section 2. Then we propose our DSS algorithm and describe its detailed operations in Section 3. We enhance the delay performance of DSS using a new dual-state approach in Section 4. Section 5 presents performance evaluation through simulation. We conclude our paper in Section 6.

2. NETWORK MODEL

A wireless network is modeled by a graph G(V, E), where V denotes the set of nodes and E denotes the set of links (each link is also represented as a pair of nodes). If there is a link between two nodes, that means that if a node transmits a packet with a fixed transmission power P, the other node can successfully receive the packet if there are no other senders at the same time. However, since we seek to schedule (or activate) as many links as possible at the same time, received signal powers from other senders will affect the success of the transmission due to the interference. That is, the transmission of a packet over a link is successful if the SINR of the received packet is above the SINR threshold θ_{th} . We assume that a single SINR threshold is used for all the links, which is carefully chosen considering the network density, e.g., [13]. For sake of exposition, we use a directed



phase 1 & phase 2 in each control mini-slot

Figure 1: Time slot. Each control mini-slot consists of two phases.

link $(i, j) \in E$ if node i can transmit a packet successfully to node j.

All links are assumed to have unit capacity (i.e., a packet can be transmitted at a unit time) and we consider a time-slotted system with a single frequency channel, where each time slot consists of a control slot and a data slot. Each control slot is used to generate a feasible transmission schedule for the data slot, and is further divided into control minislots. That is, a link schedule generated in the control slot is used for transmitting data packets during the data slot. A feasible schedule in our model is a set of links that can be active simultaneously, each with a sufficient SINR value at the receiver of a link. We use a vector $\{0,1\}^{|E|}$ to denote a schedule $\vec{x}(t)$ in time slot t, where $x_i(t)=1$ if link i is active in time slot t and 0 otherwise. Slightly abusing the notation, we also denote the set of active links at slot t by x(t), i.e., $i \in x(t)$ implies that $x_i(t)=1$.

Let λ_i denote the arrival rate of data packets at link $i \in E$, and let $\lambda = \{\lambda_1, \lambda_2, ..., \lambda_{|E|}\}$ be the set of these arrival rates. The *capacity region* of a scheduling policy is the set of all the arrival rates λ for each of which there exists a scheduling algorithm that can stabilize the network. Let \mathcal{M} be the set of all feasible schedules in our network model. Then as in [1], the capacity region can be defined by

$$\Lambda = \{ \lambda \mid \exists \mu \in Co(\mathcal{M}), \lambda < \mu \}, \tag{1}$$

where $Co(\mathcal{M})$ is the convex hull of the set of feasible schedules in \mathcal{M} . We say that a scheduling algorithm achieves optimal throughput, if it can keep all the queues in the network stable for any feasible arrival rates, i.e., any arrival rate belonging to Λ .

3. DISTRIBUTED SINR-BASED SCHEDUL-ING ALGORITHM (DSS)

We propose a distributed scheduling scheme that operates in a CSMA network, where the set of simultaneously active links is determined considering the SINR interference model. Similar to [10], at a given time slot t, we build a new transmission schedule x(t) by combining the previous transmission schedule x(t-1) at slot t-1 and a decision vector m(t) at slot t. The decision vector represents the set of randomly selected links that can be simultaneously activated with the links in x(t-1) without any SINR violation. That is, $m(t) \cup x(t-1)$ is a feasible schedule. For each link $l \in m(t) \cup x(t-1)$, the proposed algorithm decides whether it will be actually activated or not at data slot (of time slot t) by a certain activation probability. (Even though they can be all activated without causing any transmission failure, this "randomization" is needed to achieve throughputoptimality, which will be detailed in Section ??.) In this way, x(t) is determined by probabilistically selecting links

from $m(t) \cup x(t-1)$. Note that the state¹ of the links in m(t) and x(t-1) are probabilistically changed only; all the other links $(\forall i \notin m(t) \cup x(t-1))$ just maintain the same state from the previous slot $(x_i(t) = x_i(t-1))$. We suppose that before starting the network scheduling, each node store received signal strength (RSS) for other sender node by letting each node broadcast in turn and having the other nodes measure RSS as in [15]. With this operation, we can assume that a receiver node can store received signal strength of for each sender. So far, we have not explained how to generate such a decision schedule (or vector) in a distributed manner under the SINR interference model, which is one of the main contributions of this paper and is detailed in the following.

