Delay-Constrained Optimal Link Scheduling in Wireless Sensor Networks

Qing Wang, Dapeng Wu and Pingyi Fan

Abstract

We consider the optimal link scheduling problem in wireless sensor networks. The optimal link scheduler under our consideration is intended to assign time slots to different users so as to minimize channel usage subject to constraints on data rate, delay bound, and delay bound violation probability; we study the problem under fading channels and a signal-to-interference-plus-noise ratio (SINR) based interference model. To the best of our knowledge, this problem has not been studied previously. We use the effective capacity model to formulate the optimal link scheduling as a mixed integer optimization problem. We first discuss a simple case, namely the scheduling with a fixed power allocation and then, extend to the case with variable transmit power. Moreover, because the mixed integer optimization problem is NP-hard, we propose a computationally feasible column-generation-based iterative algorithm to search for a sub-optimal solution to the problem. Finally, we design a medium access control (MAC) protocol to implement our optimal link scheduling strategy in practical wireless networks. Simulation results demonstrate that our proposed scheme achieves a larger throughput, a larger admission region, and a higher power efficiency than a benchmark time division multiple access (TDMA) system.

Index Terms

Link scheduling, delay constraint, effective capacity, column-generation

I. Introduction

Typically, an optimal link scheduling problem in sensor networks or ad hoc networks is intended to schedule time slots and possibly transmit powers for multiple users so that certain criterion (such as throughput, spatial reuse or fairness index) is optimized. The key issue in the design of link scheduling is how to model and mitigate/avoid interference. In the literature, there are two channel models to characterize interference, i.e., 1) the protocol interference model or disk model and 2) the physical model [1]. In the disk model, also called the collision model, an intended receiver, say, node i, is interfered by an unintended

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transmitter, say, node j, if the distance between node i and node j is less than a fixed distance called interference range. In the physical model, node k can communicate directly with node i if the received SINR at node i exceeds a specified threshold. While the physical model is more accurate, it is also more difficult to solve the link scheduling problem under the SINR constrains, especially in the case of dynamic power adaptation, where each node is allowed to vary its transmit power in order to reduce interference on other links.

Now, we discuss the formulations of the optimal link scheduling problem and the solution space. The optimal link scheduling problem can be formulated by optimizing the total network throughput or spatial reuse, the uniform throughput [1], max-min fairness [2], minimum potential delay fairness, proportional fairness [3], possibly subject to some constraints on power, channel resources, and/or quality of service (QoS). The solution under the disk model, is usually based on a link-contention graph [4] or a conflict graph [1]. The idea is to find the maximum independent sets so that the nodes in a maximum independent set can transmit simultaneously without causing collision while potential interfering users are allotted disjoint time slots (i.e., they belong to different maximum independent sets). Such a scheduling problem is equivalent to the well-known graph coloring problem [2]. In [5], the authors called the problem of determining a minimum-length schedule that satisfies given link demands in a wireless network and is subject to the SINR constraints, as *Max-SIR-Matching* problem. Since the graph coloring problem and the Max-SIR-Matching problem are both NP-hard, people seek for heuristic algorithms or polynomial-time approximation algorithms [6]. Hence, under the disk model, interference is avoided by assigning potential interfering users disjoint time slots.

On the other hand, the optimal scheduling problem under the physical model, is a mixed integer program [7][8] since the transmit power is continuous while independent sets are discrete. In [9], an optimal scheduling problem under the physical model is formulated as the minimum length scheduling problem (MLSP) subject to traffic demand of each link. A column-generation-based algorithm was proposed to solve the problem under fixed transmit power. The authors also extended their algorithm to the case with variable transmit power.

Different from the existing works that either use the disk model or the physical model, in this paper, we use the effective capacity technique [10] to quantify the effect of interference on system performance, which we call effective capacity model. Since we consider fading channels, the received SINR is random variable, actually, a stochastic process. Hence, it is possible to use less transmit power to reach the same distance, resulting in resource efficiency. In addition, different from the existing works, we consider statistic delay performance, i.e., the triplet of data rate, delay bound, and delay bound violation probability. Our intention is to leverage time diversity in fading to achieve resource efficiency. Since the effective capacity model captures the effect of time diversity in fading channels, we will use the effective capacity model in the design of optimal scheduling. Note that both the physical model and the effective capacity model are based on SINR.

The rest of this paper is organized as follows. We discuss some related works in Section II. In Section III, to make the effective capacity model more clear, we review some basic concepts and important results in the theory of effective capacity. In Section IV, we describe our network model and formulate the link scheduling problem for the fixed power case. In Section V, we develop a column-generation-based solution to the optimal scheduling problem. In Section VI, we study the link scheduling problem for the variable power case. In Section VII, we conduct performance analysis for the optimal link scheduler. Section VIII presents our design of an MAC protocol to implement the optimal link scheduling scheme. Section IX shows the simulation results. Section X concludes the paper.

II. Related Works

The link-scheduling problem has been a very hop topic in wireless multihop networks. Its key idea is to find a TDMA schedule satisfying requirements such as admissible link rates, fairness, power efficiency, robustness of routing, and interference constraints. To achieve some of these demands, people have studies joint power control (or routing) and link scheduling problems in the last two decades. Next, we review some representative related works as follows.

As a first attempt, Hajek and Sasaki [11] presented a centralized polynomial-time algorithm to find a minimum-length schedule in wireless networks, given the link traffic requirements. The basic idea is to represent the network by an undirected graph. But interference constraints were not considered. The analysis of the interference case was studied under the model of conflict graph [12]. In this model, arcs in a conflict graph connect nodes, which represent the links (in the wireless network) that can not transmit simultaneously due to mutual interference. Actually, for the joint routing and link scheduling problem, it can be formulated as a graph coloring problem, since wireless contentions can be modeled by conflict graphs and moreover, coloring on a conflict graph is equivalent to finding a set of independent sets with appropriate cardinality [13] which leads to a conflict-free schedule [14][15]. In Ref. [16], the authors studied link scheduling under a protocol interference model (PrIM) with fixed transmission power. They used graph coloring method based on a linear programming formulation to find a flow route whose achieved throughput is at least a constant fraction of the optimum. In Ref. [17], the authors proposed a versatile framework for joint design of routing and link scheduling under the formulation of constrained linear programming problems for wireless mesh networks (WMN) with a predefined system hierarchy in which MRs (*Mesh Routers*) form the backbone which can physically cover a large region using wireless multihop communication. Other similar works include Ref. [18], in which the proposed linear programming solution was developed to produce a transmission schedule which is also interference-free while maximizing the system throughput. In addition, Ref. [15] showed the scaling of the average packet delay with respect to the overall load on the network and the chromatic number of the link conflict graph; and in Ref. [19], the authors also studied the delay performance and proposed a linear integer programming formulation for the link scheduling problem in TDM wireless mesh networks under a sink-tree topology and constant bit rate traffic. Meanwhile, fairness problem and power efficiency in link scheduling have been taken into consideration in algorithm/protocol designs for multihop wireless networks. The max-min fair scheduling was studied in [20], [21] and [22]. In [23], Hou et al. advocated the use of lexicographical max-min (LMM) fair rate allocation for the nodes in wireless sensor networks. Almost in the same time, a distributed fair scheduling algorithm with the consideration of power control was proposed in [24]. Since power efficiency is significant for wireless sensor networks, for the joint power control and link scheduling problem, ElBatt and Ephremides [14] proposed a simple two-phase heuristic to minimize the total power consumption via two alternating phases, i.e., power control in the first phase and link scheduling in the second phase. In [25], Behzad and Rubin studied a similar problem, but focused on how to minimize the schedule length. Furthermore, in [26], Borbash and Ephremides showed that the general problem of determining a minimum-length schedule that satisfies given link demands in a wireless network and SINR constraints is NP-hard. After this work, though many polynomial-time approximation algorithms were proposed, the minimum-length scheduling problem of computing the true optimal solution still remains open. However, these approximation algorithms can be used in practice. Moreover, Ref. [27] examined joint link scheduling and power control with the objective of a good tradeoff between throughput and fairness. The problem was first formulated as a mixed integer linear program (MILP) and an effective polynomial-time heuristic algorithm was given. It sought for a transmission schedule and power assignment leading to a maximum throughput subject to the maximum power and interference constraints in each time slot. In Ref. [28], the authors showed that optimal non-preemptive link scheduling (NPLS) problems are generally NP-hard and are provably harder to solve than link scheduling without such a constraint. To tackle the problem, a low-complexity list link scheduling (LLS) algorithm based on graph model was proposed to approximate the optimal NPLS by carefully constructing the link-ordering list. Ref. [29] presented a method that finds conflict-free TDMA schedules with minimum scheduling delay; the authors devised an algorithm to seek for the transmission order with minimum delay on overlay tree topologies and used it with a modified Bellman-Ford algorithm to find minimum delay schedules in polynomial time.

