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Maximal throughput scheduling based on the physical interference model using learning automata

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ABSTRACT

Wireless link scheduling is one of the major challenging issues in multi-hop wireless networks when they need to be designed in distributed fashion. This paper improves the general randomized scheduling method by using learning automata based framework that allows throughput optimal scheduling algorithms to be developed in a distributed fashion. A distributed scheduling algorithm that operates on more realistic conflict graph was proposed based on the physical interference model. This model uses a combination of a distributed learning automata based on the pick algorithm and an algorithm that compares successive scheduling solutions. Comparison was made by creating spanning tree on the conflict graph of the two consecutive schedules. Briefly, a distributed scheduling schemes was proposed, that: (i) is throughput optimal, (ii) intelligently choose links for new schedule, and (iii) message and time complexity is in $O(n^3)$.

1. Introduction

Medium access control (MAC) level wireless link scheduling has been one of the most challenging problems in multi-hop wireless networks over the last decades. Scheduling in wireless networks involves allocating network resources among competing network users in uncertain environments generated by fully stochastic network dynamics. In addition, scheduling is the main part of joint scheduling, routing and congestion control policies in network utility maximization frameworks and the efficient algorithms presented in this section, will pave the way for more effective methods of reaching the optimal solution for joint resource allocation problems.

Basic studies on scheduling, is mainly developed in seminal work by Tassiulas and Ephremides [1] in constraint queuing systems. They studied the throughput of scheduling policy, which is characterized by stability throughput region Λ, that is, the set of all vectors of arrival rates for which the system is stable. They characterized optimal policy that its stability region dominates all other stability regions. Though their method reaches all the achievable throughput regions, the nature of the proposed method is based on the centralized computations that may have some issue in realistic applications. Based on simple pick-and-compare algorithms comparison, they proposed a low complexity randomized algorithm that greedily reach optimal throughput, but was still executed on centralized fashion [2].The approach presented in the study by [2] is as follows. In each time slot, a candidate solution is randomly obtained for the maximum weighted matching problem. The maximum weights are replaced, if the sum of the weights of the selected links is higher than the value of the current solution. The use of this approach guarantees the achievement of 100% throughput under certain conditions of how the matching is obtained.

Lin and Shroff [3] studied the impact of imperfect scheduling on cross layer rate control. They showed that the use of a maximal weight matching algorithm may achieve up to 50% of achievable throughput region, in the distributed fashion distributed along with congestion control. They designed fully distributed cross layer congestion control and scheduling algorithm for the node-exclusive interference model.

In a recent study by Eryilmaz et al. [4] inspired by pick-and-compare algorithm, they developed a scheduling problem in the two-hop interference model. They proposed a general framework to be developed in two-hop interference that allows some distributed algorithms with polynomial communication and computation complexity model in wireless networks. Another work was also presented based on the physical interference model that used a randomized algorithm for link activation based on transmission successfulness and two level of priority consideration. They proved their work in the multi-hop wireless networks context, guarantees full throughput efficiency in a distributed manner [5].

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Recently, there have been several efforts towards the analysis and design of wireless multi-hop networks under more general interference models than the graph-based interference model. In the study by [6], mixed-integer linear programming formulation was developed for minimizing the schedule length over a time division multiple access (TDMA) wireless multi-hop networks, based on the joint MAC scheduling and power control under the physical interference model. Our work is different from the proposed distributed algorithm by [6] in that the mentioned work is sub-optimal, and is based on a relaxed physical interference model, where it only considers the impact of single transmitter on interference. Similar work by [7] also uses this relaxed physical interference model to study the performance of the scheduling mechanism of the MAC protocol. The physical model used in this paper considered only pairwise interference and also neglected noise.

Some recent studies' results [8–11] have addressed some challenges related to scheduling problem under the physical interference model, but their solutions only guarantee sub-optimal approximation of the maximum achievable throughput. The work presented in [10] develops interference-aware scheduling protocols under the arbitrary physical interference model, such that, it considers different transmission power control settings, that is, uniform and monotone power controls. The later work develops a greedy maximal scheduling as Longest-Queue-First (LQF) policy under the SINR interference model. This paper employed the ρ-local pooling technique, showed that LQF scheduling achieves zero throughput in the worst case and provided a sufficient condition for LQF scheduling to achieve maximum throughput in the special case of network topology.