We first divide a control slot into M control mini-slots, where each mini-slot consists of two phases. Note that the active links at slot t-1 (i.e. x(t-1)) are not candidates to be included in m(t) since they are already eligible links to be activated probabilistically at slot t. The candidate links for m(t) should satisfy two constraints: (i) they are the inactive links at time t-1, and (ii) they can be active without making the links in x(t-1) violate the SINR threshold. Thus, at time slot t, a candidate link for m(t) checks whether it has a packet to send, and if so, it picks a random backoff counter in [0, M-1]. The control mini-slots are used for the backoff process to elect the links for m(t). Each sender of a candidate link will decrement its backoff counter by one at each mini-slot.

Suppose that the backoff timer of a particular sender of a candidate link, say s1, expires at mini-slot $m1^2$ (in slot t) while the senders of other candidate links are still decrementing their timers. Then s1 broadcasts a small control packet which contains the corresponding receiver (say r1) information during the first phase of mini-slot m1. If r1 successfully receives the control packet, there is no action in the second phase. Then s1 deems that its link is included in m(t). The other nodes that receive the control packet merely add the received signal power into its interference power level. Note that even if a node cannot decode a packet (e.g., it is located outside the transmission range), it can still measure its received signal power.

Now suppose that sometime later the backoff counter of the second winning sender, say s2, expires at mini-slot m2, and s2 broadcasts a control packet during the first phase of mini-slot m2. Assume that its corresponding receiver r2 receives the packet successfully but its calculated SINR is less than the SINR threshold, θ_{th} . It then broadcasts a busy tone in the second phase of mini-slot m2. When s2 receives this busy tone, it concludes that its link cannot be activated at slot t. So the link (whose sender is s2) cannot be included in m(t). Note that in this case, other nodes will not add the received signal power to their interference power since the link is not scheduled. In this way, the links for m(t) satisfying the SINR requirement are added up one by one during the control slot. Note, that not only the intended receiver of a control packet checks the SINR requirement, but also all the receivers in m(t) so far and in x(t-1) will check whether their receptions can still meet the SINR threshold

when the link (of the control packet) is activated. If any of the receptions cannot meet the SINR threshold due to the new link (that wins the backoff process), then the interfered receiver will send a busy tone signal, which indicates that the new link must drop its attempt to join m(t).

There is one more case that we need to consider. Due to random backoff nature, there can be a collision among the senders of the links that wish to join m(t). In this case, the intended receiver cannot decode the packet successfully and even if the SINR threshold is not satisfied, it cannot send a busy tone. In this case, any node that detects the collision (i.e. the measured signal is strong but not decodable) will send the busy tone. Then the links whose senders cause the collision will not be included in m(t).

By the above process, a new link will only be added to m(t) as long as it does not interfere with the existing links in m(t) and in x(t-1). When the control slot is over, we obtain the final schedule m(t) for slot t. Let $d(t) = m(t) \cup x(t-1)$, which is a feasible schedule. With the schedule d(t), we determine the transmission schedule $\vec{x}(t)$ as

$$x_i(t) = \begin{cases} d_i(t) & \text{with probability } p_i \\ 0 & \text{with probability } 1 - p_i \end{cases}$$
 (2)

where $d_i(t)$ is 1 if link i is included in d(t). Each link i in d(t) is activated with a link activation probability p_i , which will be detailed later. Eventually, in the data slot of slot t, the links in x(t) transmit data packets.

4. DUAL-STATE APPROACH

Even though it is proven that using the distributed random backoff process for scheduling links (in both Q-CSMA [10] and our algorithm) can achieve throughput optimality, the delay performance of the algorithm can be poor. In this section, we introduce a dual-state approach that improves the delay performance of the DSS scheduling³. Looking at our proposed DSS algorithm, the transmission schedule x(t) is unlikely to be a maximal schedule⁴ since x(t) is definitely a subset of d(t). This implies that there is a possibility that additional links can be added to x(t) without interfering with the already scheduled links. Although the presence of non-maximal schedules is not the main cause of poor delay performance, it is obvious that activation of additional links (while maintaining the feasibility of the schedule) can improve the delay performance. Then an important question is how can we activate more links than x(t) while maintaining throughput optimality.