Different from the existing works, first, for the fading case discussed in the paper, we use the effective capacity technique/model [10] which captures the effect of time diversity in fading channels to increase the resource efficiency and quantify the effect of interference on system performance, which significantly extends the previous related works. Second, in our joint power control and link scheduling problem, we study the statistical delay performance for each link, including the delay bound and delay bound violation probability, which has a great impact on the end-to-end delay so it has a more practical use in system design. Finally, we propose a new distributed protocol to implement the link scheduling based on the column generation algorithm. Meanwhile, to evaluate the efficiency of our proposed scheme, we compare with some existing approaches, including the works [19][29], which also considered delay and channel efficiency. In summary, we aim to find the shortest schedule that can achieve the specified link traffic demands, power efficiency, and QoS requirements such as link rates, delay bound, and delay bound violation probability under SINR constraints.

III. Review of Effective Capacity Theory

Effective Capacity (EC) [10] is a connection-layer model in which a wireless link is modeled by two EC functions, respectively the probability of nonempty buffer $\gamma(\mu)$ and the QoS exponent of this connection $\theta(\mu)$. Both of them are functions of the source traffic rate μ. Specifically, the key idea in the theory of effective capacity is that, if the source traffic has a communication delay bound of D_{max} and can only tolerate a delay-bound violation probability of ε at most, then we need to limit the source data rate to a maximum of μ, where μ is the solution to $\varepsilon = \gamma(\mu)e^{-\theta(\mu)D_{max}}$ in which $\theta(\mu) = \mu\alpha^{-1}(\mu)$. Here $\alpha(\cdot)$ is exactly the originally defined function of effective capacity and $\alpha^{-1}(\cdot)$ is the inverse function. We give the detail as follow.

Let $r(t)$ be the instantaneous channel capacity at time t. Define $S(t) = \int_0^t r(\tau)d\tau$, which is the service provided by the channel. Suppose the channel is ergodic and stationary. Then the effective capacity function of $r(t)$ is defined as

$$\alpha(u) = \frac{-\Lambda(-u)}{u}, \quad \forall u > 0 \tag{1}$$
$$\text{where} \quad \Lambda(-u) = \lim_{t\to\infty} \frac{1}{t} \log E[e^{-uS(t)}]$$

Thus, if we can derive the effective capacity function $\alpha(u)$ based on different kinds of fading channels, then we can find the QoS exponent function $\theta(\cdot)$, according to $\theta(\mu) = \mu\alpha^{-1}(\mu)$. Finally, associated with the QoS requirement of the source traffic, respectively the communication delay bound of D_{max} and a delay-bound violation probability ε, we can estimate the probability of nonempty buffer $\gamma(\mu)$ and then tune the source rate μ to guarantee its QoS requirement. Now, we can see that the effective capacity model is actually a triplet of data rate, delay bound and delay bound violation probability, i.e., $\{\mu, D_{max}, \varepsilon\}$ or another useful form, i.e. $\{\mu, D_{max}, P_{err}\}$ also derived by the authors in [10], where P_{err} is the packet error probability and the relation between them is given by $u = -\log P_{err}/(\mu \cdot D_{max})$. Since the effective capacity model captures the effect of channel fading on the queueing behavior of the link, we select this model to formulate and solve the link scheduling problem in this paper.

IV. Formulation of the Link Scheduling Problem for Fixed Power Case

We model a sensor network by a set of N nodes, denoted by set $\mathcal{N}$, and a set of directed links, denoted by set $\mathcal{E}$. Assume that a node can not transmit and receive simultaneously; a node i can communicate with only one node j ($j \neq i$) at any time. Assume that for each link $\{i, j\} \in \mathcal{E}$, transmitting node i can communicate directly with receiving node j with specified QoS (SINR or BER or delay) satisfied. Let $P_i(t)$ be the transmission power for node i at time t, $G_{ij}(t)$ the gain of the fading channel from node i to node j and η_j be the variance of the thermal noise at receiver j. The SINR at receiver j due to transmission from node i is given by

$$SINR_{ij}(t) = \frac{P_i(t)G_{ij}(t)}{\eta_j + \sum_{l\neq i,j} P_l(t)G_{lj}(t)} \tag{2}$$

Assume that each link $\{i, j\} \in \mathcal{E}$ has a traffic demand of $r_s^{(ij)}$ bits/sec, which needs to be transmitted across the link with delay bound $D_{max}^{(ij)}$ and delay bound violation probability $P_{err}^{(ij)}$.

Now, we formulate the optimal link scheduling problem. Considering an SINR-based scheduler where S time slots of lengths $\{w_k\}$ (k=1,· · ·,S and $w_k \in (0,1]$) are used to schedule links in $\mathcal{E}$ with QoS requirements $\{r_s^{(ij)}, D_{max}^{(ij)}, P_{err}^{(ij)}\}$. If there is no traffic demand for a specific link $\{i,j\}$, then $r_s^{(ij)} = 0$. Denote the transmission power of node i in slot k by $P_i^{(k)}$. Assume that $P_i^{(k)}$ $(\forall i \in \mathcal{N}, \forall k \in \{1,\cdots,S\})$ can only take two values, i.e., 0 and P_0. $P_i^{(k)} = 0$ means that node i does not transmit in slot k, while $P_i^{(k)} = P_0$ means that node i transmits in slot k. Clearly, here we use a fixed power allocation scheme. Our optimal scheduling problem is given by

$$\min_{\{w_k\}\{P_i^{(k)}\}} \quad \sum_{k=1}^{S} w_k \tag{3}$$

$$s.t. \quad P_i^{(k)} \in \{0, P_0\}, \forall i \in \mathcal{N}, \forall k \in \{1,\cdots,S\} \tag{4}$$

$$w_k \in (0,1], \forall k \in \{1,\cdots,S\} \tag{5}$$

$$\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u_{ij}^*) \geq r_s^{(ij)}, \forall \{i,j\} \in \mathcal{E} \tag{6}$$

where

$$u_{ij}^* = \frac{-\log P_{err}^{(ij)}}{r_s^{(ij)} \times D_{max}^{(ij)}}, \tag{7}$$

and

$$\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u) = \sum_{k=1}^{S} w_k \times \alpha_{ij,P_i^{(k)}}(w_k \times u), \tag{8}$$

where

$$\begin{aligned} \alpha_{ij,P_i^{(k)}}(u) &= \lim_{t\to\infty} \frac{-1}{ut} \log E[e^{-u\int_0^t W \log(1+SINR_{ij,k}(\tau))d\tau}] \\ & \quad u \geq 0, \end{aligned} \tag{9}$$

where W is the channel bandwidth and

$$SINR_{ij,k}(t) = \frac{P_i^{(k)}(t) G_{ij}(t)}{\eta_j + \sum_{l\neq i,j} P_l^{(k)}(t) G_{lj}(t)}. \tag{10}$$

We call the optimal scheduler resulted from (3) through (6), *SINR-EC scheduler* under fixed power. Note that (9) is the expression for the effective capacity function according to its definition in (1); and (8) is derived from Propositions 1 and 2, which are given below.

Proposition 1: Scaling law for effective capacity function:

The effective capacity function $\alpha_{ij,P_i^{(k)},w_k}(u)$ for Link $\{i,j\}$ under the SINR-EC scheduler with time fraction w_k ($w_k \in (0,1]$) and transmission power $P_i^{(k)}$, satisfies

$$\alpha_{ij,P_i^{(k)},w_k}(u) = w_k \times \alpha_{ij,P_i^{(k)}}(w_k \times u), \tag{11}$$

where $\alpha_{ij,P_i^{(k)}}(u)$ is the effective capacity function for Link $\{i,j\}$, defined by (9).
For a proof of Proposition 1, see Appendix A.

Proposition 2: Additivity law for effective capacity function:
Assume that the channel gains of Link $\{i,j\}$ in different slots are independent of each other. The effective capacity function $\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u)$ for Link $\{i,j\}$ under the SINR-EC scheduler with time fractions $\{w_k\,(k=1,\cdots,S)\}$ ($w_k \in (0,1]$, $\forall k$) and corresponding transmission powers $\{P_i^{(k)}\,(k=1,\cdots,S)\}$, satisfies

$$\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u) = \sum_{k=1}^{S} w_k \times \alpha_{ij,P_i^{(k)}}(w_k \times u), \tag{12}$$

For a proof of Proposition 2, see Appendix B. In practice, if the correlation between the channel gains in different slots is small, we use $\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u) \approx \sum_{k=1}^{S} w_k \times \alpha_{ij,P_i^{(k)}}(w_k \times u)$.

If Problem (3) results in a solution with $\sum w_k \leq 1$, then this solution or the scheduling process is feasible; otherwise it is not feasible since we assume there is only one channel. The S time slots could form a super-frame and the same slot pattern repeats in each super-frame. We assume admission control is in place, which works as below: for a new link requesting for admission, if the corresponding problem (3) results in a solution with $\sum w_k \leq 1$, then the new link can be accepted by the admission control. Here, we just give a general idea for the MAC. Actually, it leads to a new MAC protocol, which will be presented in Section VIII. In addition, we can see that in a schedule, a link may be active in one or multiple time slots. In a slot, multiple links may satisfy their SINR condition simultaneously so that all of these links can be activated; this group of active links in the same time slot form a matching [5], [9]. It can be shown that allowing multiple active links in a matching increases the throughput of the whole network.