In this paper, an adaptive learning automata was developed based on the distributed randomized scheduling algorithm that can fully utilize the throughput region of a multi-hop wireless network under the realistic Signal to Interference and Noise Ratio (SINR) model. We introduce a new conflict graph based on the physical model, such that it can be used in the construction of the spanning tree between two successive scheduling graphs. Also, we develop a new version of 'Compare' algorithm that can operate in a distributed fashion under the physical interference model to compare two consecutive scheduling. To do this, we used our physical conflict graph that is presented in the later. In Section 2, the system model from three different perspectives, including the interference model, network model and stochastic automata game model of the network was presented. In Section 3, collection of distributed algorithms based on randomized pick-and-compare method was proposed that could practically be developed in more realistic wireless network. Section 4 provides some simulation results and finally, the results of this paper were summarized in Section 5.

2. Models

2.1. Interference model

According to intrinsic difficulty in the modeling of wireless network physical layer, in contrast with wired link networks, wireless links capacity are dependent on one another, so they suffer from mutual interference required to model the wireless channel interference accurately. Several studies within the literature have considered the simplified graph based on the interference model. In a comparative study presented by [12], they investigated two of such model, the interference range model which uses fixed distance ranges, and the physical SINR model which specifies the ability of packet reception in receiver by comparing the desired sender signal strength with cumulative interference generated by other senders. From their results, it can be concluded that a different physical layer model will lead to a different result. Specifically, the interference range model misleadingly predicts the throughput as the function of the transmitted power. More precisely for an N node grid mesh network, the interference range model predicts a $\Theta(1/N)$ trend for the throughput. In contrast, under the SINR additive interference model, the capacity achieved for an N node grid mesh network is actually $O(1/N^{3/2})$ [12]. These conflicting results revealed the importance of choosing more realistic physical layer model.

In terms of wireless resource allocation, the interference model is considerably important in wireless link scheduling algorithms. Many studies consider simple models of interference, such that the main issues of their classes of algorithms are faced with conflicting pairs of links constraints. In this kind of constraints, certain pairs of wireless links are specified that no two links that constitute a conflicting pairs can simultaneously be activated. Scheduled links set is any set of wireless links that does not include conflicting pairs of links. So the solution of wireless link scheduling problem is equivalent to the computation of maximum weight matching of graph, whereas it becomes NP-Hard under more general interference model in wireless networks [13]. The numerous variety of solutions have significant result gained for the problem, but most of them easily use simple binary interference model, e.g., hop-based, range-based or protocol interference model [13]. Under these types of interference models conflicting links were predetermined by conflict graph, but in realistic wireless networks, interference on links was determined by global additive noise rather than distance metrics of transmission range.

The interference model can be formulated as follows. Consider a network of n wireless nodes, $n_1, n_2, \dots, n_N$. A message from a transmitter n_s can successfully be decoded by a receiver n_r if and only if $\frac{P_r}{I_r+N} \geq \beta$ for a hardware dependent ratio β. In this equation, P_r is the signal strength of the message at the receiver n_r, I_r is the sum of all interferences at n_r and N is the ambient noise. In the physical model of signal propagation, the signal strength P_r is modeled as a decreasing function depending on the distance between n_s, n_r more precisely $P_r = \frac{1}{d(n_s+n_r)^{\alpha}}$, where α is called the path-loss exponent, a constant dependent on the medium, typically between 2 and 6 [14].

Some of the factors that have effect on the rate of wireless links are application protocol level parameters like bit error rate (BER) and coding error; so information are transmitted from the upper layer at rate $(1-BER)\theta_l R_l$, where $0 < \theta_l \leq 1$ is the coding error and R_l is the rate of wireless link l [15]. Physical level factors are the second type of factors that the realistic rate of wireless links depends on. These factors constitute a probabilistic model for the channel state of physical wireless links [16]. The channel states are modeled by gain matrix $G = [G_{ij}]_{L\times L}$, where G_{ij} is the power gain from the transmitter on link j to the receiver on link i. The vector of transmitter powers is given by $S = [S_l]_L$. The link rate function is assumed to be of the form [16]:

$$R_l(S, G) = \log\left(1 + \frac{\phi K G_{ll} S_l}{\sum_{j\neq l} G_{lj} S_j + N_{amb}}\right) \tag{1}$$

where $K = -1.5/\log(5BER)$, is a scaling parameter for the received power, ϕ is the coding gain associated with a choice of convolutional code and N_{amb} is the ambient noise. The probability distribution of G is unknown to the network. The link rates can also vary, because the channel varies randomly, thereby resulting in congestion and queuing delay at the link buffers. The notations are listed in Table 1.

2.2. Network model

Considering a wireless mesh network where $N = \{1, 2, \dots, n\}$ is the set of nodes and $L = \{(i, j) : i, j \in N\}$ is the set of directed links in mesh routers backbone. Due to environmental limitations and