This question motivates us to develop a dual-state approach. The dual-state approach can be described as follows. We consider two kinds of states; one for actual transmission, $d(t) = m(t) \cup x(t-1)$, and the other for Markovian state transition, x(t). The central idea of the dual-state approach is that while the system is viewed as a nominal state x(t), the actually activated links are d(t). That is, at slot t, even though all the links in d(t) are activated, the system's state is virtually deemed to be x(t); thus, x(t+1) will be derived from x(t). Recall that all the links in d(t) constitutes a feasible schedule. In this way, we can observe that x(t) evolves

¹A state of a link i at slot t is active or not, which is denoted by $x_i(t) = 1$ or 0, respectively.

²More precisely, this means that if s1 picks up its backoff counter m1-1, its backoff counter becomes zero at the end of mini-slot m1-1 and then it will attempt to join m(t) at mini-slot m1.

³The proposed dual-state approach can be applied to both Q-CSMA [10] under graph-based interference model and DSS under SINR-based interference model.

⁴If no more link can be added to a given schedule without interfering any of the existing links, then it is called a maximal schedule.

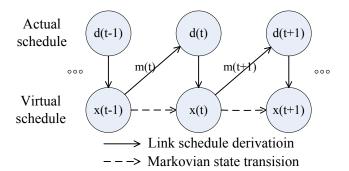


Figure 2: Scheduling process under dual-state approach. The *virtual schedule* x(t) is used to determine the next transmission schedule while d(t) is used for actual link activation.

in the Markovian manner. Fig. 2 shows how the scheduling process goes ahead in the dual-state approach. Starting from the previous virtual state x(t-1), the decision schedule m(t) is determined. Then, d(t) is easily determined since $d(t) = x(t-1) \cup m(t)$. The virtual state x(t) from d(t) is determined using a probabilistic method as in Eq. (2).

One difficulty is that we need to generate m(t) from the virtual schedule x(t-1), and not from the actual d(t-1). This means that each node should figure out the interference power level when the links in x(t-1) are activated. To this end, we dedicate the first control mini-slot for special usage, not for backoff process. That is, all the links in x(t-1) are activated in the first mini-slot in the dual-state approach, so that a node can measure the interference power level. In this way, we can generate m(t) from x(t-1), not from x(t-1). Note that the random backoff counter is selected from range x(t-1); the mini-slot 0 is dedicated to figure out x(t-1).

5. PERFORMANCE EVALUATION

In this section, we evaluate performance of different scheduling schemes the SINR based interference model. We consider network graphs with nodes that are placed on an area of 100 x 100 square units. We construct the topologies as follows. We first place a sender node at random in the area, and add a receiver node at a random location within distance 10 from the sender. Repeating the procedure, we generate two sets of sender-receiver topologies with 25 and 49 links (i.e., total 50 and 98 nodes), respectively (However, we omit the 49 links cases in this short paper version.). The signal transmitted by a sender attenuates as it propagates over space. For radio propagation model, we adopt simple two ray-ground model [16] and all the other channel effects (e.g., short and long term fading, etc.) are not considered. At the receiver, we assume that the signal can be decoded if the received signal ratio to interference plus noise (SINR) is over a certain threshold, and that all the links have the same SINR threshold value θ_{th} , which is set to 10 dB. For each link, we consider single-hop traffic with Poisson packet arrivals, where mean arrival rate is either 0.4 or 0.6 (chosen at random).

We compare the performance of CSMA scheduling schemes including DSS-Dual (DSS-D), Q-CSMA, HQ-CSMA with centralized schemes of GMS and MWS. For CSMA scheduling schemes, we set link weight $w_i(t) = \log(cq_i(t))$ with constant c = 0.1 as in [11], and vary the different number of control mini-slots M. We also include in our evaluation the

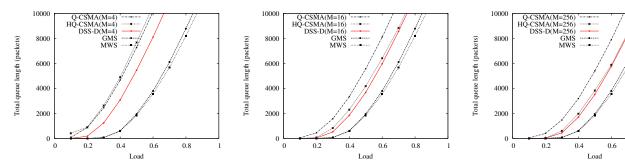
Hybrid Q-CSMA scheme (HQ-CSMA) is proposed to improve delay performance of Q-CSMA by adopting a greedy approach while maintaining throughput optimality. It classifies the control mini-slot into two sets; (i) one set (W_0 mini-slots) is used to active links whose weights are greater than some threshold w_0 following Q-CSMA algorithm, and (ii) the rest is used to find additional active links among those whose weight is lower than w_0 in a greedy manner. For more details, we refer to [11].