If we do not allow interference, i.e., at any time, only one node is allowed to transmit, then we call the optimal scheduler resulted from (3) through (6) with SINR in (10) replaced by SNR, as *No-Interference TDMA* (NI-TDMA) scheduler under fixed power. We will use the NI-TDMA scheduler as a benchmark to evaluate the performance of our proposed SINR-EC scheduler.

Unfortunately, the optimization problem specified by (3) through (6) is NP-hard. Note that for $S = 1$, non-fading channels, $0 \leq P_i^{(k)} \leq P_0$, and $\{D_{max}^{(ij)} = \infty, P_{err}^{(ij)} = 0\}$, the problem has been solved for

CDMA cellular systems [30], using quasi-convexity. To solve (3) through (6), one may resort to one of the following three methods: 1) column generation [9], 2) polynomial time approximation algorithm [6], and 3) branch and price [31]. In this paper, we focus on the column generation method. Next, in Section V, we present a column generation based algorithm to solve the optimal link scheduling problem.

V. A Column-Generation-Based Solution To the Optimal Scheduling Problem

First, we give the basic idea of column generation algorithm. Column generation is an iterative algorithm for solving huge linear or integer programming problems where the number of variables is too large to be considered explicitly. While experience suggests that only a small subset of these variables are found in the optimal solution and the rest of these variables will be non-basic and always take a value of zero in the optimal solution. Therefore, column generation leverages this idea by generating only those variables which have the potential to improve the objective function. Consequently, the huge problem can be simplified. More specifically, in the column generation algorithm, the original problem is decomposed into a master problem and a subproblem. The master problem and subproblem could be either linear or integer program depending on the problem formulation, such as the examples in Ref. [9]. The strategy of this decomposition procedure is to operate iteratively on two separate but easier-to-solve problems. During each iteration, the algorithm tries to determine whether any variables exist that have a *negative reduced cost* (in the case of minimization problem) and adds the variable with the most negative reduced cost to the master problem. So the key idea of the column generation algorithm is to sequentially improve the current solution by first solving a subproblem that identifies a single new variable (a column) and adding it to the master problem, then solving the master problem, repeating this process until the algorithm terminates under some user-specified stopping criteria. In particular, the variables or saying columns here are now matchings and elements of the power set of links in our scheduling problem.

With the basic knowledge of the column generation algorithm, next we describe how to solve our scheduling problem. We present the main idea as below. Denote $\mathcal{M}$ the power set of $\mathcal{E}$, i.e., $\mathcal{M}$ contains all possible combinations of members in $\mathcal{E}$. The master problem is a restriction of the original problem (3) through (6). The master problem uses only a subset of columns indexed by $s \in \{1, \cdots, |\mathcal{M}|\}$, where $|\mathcal{M}|$ is the cardinality of $\mathcal{M}$. The master problem is first initialized in a random way with any $\mathcal{S} \subset \mathcal{M}$ that satisfies (4) through (6). For each transmitter $i \in \{i, j\} \in \mathcal{S}$, the transmit power $P_i^{(k)}, (\forall k)$ is equal to P_0. So the master problem is given by

$$\min_{\{w_k\}} \quad \sum_{k=1}^{|S|} w_k \tag{13}$$

$$s.t. \quad w_k \in (0,1], \forall k \in \{1, \cdots, |S|\} \tag{14}$$

$$\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u_{ij}^*) \geq r_s^{(ij)}, \forall \{i,j\} \in \mathcal{E} \tag{15}$$

Since this formulation optimizes over a subset $\mathcal{S}$ of all feasible solutions, the optimal solution to (13) through (15) provides an upper bound for the original problem (3) through (6).

In each iteration, after the master problem (13) through (15) is solved, if the solution to the master problem also provides the solution to the original problem (3) through (6), the procedure terminates; otherwise, we need to solve a sub-problem, which identifies a new column (independent set) that can improve the current solution. The sub-problem for generating a new column is formulated as below. For each member $\mathcal{S}_m \in \mathcal{M}\backslash\mathcal{S}$, which refers to the set of all columns that is in $\mathcal{M}$ but are not in $\mathcal{S}$. The dual variable corresponding to (14) is ξ_{ij} and the reduced cost ϖ_m for any column m in the master problem is expressed by $\varpi_m = 1 - \sum_{\{i,j\}\in\mathcal{S}_m} \xi_{ij}\alpha^{(m)}_{ij,\{P_i^{(k)}\},\{w_k\}}(u_{ij}^*)/r_s^{(ij)}$ so the sub-problem is given by

$$\varpi_m = \min_{\{\xi_{ij}\}}\{1 - \sum_{\{i,j\}\in\mathcal{S}_m} \xi_{ij}\alpha^{(m)}_{ij,\{P_i^{(k)}\},\{w_k\}}(u_{ij}^*)/r_s^{(ij)}\} \tag{16}$$

$$s.t. \quad P_i^{(k)} \in \{0, P_0\}, \forall i \in \{i,j\} \in \mathcal{S}_m \tag{17}$$

where

$$\alpha^{(m)}_{ij,\{P_i^{(k)}\},\{w_k\}}(u) = \lim_{t\to\infty} \frac{-1}{ut} \log E[e^{-u\int_0^t W\log(1+SINR_{ij,m}(\tau))d\tau}] \quad \forall u \geq 0 \tag{18}$$

where

$$SINR_{ij,m}(t) = \frac{P_0 G_{ij}(t)}{\eta_j + \sum_{l\neq i,j,\&\{l,j\}\in\mathcal{S}_m} P_0 G_{lj}(t)} \tag{19}$$

If the cost $\varpi_m < 0$, then add the column induced by $\mathcal{S}_m$ to $\mathcal{S}$ as a new member. Since there are exponential number of members in $\mathcal{M}$, in practice, we need to randomly select $\mathcal{S}_m$ from $\mathcal{M}\backslash\mathcal{S}$; the sub-problem stops when the solution to the master problem provides an ϵ-approximation solution [6] to the original problem (3) through (6). (In our simulation, we take $\epsilon = 10^{-4}$.) The value ϵ indicates how far our obtained solution is away from the optimal solution for the original problem. The paper [6] proved the relationship between the approximation ratio and the number of iterations required so it guarantees a high probability that by adequate iterations we can find a solution with an acceptable approximation ratio to the minimum value. Actually, the reason of having an ϵ-approximation solution is to have a comparable polynomial time (randomized) algorithm [32].

Until now, we have formulated the basic optimal link scheduling problem in sensor networks with QoS requirement in Section IV and also showed how to use a column-generation-based algorithm to solve the original complex optimization problem for a fixed power case. Next, we extend our approach to a more complicated case where variable power is used in the scheduling problem.

VI. The Optimal Link Scheduling Problem Under Variable Transmit Power

Though simultaneous transmissions in each matching can increase the frequency spatial reuse of the network, the fixed power allocation, namely only using the maximum transmit power P_0, may cause strong interference for the other on-going transmissions in the neighborhood. Therefore, to further mitigate the interference and increase the frequency spatial reuse, we introduce a power control scheme into the original optimal scheduling process. The experimental results in Section IX verify that this more flexible scheduling scheme with variable transmit power leads to a better performance.

Like the fixed power case, we first formulate the optimal scheduling problem under variable transmit power as follows.

$$\min_{\{w_k\}\{P_i^{(k)}\}} \quad \sum_{k=1}^{S} w_k \tag{20}$$

$$s.t. \quad 0 \leq P_i^{(k)} \leq P_0, \forall i \in \mathcal{N}, \forall k \in \{1, \cdots, S\} \tag{21}$$

$$w_k \in (0, 1], \forall k \in \{1, \cdots, S\} \tag{22}$$

$$\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u_{ij}^*) \geq r_s^{(ij)}, \forall \{i, j\} \in \mathcal{E} \tag{23}$$

where

$$u_{ij}^* = \frac{-\log P_{err}^{(ij)}}{r_s^{(ij)} \times D_{max}^{(ij)}} \tag{24}$$

and

$$\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u) = \sum_{k=1}^{S} w_k \times \alpha_{ij,P_i^{(k)}}(w_k \times u) \tag{25}$$

where $\alpha_{ij,P_i^{(k)}}(u)$ is defined by (9). We call the optimal scheduler resulted from (20) through (23), *SINR-EC scheduler* under variable power.

If we do not allow interference, i.e., at any time, only one node is allowed to transmit, then we call the optimal scheduler resulted from (20) through (23) with SINR in (10) replaced by SNR, as *No-Interference TDMA* (NI-TDMA) scheduler under variable power. We will use the NI-TDMA scheduler as a benchmark to evaluate the performance of our proposed SINR-EC scheduler.

To solve the optimal scheduling problem under variable power, again we use the column generation method. We explain our idea as below. The master problem also uses only a subset of columns indexed by $s \in \{1, \cdots, |\mathcal{M}|\}$. The master problem is first initialized with any $\mathcal{S} \subset \mathcal{M}$ that satisfies (5), (6) and $0 \leq P_i^{(k)} \leq P_0, (\forall i \in \mathcal{N}, \forall k \in \{1, \cdots, |\mathcal{S}|\})$. So the master problem is formulated as below.

$$\min_{\{w_k\}} \quad \sum_{k=1}^{|\mathcal{S}|} w_k \tag{26}$$

$$s.t. \quad w_k \in (0,1], \forall k \in \{1, \cdots, |\mathcal{S}|\} \tag{27}$$

$$\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u_{ij}^*) \geq r_s^{(ij)}, \forall \{i,j\} \in \mathcal{E} \tag{28}$$

Since this formulation optimizes over a subset $\mathcal{S}$ of all feasible solutions, the optimal solution to (26) through (28) provides an upper bound for the original scheduling problem. Note that (26) is optimized over $\{w_k\}$; the transmit power $P_i^{(k)}$ are determined by the sub-problem, which is described as below.

The sub-problem for generating a new column is formulated as follows. First, randomly select K members from $\mathcal{M} \backslash \mathcal{S}$. K can take any positive integer not larger than the cardinality of the set $\mathcal{M}$ $mathcalS$. Denoting these K members by $\mathcal{S}_m (m = 1, \cdots, K)$, i.e., mth element of the set, for each $\mathcal{S}_m$, the sub-problem is given by

$$\zeta_m \quad = \quad \max_{\{P_i : i \in \{i,j\} \in \mathcal{S}_m\}} \sum_{\{i,j\} \in \mathcal{S}_m} \alpha_{ij,P_i}^{(c1)}(u_{ij}^*)/r_s^{(ij)} \tag{29}$$

$$s.t. \quad 0 \leq P_i \leq P_0, \forall i \in \{i,j\} \in \mathcal{S}_m \tag{30}$$

where

$$u_{ij}^* = \frac{-\log P_{err}^{(ij)}}{r_s^{(ij)} \times D_{max}^{(ij)}} \tag{31}$$

and

$$\alpha_{ij,P_i}^{(c1)}(u) \quad = \quad \lim_{t \to \infty} \frac{-1}{ut} \log E[e^{-u \int_0^t W \log(1+SINR_{ij,m}(\tau))d\tau}], \quad u \geq 0, \tag{32}$$

where

$$SINR_{ij,m}(t) = \frac{P_i G_{ij}(t)}{\eta_j + \sum_{l \neq i,j, \& \{l,j\} \in \mathcal{S}_m} P_l G_{lj}(t)} \tag{33}$$

The maximization in (29) is over $\{P_i\}$ only, unlike (3). This is similar to CDMA power control with a single slot only [30], i.e., choosing the powers that maximize the total capacity (for $\mathcal{S}_m$), weighted by $\{1/r_s^{(ij)}\}$. Let $m^* = \arg\max_m \zeta_m$. Then add the column induced by $\mathcal{S}_{m^*}$ to $\mathcal{S}$ as a new member and assign the transmit powers

$$\{P_i^{(k)} : i \in \{i,j\} \in \mathcal{S}_{m^*}\} = \arg \max_{\{P_i : i \in \{i,j\} \in \mathcal{S}_{m^*}\}} \sum_{\{i,j\} \in \mathcal{S}_{m^*}} \frac{\alpha_{ij,P_i}^{(c1)}(u_{ij}^*)}{r_s^{(ij)}} \tag{34}$$

Since there are exponential number of members in $\mathcal{M}$, to have a polynomial time algorithm, we also need to terminate the sub-problem when the solution to the master problem provides an ϵ-approximation solution to the original problem.

VII. Performance Analysis

In this section, we analyze the performance of our SINR-EC scheduler in terms of admission region of QoS-assured flows, and throughput gain.

We first examine the performance of our SINR-EC scheduler in the aspect of admission region of QoS-assured one-hop flows. We only consider one-hop flows here since it is much easier to analyze the admission region for one-hop flows; our future work will address the admission region of multi-hop flows. We assume that the system under study has an admission control module [33] to ensure that the admitted one-hop flows have their requested QoS satisfied. Assume that there are L QoS classes. QoS class l ($l = 1, \cdots, L$) is specified by bit rate $r_s^{(l)}$, delay bound $D_{max}^{(l)}$, and delay bound violation probability $P_{err}^{(l)}$. Assume that for QoS class l ($l = 1, \cdots, L$), the maximum number of admitted QoS-assured one-hop flows under the the NI-TDMA scheme is N_l. Then the vector $[N_1, \cdots, N_L]$ specifies a point on the boundary of the admission region or the capacity region for the NI-TDMA; that is, the NI-TDMA is able to simultaneously support all these flows, i.e., N_l one-hop flows for QoS class l ($l = 1, \cdots, L$). The flows of all QoS classes share the same wireless resource (i.e., the same frequency band), and there are many Pareto-optimal values for $[N_1, \cdots, N_L]$. All Pareto-optimal vectors $[N_1, \cdots, N_L]$ specify the boundary of the admission region for the NI-TDMA. Compared to the NI-TDMA, the admission region under our SINR-EC scheduler is increased by a factor of $\lfloor 1/\sum_{k=1}^{S} w_k \rfloor$, according to the following proposition.

Proposition 3: Assume that $[N_1, \cdots, N_L]$ specifies a point on the admission region under the NI-TDMA and the percentage of channel use under the NI-TDMA is 100%. Suppose that our SINR-EC scheduler is also able to simultaneously support all these flows, i.e., N_l one-hop flows for QoS class

l ($l = 1, \cdots, L$), and the percentage of channel use under our SINR-EC scheduler is $\sum_{k=1}^{S} w_k < 1$. Then $[N_1 \times \lfloor 1/\sum_{k=1}^{S} w_k \rfloor, \cdots, N_L \times \lfloor 1/\sum_{k=1}^{S} w_k \rfloor]$ is within the admission region under our SINR-EC scheduler, where $\lfloor x \rfloor$ is the largest integer that is less than or equal to x.

For a proof of Proposition 3, see Appendix C.

Next, we consider the performance of our SINR-EC scheduler in terms of throughput gain. The following proposition states that the throughput under our SINR-EC scheduler is increased by a factor of $1/\sum_{k=1}^{S} w_k$ under the same delay bound and delay bound violation probability.

Proposition 4: Assume that $[N_1, \cdots, N_L]$ specifies a point on the admission region under the NI-TDMA and the percentage of channel use under the NI-TDMA is 100%. Suppose that our SINR-EC scheduler is also able to simultaneously support all these flows, i.e., N_l one-hop flows for QoS class l ($l = 1, \cdots, L$), and the percentage of channel use under our SINR-EC scheduler is $\sum_{k=1}^{S} w_k < 1$. Then, if our SINR-EC scheduler is allowed to have 100% channel use, then for QoS class l ($l = 1, \cdots, L$), our SINR-EC scheduler can satisfy bit rate $r_s^{(l)}/\sum_{k=1}^{S} w_k$, delay bound $D_{max}^{(l)}$, and delay bound violation probability $P_{err}^{(l)}$.

For a proof of Proposition 4, see Appendix D.

Propositions 3 and 4 are valid for both the fixed power case and the variable power case. This is because the fixed power case and the variable power case have the same structure for time fraction allocation and power allocation, except that the variable power case allows powers to be changeable over different slots.

Propositions 3 and 4 show that our SINR-EC scheduler achieves a larger admission region of QoS-assured flows and a higher throughput than the NI-TDMA. This is due to frequency spatial reuse and interference mitigation obtained by our SINR-EC scheduler.

VIII. A Distributed Protocol To Implement the Optimal Link Scheduling

In this section, we present our design of a new MAC protocol to implement the proposed optimal link scheduling. To illustrate it, we consider the case where all transmitting nodes use fixed transmit power.

First, we use the scheme in the previous works [34][35] to form clusters of nodes. That is, each cluster will elect a cluster head. A cluster head is used to coordinate the transmission initiation by periodically transmitting a beacon signal so that all other nodes can set up their networking parameters. The MAC is a TDMA-like protocol based on a well-defined super frame similar to that in IEEE 802.15.3. A super frame consists of a beacon, a contention access period (CAP), management channel time allocation (MCTAs), and channel time allocations (CTAs), as shown in Fig. 2. The MCTAs and CTAs together form a contention-free period (CFP). All nodes in a cluster will synchronize to the cluster head based on the preamble in the beacon from the cluster head.