The overall performance gap between the centralized maximal scheduling schemes (GMS and MWS) and the distributed CSMA-based scheduling schemes (Q-CSMA, HQ-CSMA, and DSS-D) becomes larger as the number of links increases and/or as the traffic load increases. In general, we can observe that the increase in network density or traffic intensity makes the network overcrowded and the performance of the CSMA-based scheduling schemes degrades. Fig. 3 illustrates the total queue lengths under the scheduling schemes in the 25-links topology. Under light traffic load, the scheduling schemes maintain the queue lengths finite and successfully stabilize the network. However, as the load increases close to the boundary of the capacity region, the queue lengths will grow rapidly. By measuring the total queue lengths over the network, we can observe the delay performance of scheduling schemes in light and heavy traffic loads. Fig. 3 shows that the centralized algorithms of GMS and MWS show the best performance and can be served as a benchmark. HQ-CSMA achieves good delay performance with large number of control mini-slots, but underperforms with very small number of control mini-slots. This is partly because that HQ-CSMA uses Q-CSMA algorithm for a fraction of control mini-slots (i.e., W_0). DSS-D scheme shows a reasonable delay performance outperforming the other CSMA-based scheduling schemes.

Fig. 4 shows the delay performance of each CSMA-based scheduling scheme with different number of control minislots. In Fig. 4(a), the performance of Q-CSMA improves as the number of mini-slots increases (e.g., from 4 to 32). However, there is a certain threshold (i.e. 32), beyond which the performance does not improve any more. Similar results can be observed for the other CSMA scheduling schemes (DSS-D and HQ-CSMA). Note that while we have not taken into account the overhead of control mini-slots, in practical system, the actual transmission time will reduce as the number of control mini-slots increases. The results of Fig. 4(a), imply that a certain amount of control mini-slots is sufficient to achieve high performance under the CSMA-based scheduling schemes, and that the value is relatively small when we compare it with the maximum number of contention minislots of IEEE 802.11 DCF (i.e., 1024).

6. CONCLUSION

A link scheduling algorithm in wireless multi-hop networks has been a crucial problem since which links in multi-hop networks can be activated simultaneously is the key performance bottleneck. However, prior scheduling algorithms in the literature have considered only graph-based interference models. In this paper, we propose a scheduling algorithm DSS-D that takes into account a SINR-based interference model. DSS-D operates in the distributed fashion in CSMA networks and achieves throughput optimality. The key characteristic of DSS-D is the dual state approach, in which more links are activated compared to other CSMA scheduling al-



(a) Throughput performance of various (b) Throughput performance of various (c) Throughput performance of various scheduling schemes (M=4).

scheduling schemes (M=16).

scheduling schemes (M=256).

Figure 3: Comparison of the proposed DSS-D scheme with Q-CSMA, HQ-CSMA, GMS, and MWS in case of 25 links. DSS-D achieves better delay performance (or the queue length) than the other CSMA-based scheduling schemes.

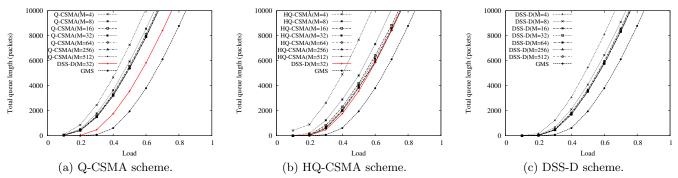


Figure 4: Performance of CSMA schemes in the network of 25 links with different traffic loads. As the number of contention mini-slots increases, each CSMA scheme has a better performance. However, beyond a certain threshold, its performance does not improve further suggesting that a certain amount of control mini-slots is sufficient to achieve high performance.

gorithms while maintaining the throughput optimality. Simulation is carried out to reveal that DSS-D exhibits the lower delay performance than other CSMA scheduling algorithms.

7. ACKNOWLEDGEMENT

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