Second, we search for a feasible solution to the optimal scheduling problem. Each cluster head randomly select one node from its cluster; all these selected nodes form $\mathcal{S}_1$; in slot CTA1, all nodes in $\mathcal{S}_1$ can transmit simultaneously at corresponding rate $r_s^{(ij)}$. $SINR_{ij}$ and $P_{err}^{(ij)}$ will be measured by the receiver j and piggybacked in the packets from node j to node i in the next superframe (assuming bi-directional traffic, e.g., interactive vedio/audio). $SINR_{ij}$ will be used to determine the physical layer parameters such as the order of modulation (if adaptive modulation is used). Denote the estimated $P_{err}^{(ij)}$ as $\hat{P}_{err}^{(ij)}$. Then, $\theta_{ij}(r_s^{(ij)})$ is estimated by $\hat{\theta}_{ij}(r_s^{(ij)}) = Pr\{D^{(ij)} > 0\}/E[D^{(ij)}]$ where $E[D^{(ij)}]$ is the expectation of the delay of the head-of-line packet for Link $\{i, j\}$ and $Pr\{D^{(ij)} > 0\}$ is the probability that $D^{(ij)} > 0$. Note that a packet that violates the delay bound $D_{max}^{(ij)}$ will be dropped by the transmitter. So repeat the same process $K-1$ times to obtain sets of nodes, $\mathcal{S}_1, \mathcal{S}_2, \cdots, \mathcal{S}_K$; the protocol will make sure all $\mathcal{S}_k$ are different. Since the problem

$$\max_{m\in\{1,2,\cdots,K\}} \sum_{\{i,j\}\in\mathcal{S}_m} \alpha_{ij,P_i}^{(c1)}(u_{ij}^*)/r_s^{(ij)} \tag{35}$$

is equivalent to the problem

$$\min_{m\in\{1,2,\cdots,K\}} \sum_{\{i,j\}\in\mathcal{S}_m} \theta_{ij}(r_s^{(ij)}) \cdot D_{max}^{(ij)}/\log P_{err}^{(ij)}, \tag{36}$$

so we can solve the following problem instead of (16)–(19),

$$m^* = \arg\max_{m\in\{1,2,\cdots,K\}} \sum_{\{i,j\}\in\mathcal{S}_m} \theta_{ij}(r_s^{(ij)}) \cdot D_{max}^{(ij)}/\log P_{err}^{(ij)} \tag{37}$$

$$s.t. \quad \hat{P}_{err}^{(ij)} \le P_{err}^{(ij)}. \tag{38}$$

After obtaining m^*, add the column induced by $\mathcal{S}_{m^*}$ to $\mathcal{S}$ as a new member and assign a slot CTA to all the nodes in $\mathcal{S}_{m^*}$. Repeat the same process and add columns to $\mathcal{S}$ until (14) and (15) are satisfied.

Third, we determine the length of slot CTA$_k$ in the superframe based on the optimal w_k values. For the scheduling scheme under variable transmit power, the process follows the same way.

IX. Simulation Results

A. Simulation Setting

1) Method for Estimating EC-function $\alpha_s(u)$: We simulate the discrete-time system depicted in Fig. 1. In this system, the data source generates packets at a *constant* rate μ. Generated packets are first sent to the (infinite) buffer at the transmitter, whose queue length is $Q(n)$, where n refers to the n-th sample-interval. The head-of-line packet in the queue is transmitted over the fading channel at data rate $r(n)$. The fading channel has a random power gain $g(n)$. We use a fluid model, that is, the size of a packet is infinitesimal. In practical systems, the results presented here will have to be modified to account for finite packet sizes.

We assume that the transmitter has perfect knowledge of the current channel gains $g(n)$ at each sample-interval. Therefore, it can use rate-adaptive transmissions and ideal channel codes, to transmit packets without decoding errors. We consider the following two cases.

1) For the case without link interference, the transmission rate $r(n)$ is equal to the instantaneous (time-varying) capacity of the fading channel, as below,

$$r(n) = B_c \log_2(1 + g(n) \times P_0/\sigma_n^2) \tag{39}$$

where B_c denotes the channel bandwidth, and the transmission power P_0 and noise variance σ_n^2 are assumed to be constant. The average SNR is fixed in each simulation run and the average SNR $SNR_{avg} = E[g(n) \times P_0/\sigma^2]$. Since we set $E[g(n)] = 1$, we have $SNR_{avg} = E[g(n) \times P_0/\sigma^2] = P_0/\sigma^2$.

2) For the case with link interference, the transmission rate $r(n)$ is equal to the instantaneous (time-varying) capacity of the fading channel, as below,

$$r(n) = B_c \log_2(1 + g(n) \times P_0/(I + \sigma_n^2)) \tag{40}$$

where I is the variance of the total link interference power at receiver j from all the other simultaneous transmitters k, i.e., $I = \sum_k P_0 \cdot d_{kj}^{-\nu}$, where d_{kj} is the distance between node k and node j, and ν is the path-loss exponent [36]; without loss of generality, we assume that the total link interference power at receiver j is a Gaussian random variable. Note that we use the SINR in the interference case. The average SINR is also fixed in each simulation run and the average SINR $SINR_{avg} = E[g(n) \times P_0/(I + \sigma^2)]$. Since we set $E[g(n)] = 1$, we have $SINR_{avg} = E[g(n) \times P_0/(I + \sigma^2)] = P_0/(I + \sigma^2)$.

We collect the following measurements from the queueing system at the n-th sampling epoch ($n = 1, 2, \cdots, N_T$): $S(n)$ the indicator of whether a packets is in service ($S(n) \in \{0, 1\}$), $Q(n)$ the number of bits in the queue (excluding the packet in service), and $\tau(n)$ the remaining service time of the packet in service (if there is one in service). We calculate the measured EC function $\alpha_s(u)$ by the following procedure.

$$\hat{\gamma} = \frac{1}{N_T} \sum_{t=1}^{N_T} S(n), \tag{41}$$

$$\hat{q} = \frac{1}{N_T} \sum_{t=1}^{N_T} Q(n), \tag{42}$$

$$\hat{\tau}_s = \frac{1}{N_T} \sum_{t=1}^{N_T} \tau(n), \tag{43}$$

$$\hat{\theta} = \frac{\hat{\gamma} \times \mu}{\mu \times \hat{\tau}_s + \hat{q}}, \tag{44}$$

$$\alpha_s(u) = \mu, \quad \text{for } u = \hat{\theta}/\mu. \tag{45}$$

In our simulations, the sampling interval δ is set to 1 milli-second. This is not too far from reality, since 3G WCDMA systems already incorporate rate adaptation on the order of 10 milli-second [37]. Each simulation run is 10,000-second long for all the scenarios, in order to obtain good estimate by the Monte Carlo method. Since the sampling interval is 1 milli-second, we have 10,000,000 samples for estimation.

2) AR(1) Rayleigh Fading Channel Simulator: Denote $h(n)$ the voltage gain in the n-th sample interval. We generate Rayleigh flat-fading voltage-gains $h(n)$ by a first-order auto-regressive (AR(1)) model as below. We first generate $\bar{h}(n)$ by

$$\bar{h}(n) = \kappa \times \bar{h}(n-1) + u_g(n), \tag{46}$$

where $u_g(n)$ are i.i.d. complex Gaussian variables with zero mean and unity variance per dimension. Then, we normalize $\bar{h}(n)$ and obtain $h(n)$ by

$$h(n) = \bar{h}(n) / \sqrt{\frac{2}{1-\kappa^2}} = \bar{h}(n) \times \sqrt{\frac{1-\kappa^2}{2}}. \tag{47}$$

It is clear that (47) results in $E[g(n)] = E[|h(n)|^2] = 1$. The coefficient κ determines the Doppler frequency, *i.e.*, the larger the κ, the smaller the Doppler frequency. Specifically, the coefficient κ can be determined by the following procedure: 1) compute the coherence time T_c by [36, page 165]

$$T_c \approx \frac{9}{16\pi f_m}, \tag{48}$$

where the coherence time is defined as the time, over which the time auto-correlation function of the fading process is above 0.5; 2) compute the coefficient κ by[1]

$$\kappa = 0.5^{\delta/T_c}. \tag{49}$$

3) Network Topology and Traffic Model: Next, we describe the network topology and the source traffic demands used in the simulation. In order to evaluate the performance of the column-generation-based algorithm for our scheduling problem, we consider a 6-node network and a 20-node network. For the 6-node network, the topology and link QoS requirements are shown in Fig. 3; note that the position of each node in Fig. 3 does not correspond to its geographic location, and Fig. 3 only shows the connectivity relationship among nodes. More specifically, the demand of traffic bit rate vector is $[120, 80, 100, 100, 110, 90, 90, 95]$ *kb/s* corresponding to the links $\{1, 2\}$, $\{2, 3\}$, $\{3, 4\}$, $\{3, 6\}$, $\{4, 5\}$, $\{5, 3\}$, $\{5, 6\}$, $\{6, 1\}$, respectively. The corresponding maximum delay bound vector is $[140, 190, 170, 170, 160, 150, 150, 130] ms$ and the delay bound violation probability vector is $[3\%, 5\%, 4\%, 4\%, 9\%, 7\%, 6.5\%, 6\%]$. These QoS requirements are typical for multimedia streaming applications.

Denote $\bar{\mathbf{G}}$ the average channel gain matrix, the element of which is average channel gain $\bar{G}_{ij} = E[G_{ij}]$ with i as the row index and j as the column index. $\bar{G}_{ij}$ is proportional to $d_{ij}^{-\nu}$ $(\nu \geq 2)$, where d_{ij} denotes the transmitter-receiver separation distance of Link $\{i, j\}$. In the simulation, we use the following $\bar{\mathbf{G}}$

$$\bar{\mathbf{G}} = \begin{bmatrix} \text{N/A} & 0.16 & 0.30 & 0.70 & 0.39 & 1.10 \\ 0.50 & \text{N/A} & 2.30 & 0.69 & 1.70 & 0.23 \\ 0.60 & 1.40 & \text{N/A} & 0.90 & 1.06 & 6.90 \\ 0.10 & 0.71 & 3.10 & \text{N/A} & 5.70 & 0.61 \\ 0.43 & 2.10 & 8.00 & 0.96 & \text{N/A} & 0.84 \\ 0.71 & 3.60 & 0.51 & 1.76 & 0.27 & \text{N/A} \end{bmatrix} \times 10^{-3}$$

where N/A means that a user will not send massages to itself. In our simulation, the power of thermal noise at the receiver is set to 3.34×10^{-9}W and the maximum transmit power P_0 is set to 1mW which means the transmission range covers tens of meters. The bandwidth of each link is 100kHz.

For the 20-node network used in our simulation, we will not show the topology and the link QoS requirements here since the description is very complicated, e.g., matrix $\bar{\mathbf{G}}$ has 400 entries.

Table I lists the parameters used in our simulations.

[1]The auto-correlation function of the AR(1) process is κ^m, where m is the number of sample intervals. Solving $\kappa^{T_c/\delta} = 0.5$ for κ, we obtain (49).

TABLE I
SIMULATION PARAMETERS.

Maximum transmit power P_0	1mW
Channel bandwidth	100kHz
Doppler frequency	100Hz
Noise power	3.34×10^{-9}W

B. Simulation Results

In this section, we show simulation results to demonstrate the efficacy of our column-generation-based algorithm for solving the optimal link scheduling problem. Our column-generation-based algorithm is implemented in C++ language. The software Lingo 9.0 with full packages is used as the optimization tool for solving the optimal link scheduling problem. The section is organized as follows. In Section IX-B.1, we evaluate the performance of our column-generation-based algorithm under fixed power for the 6-node network. Section IX-B.2 presents performance results of our column-generation-based algorithm under variable power for the 6-node network. In Section IX-B.3, we evaluate the performance of our column-generation-based algorithm under fixed power and variable power for the 20-node network. In Section IX-B.4, we compare on the channel use with the other two performing approaches from [19] and [29], respectively as mentioned in Section II, which also stressed the delay problem.

1) Performance under Fixed Power for the 6-node Network: In this section, we compare the performance of our SINR-EC scheduler with that of the NI-TDMA under fixed power for the 6-node network.

Table II shows all the feasible matchings[2] under fixed power for our SINR-EC scheduler. All the links in a matching can simultaneously transmit while satisfying the QoS requirement of each link, which is specified by bit rate r_s, delay bound D_{max}, and delay bound violation probability P_{err}; in other words, all the links in a matching can simultaneously transmit while satisfying (6).

We first run simulations for the NI-TDMA under the setting specified by Table I and estimate the effective capacity of each channel. Then, we run simulations for our SINR-EC scheduler under the settings specified by Tables I, II, and III, which achieves the same effective capacity of each channel as that in the NI-TDMA.

From Table III, we know that $\sum_{k=1}^{S} w_k = 60\%$, where w_k is normalized by the 100% channel use of the NI-TDMA. Hence, our SINR-EC scheduler uses 40% less channel resource than the NI-TDMA. The saved channel resource can be used to admit more QoS-assured flows or support a higher throughput

[2] A matching or independent edge set in a graph is a set of edges without common vertices.

for elastic traffic such as TCP traffic. Compared to the NI-TDMA, the throughput under our SINR-EC scheduler is increased by a factor of $1/\sum_{k=1}^{S} w_k = 166.7\%$ under the same delay bound and delay bound violation probability (refer to Proposition 4). Our SINR-EC scheduler uses 60% total power of all nodes in the case of the NI-TDMA; i.e., our SINR-EC scheduler uses 40% less total power of all nodes, compared to the NI-TDMA. Hence, our SINR-EC scheduler is more energy efficient.

2) Performance under Variable Power for the 6-node Network: In this section, we compare our SINR-EC scheduler under variable power with 1) our SINR-EC scheduler under fixed power and 2) the NI-TDMA under fixed power for the 6-node network.

Table IV shows all the feasible matchings under variable power for our SINR-EC scheduler. All the links in a matching can simultaneously transmit while satisfying the QoS requirement of each link, i.e., satisfying (6). It is observed that variable power brings about great advantages. First, the number of feasible matchings becomes much larger. There are totally 20 different matchings, i.e., twice of that in the fixed power case, and even three links could be active simultaneously. Thus, the link scheduling under variable power becomes more flexible than that under fixed power. Second, the interference between the simultaneously active links could be greatly mitigated by variable power allocations so that we can achieve high degree of frequency spatial reuse in the whole wireless network.

We run simulations for our SINR-EC scheduler under the settings specified by Tables I, IV, and V, which achieves the same effective capacity of each channel as that in the NI-TDMA.

From Table V, we know that $\sum_{k=1}^{S} w_k = 54.66\%$, where w_k is normalized by the 100% channel use of the NI-TDMA. Hence, our SINR-EC scheduler uses 45.34% less channel resource than the NI-TDMA. The saved channel resource can be used to admit more QoS-assured flows or support a higher throughput for elastic traffic such as TCP traffic. Compared to the NI-TDMA, the throughput under our SINR-EC scheduler is increased by a factor of $1/\sum_{k=1}^{S} w_k = 182.9\%$ under the same delay bound and delay bound violation probability. Our SINR-EC scheduler uses 25.6% total power of all nodes in the case of the NI-TDMA; i.e., our SINR-EC scheduler uses 74.4% less total power of all nodes, compared to the NI-TDMA.

Compared to the results in Section IX-B.1, the SINR-EC scheduler under variable power is more power efficient than the SINR-EC scheduler under fixed power; this is because using fixed maximum power P_0 causes high level of interference, resulting in fewer number of links that can be simultaneously activated.

This becomes evident if we compare Table II with Table IV. As shown in Table II, at most two links can be activated simultaneously under fixed power, while three links can be simultaneously activated under variable power as shown in Table IV. So the degree of frequency spatial reuse under variable power is higher than that under fixed power.

3) Performance under Fixed Power and Variable Power for the 20-node Network: In this section, we study the performance of our SINR-EC scheduler under fixed power and variable power for the 20-node network.

We do not show the topology and the link QoS requirements for the 20-node network since the description is very complicated. We study the SINR-EC scheduler under four scenarios, i.e., the number of links that have traffic demands are 10, 20, 30 and 40, respectively.

We run simulations for our SINR-EC scheduler for both fixed power and variable power under the settings specified by Table I, which achieves the same effective capacity of each channel as that in the NI-TDMA.

Table VI shows the percentage of channel use, throughput gain, and capacity gain of our SINR-EC scheduler under fixed power and variable power, for four different numbers of links that have traffic demands. In Table VI, w_k is normalized by the 100% channel use of the NI-TDMA. The capacity gain of our SINR-EC scheduler over the NI-TDMA, is defined by $\lfloor 1/\sum_{k=1}^{S} w_k \rfloor = 1$; i.e., compared to the NI-TDMA, the admission region under our SINR-EC scheduler is increased by a factor of $\lfloor 1/\sum_{k=1}^{S} w_k \rfloor$ (refer to Proposition 3). It is observed that as the number of traffic links increases, the SINR-EC scheduler under variable power achieves a faster increase of throughput gain than the SINR-EC scheduler under fixed power. This is because under variable power, a larger number of traffic links provides an increased opportunity for frequency spatial reuse while under fixed power, a higher level of interference from simultaneous transmissions might reduce this opportunity. The higher level of interference under fixed power can also be confirmed by Table VII where the SINR-EC scheduler under fixed power consumes more power than the SINR-EC scheduler under variable power.

Table VII shows the power efficiency of our SINR-EC scheduler under fixed power and variable power, for four different numbers of links that have traffic demands. It can be observed that as the number of traffic links increases, the SINR-EC scheduler saves more power. It is also observed that the SINR-EC scheduler under variable power achieves a higher power efficiency and a lower level of interference than the SINR-EC scheduler under fixed power.

4) Performance comparison with the other two performing schemes for a 20-node Network: To evaluate the efficiency of our SINR-EC scheduler, we compare our scheme with the approach from Cappanera et al [19] and the scheme proposed by Djukic and Valaee [29], as mentioned in Section II. For the fairness of comparison, we use the same randomly generated 20-node network, including the node positions, link numbers, channel conditions, etc, with the same source rate and delay bound requirement.

Table VIII shows the channel use of the three different schemes, all normalized by the 100% channel use of the NI-TDMA, in a fixed power case. It can be observed that our SINR-EC scheduler outperforms the other two approaches. One reason for this is that our scheduler does better for a completely random networks while not only for random sink-tree or overlay tree topologies, for example in scheduling the multiple unicast flows more efficiently.

To summarize, the simulation results have demonstrated that compared to the NI-TDMA and some other popular approaches, our SINR-EC scheduler uses less channel resource, achieves a larger throughput, a larger admission region, and a higher power efficiency. For all the simulations, we have verified that the QoS requirements (data rate, delay bound, delay bound violation probability) of each flow are satisfied.

X. CONCLUSIONS

In this paper, we studied the optimal link scheduling problem in wireless sensor networks. The optimal link scheduler assigns time slots to different users so as to minimize channel usage subject to constraints on data rate, delay bound, and delay bound violation probability; we studied the problem under fading channels and an SINR-based interference model. To the best of our knowledge, this problem has not been studied previously. We used the effective capacity model to formulate the optimal link scheduling as a mixed integer optimization problem for both the fixed and variable power case. Moreover, because the mixed integer optimization problem is NP-hard, we proposed a computationally feasible column-generation-based iterative algorithm to search for a sub-optimal solution to the problem. Finally, to facilitate the implementation of the optimal link scheduling strategy in practical sensor networks, we designed a distributed MAC protocol. Simulation results show that our proposed SINR-EC scheduler achieves a larger throughput, a larger admission region, and a higher power efficiency, compared to the NI-TDMA scheduler.

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Appendix

A. *Proof of Proposition 1:*

Proof: From (1), for Link $\{i,j\}$, we have

$$\alpha_{ij,P_i}(u) = -\lim_{t\to\infty}\frac{1}{ut}\log E[e^{-u\int_0^t r_{ij,P_i}(\tau)d\tau}],\ \forall\ u \geq 0, \tag{50}$$

where $r_{ij,P_i}(t)$ is the instantaneous channel capacity of link $\{i,j\}$ with transmit power $P_i(t)$, i.e. $r_{ij,P_i}(t) = W\log[1+SINR_{ij,P_i}(t)]$ where $SINR_{ij,P_i}(t)$ is defined by (2). Then, for all $u > 0$, we have

$$\begin{aligned}
\alpha_{ij,P_i^{(k)},w_k}(u) &\overset{(a)}{=} \frac{-\lim_{t\to\infty}\frac{1}{t}\log E[e^{-u\int_0^t r_{ij,P_i^{(k)},w_k}(\tau)d\tau}]}{u} \\
&\overset{(b)}{=} \frac{-\lim_{t\to\infty}\frac{1}{t}\log E[e^{-u\int_0^t w_k\times r_{ij,P_i^{(k)}}(\tau)d\tau}]}{u} \\
&= \frac{-\lim_{t\to\infty}\frac{w_k}{t}\log E[e^{-(w_k\times u)\int_0^t r_{ij,P_i^{(k)}}(\tau)d\tau}]}{w_k\times u} \\
&= w_k\times\alpha_{ij,P_i^{(k)}}(w_k\times u)
\end{aligned} \tag{51}$$

where (a) $r_{ij,P_i^{(k)},w_k}(t)$ is the instantaneous channel capacity of Link $\{i,j\}$ with time fraction w_k and the corresponding transmit power $P_i^{(k)}$; (b) is due to scaling law in TDMA, i.e., $r_{ij,P_i^{(k)},w_k}(t) = w_k\times r_{ij,P_i^{(k)}}(t)$.

■

B. *Proof of Proposition 2:*

Proof: From (1), for Link $\{i,j\}$, we have

$$\alpha_{ij,P_i}(u) = -\lim_{t\to\infty}\frac{1}{ut}\log E[e^{-u\int_0^t r_{ij,P_i}(\tau)d\tau}],\ \forall\ u \geq 0, \tag{52}$$

where $r_{ij,P_i}(t)$ is the instantaneous channel capacity of link $\{i,j\}$ with transmit power $P_i(t)$, i.e., $r_{ij,P_i}(t) = W\log[1+SINR_{ij,P_i}(t)]$ where $SINR_{ij,P_i}(t)$ is defined by (2). Then, for all $u > 0$, the effective capacity function $\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u)$ for Link $\{i,j\}$ under the SINR-EC scheduler with time fractions $\{w_k\,(k=1,\cdots,S)\}$ ($w_k \in (0,1]$, $\forall k$) and corresponding transmission powers $\{P_i^{(k)}\,(k=1,\cdots,S)\}$, is given by

$$
\begin{aligned}
\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u) &\overset{(a)}{=} \frac{-\lim_{t\to\infty}\frac{1}{t}\log E[e^{-u\int_0^t r_{ij,\{P_i^{(k)}\},\{w_k\}}(\tau)d\tau}]}{u} \\
&= \frac{-\lim_{t\to\infty}\frac{1}{t}\log E[e^{-u\int_0^t \sum_{k=1}^{S} r_{ij,P_i^{(k)},w_k}(\tau)d\tau}]}{u} \\
&\overset{(b)}{=} \frac{-\lim_{t\to\infty}\frac{1}{t}\log E[e^{-u\int_0^t \sum_{k=1}^{S} w_k\times r_{ij,P_i^{(k)}}(\tau)d\tau}]}{u} \\
&= \frac{-\lim_{t\to\infty}\frac{1}{t}\log E[e^{-u\sum_{k=1}^{S}\int_0^t w_k\times r_{ij,P_i^{(k)}}(\tau)d\tau}]}{u} \\
&= \frac{-\lim_{t\to\infty}\frac{1}{t}\log E[\prod_{k=1}^{S} e^{-u\int_0^t w_k\times r_{ij,P_i^{(k)}}(\tau)d\tau}]}{u} \\
&\overset{(c)}{=} \frac{-\lim_{t\to\infty}\frac{1}{t}\log \prod_{k=1}^{S} E[e^{-u\int_0^t w_k\times r_{ij,P_i^{(k)}}(\tau)d\tau}]}{u} \\
&= \frac{-\lim_{t\to\infty}\frac{1}{t}\sum_{k=1}^{S}\log E[e^{-u\int_0^t w_k\times r_{ij,P_i^{(k)}}(\tau)d\tau}]}{u} \\
&= \sum_{k=1}^{S}\frac{-\lim_{t\to\infty}\frac{w_k}{t}\log E[e^{-(w_k\times u)\int_0^t r_{ij,P_i^{(k)}}(\tau)d\tau}]}{w_k\times u} \\
&= \sum_{k=1}^{S} w_k\times\alpha_{ij,P_i^{(k)}}(w_k\times u)
\end{aligned}
\tag{53}
$$

where (a) $r_{ij,\{P_i^{(k)}\},\{w_k\}}(\tau)$ is the instantaneous channel capacity of Link $\{i,j\}$ under the SINR-EC scheduler with time fractions $\{w_k\,(k=1,\cdots,S)\}$ ($w_k \in (0,1]$, $\forall k$) and corresponding transmission powers $\{P_i^{(k)}\,(k=1,\cdots,S)\}$; (b) is due to scaling law in TDMA, i.e., $r_{ij,P_i^{(k)},w_k}(t) = w_k \times r_{ij,P_i^{(k)}}(t)$; (c) is because the channel gains in different slots are independent of each other. ■

C. Proof of Proposition 3:

Proof: We first prove the case where $\sum_{k=1}^{S} w_k = 0.5$, i.e., $1/\sum_{k=1}^{S} w_k = 2$. Assume that an existing one-hop flow of QoS class l over Link $\{i,j\}$ under our SINR-EC scheduler is assigned with time fractions $\{w_k\,(k=1,\cdots,S)\}$ ($w_k \in (0,1]$, $\forall k$) and corresponding transmission powers $\{P_i^{(k)}\,(k=1,\cdots,S)\}$; since $\sum_{k=1}^{S} w_k = 0.5$, we can admit an additional flow of QoS class l over Link $\{i,j\}$ under our SINR-EC scheduler with time fractions $\{w_k\,(k=S+1,\cdots,2S)\}$ ($w_k \in (0,1]$, $\forall k$) and corresponding transmission powers $\{P_i^{(k)}\,(k=S+1,\cdots,2S)\}$, where $w_k = w_{k-S}\,(k=S+1,\cdots,2S)$ and $P_i^{(k)} = P_i^{(k-S)}\,(k = S+1,\cdots,2S)$; hence $\sum_{k=S+1}^{2S} w_k = 0.5$ and the total channel use under our SINR-EC scheduler is

$\sum_{k=1}^{2S} w_k = 1$. In other words, for each existing one-hop flow of QoS class l over Link $\{i, j\}$, we can admit an additional flow of QoS class l over Link $\{i, j\}$ with the same time fractions and transmission powers. Then, the additional N_l flows of QoS class l ($l = 1, \cdots, L$) under our SINR-EC scheduler have their requested QoS satisfied since they are allocated with the same time fractions and transmission powers, and the interference patterns are exactly the same as the existing N_l flows of QoS class l ($l = 1, \cdots, L$). Hence, $[2N_1, \cdots, 2N_L]$ is within the admission region under our SINR-EC scheduler.

Now we prove the case where $\lfloor 1/\sum_{k=1}^{S} w_k \rfloor > 2$. Assume that an existing one-hop flow of QoS class l over Link $\{i, j\}$ under our SINR-EC scheduler is assigned with time fractions $\{w_k\,(k = 1, \cdots, S)\}$ ($w_k \in (0, 1]$, $\forall k$) and corresponding transmission powers $\{P_i^{(k)}\,(k = 1, \cdots, S)\}$. We can admit additional $\lfloor 1/\sum_{k=1}^{S} w_k \rfloor - 1$ flows of QoS class l over Link $\{i, j\}$ under our SINR-EC scheduler; the first additional flow is assigned with time fractions $\{w_k\,(k = S+1, \cdots, 2S)\}$ ($w_k \in (0, 1]$, $\forall k$) and corresponding transmission powers $\{P_i^{(k)}\,(k = S+1, \cdots, 2S)\}$, where $w_k = w_{k-S}\,(k = S+1, \cdots, 2S)$ and $P_i^{(k)} = P_i^{(k-S)}\,(k = S+1, \cdots, 2S)$; the second additional flow is assigned with time fractions $\{w_k\,(k = 2S+1, \cdots, 3S)\}$ ($w_k \in (0, 1]$, $\forall k$) and corresponding transmission powers $\{P_i^{(k)}\,(k = 2S+1, \cdots, 3S)\}$, where $w_k = w_{k-2S}\,(k = 2S+1, \cdots, 3S)$ and $P_i^{(k)} = P_i^{(k-2S)}\,(k = 2S+1, \cdots, 3S)$; repeat the same assignments for other additional flows. In other words, for each existing one-hop flow of QoS class l over Link $\{i, j\}$, we can admit additional $\lfloor 1/\sum_{k=1}^{S} w_k \rfloor - 1$ flows of QoS class l over Link $\{i, j\}$ with the same time fractions and transmission powers as the existing one. Then, the additional $N_l(\lfloor 1/\sum_{k=1}^{S} w_k \rfloor - 1)$ flows of QoS class l ($l = 1, \cdots, L$) under our SINR-EC scheduler have their requested QoS satisfied since they are allocated with the same time fractions and transmission powers, and the interference patterns are exactly the same as the existing N_l flows of QoS class l ($l = 1, \cdots, L$). The total channel use under our SINR-EC scheduler is $(\sum_{k=1}^{S} w_k) \times (\lfloor 1/\sum_{k=1}^{S} w_k \rfloor) \leq 1$. Hence, $[N_1 \times \lfloor 1/\sum_{k=1}^{S} w_k \rfloor, \cdots, N_L \times \lfloor 1/\sum_{k=1}^{S} w_k \rfloor]$ is within the admission region under our SINR-EC scheduler. ■

D. Proof of Proposition 4:

Proof: Without loss of generality, we examine a flow of an arbitrary QoS class $l \in \{1, \cdots, L\}$, and assume the flow is over certain link $\{i, j\} \in \mathcal{E}$. From the formulation of our scheduling problem, i.e., (3) through (6), we know that, when the percentage of channel use $\sum_{k=1}^{S} w_k < 1$, our SINR-EC scheduler guarantees $\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u_{ij}^*) \geq r_s^{(l)}$ in (6), where $u_{ij}^* = \frac{-\log P_{err}^{(l)}}{r_s^{(l)} \times D_{max}^{(l)}}$. Since the QoS class l that we examine is arbitrary, our SINR-EC scheduler guarantees

$$\alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u_{ij}^*) \geq r_s^{(l)}, \quad \forall l \in \{1, \cdots, L\}. \tag{54}$$

It means that, when the percentage of channel use $\sum_{k=1}^{S} w_k < 1$, our scheduler can satisfy bit rate $r_s^{(l)}$, delay bound $D_{max}^{(l)}$, and delay bound violation probability $P_{err}^{(l)}$ for all QoS classes, i.e., $l = 1, \cdots, L$.

Now we derive the effective capacity for the case where the percentage of channel use under our SINR-EC scheduler is 100%. Assume that an existing one-hop flow of QoS class l over Link $\{i, j\}$ under our SINR-EC scheduler (3) through (6) is assigned with time fractions $\{w_k\,(k = 1, \cdots, S)\}$ ($w_k \in (0, 1]$, $\forall k$) and corresponding transmission powers $\{P_i^{(k)}\,(k = 1, \cdots, S)\}$. Then, 100% channel use under our SINR-EC scheduler can be achieved by time fractions $\{w_k / \sum_{k=1}^{S} w_k\,(k = 1, \cdots, S)\}$ ($w_k \in (0, 1]$, $\forall k$) and corresponding transmission powers $\{P_i^{(k)}\,(k = 1, \cdots, S)\}$. Then the effective capacity of Link $\{i, j\}$ under 100% channel use is

$$\begin{aligned}
\alpha_{ij,\{P_i^{(k)}\},\{w_k/\sum_{k=1}^{S} w_k\}}(u_{ij}^* \sum_{k=1}^{S} w_k) &\overset{(a)}{=} \sum_{k=1}^{S} \frac{w_k}{\sum_{k=1}^{S} w_k} \times \alpha_{ij,P_i^{(k)}}(\frac{w_k}{\sum_{k=1}^{S} w_k} \times u_{ij}^* \sum_{k=1}^{S} w_k) && (55)\\
&= \frac{1}{\sum_{k=1}^{S} w_k} \sum_{k=1}^{S} w_k \times \alpha_{ij,P_i^{(k)}}(w_k \times u_{ij}^*) && (56)\\
&\overset{(b)}{=} \frac{1}{\sum_{k=1}^{S} w_k} \alpha_{ij,\{P_i^{(k)}\},\{w_k\}}(u_{ij}^*) && (57)\\
&\overset{(c)}{\geq} r_s^{(l)} / \sum_{k=1}^{S} w_k, \quad \forall l \in \{1, \cdots, L\}, && (58)
\end{aligned}$$

where (a) is due to (12) in Proposition 2; (b) is also due to (12) in Proposition 2; and (c) is due to (54). Since $\alpha_{ij,\{P_i^{(k)}\},\{w_k/\sum_{k=1}^{S} w_k\}}(u_{ij}^* \sum_{k=1}^{S} w_k) \geq r_s^{(l)} / \sum_{k=1}^{S} w_k$ and $u_{ij}^* \sum_{k=1}^{S} w_k = \frac{-\log P_{err}^{(l)}}{(r_s^{(l)}/\sum_{k=1}^{S} w_k) \times D_{max}^{(l)}}$, hence our SINR-EC scheduler with 100% channel use can satisfy bit rate $r_s^{(l)} / \sum_{k=1}^{S} w_k$, delay bound $D_{max}^{(l)}$, and delay bound violation probability $P_{err}^{(l)}$, for QoS class l ($l = 1, \cdots, L$). ■

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TABLE II

MATCHINGS UNDER FIXED POWER

Matching index	Number of links in a matching	Links in a matching
1	1	$\{1, 2\}$
2	1	$\{2, 3\}$
3	1	$\{3, 4\}$
4	1	$\{3, 6\}$
5	1	$\{4, 5\}$
6	1	$\{5, 3\}$
7	1	$\{5, 6\}$
8	1	$\{6, 1\}$
9	2	$\{2, 3\}$,$\{4, 5\}$
10	2	$\{6, 1\}$,$\{2, 3\}$

TABLE III

SCHEDULE OF OUR SINR-EC SCHEDULER UNDER FIXED POWER FOR THE 6-NODE NETWORK

Time-slot k	Active links $\{i, j\}$	Percentage of channel use w_k	Corresponding power $P_i^{(k)}$ (mW)
1	$\{1, 2\}$	9.192%	1
2	$\{6, 1\}$,$\{2, 3\}$	40.068%	1,1
3	$\{3, 4\}$	4.002%	1
4	$\{3, 6\}$	2.934%	1
5	$\{4, 5\}$	0.372%	1
6	$\{5, 3\}$	1.272%	1
7	$\{5, 6\}$	2.160%	1

TABLE IV

MATCHINGS UNDER VARIABLE POWER

Matching index	Number of links in a matching	Links in a matching
1	1	$\{1, 2\}$
2	1	$\{2, 3\}$
3	1	$\{3, 4\}$
4	1	$\{3, 6\}$
5	1	$\{4, 5\}$
6	1	$\{5, 3\}$
7	1	$\{5, 6\}$
8	1	$\{6, 1\}$
9	2	$\{2, 3\}$,$\{4, 5\}$
10	2	$\{6, 1\}$,$\{2, 3\}$
11	2	$\{1, 2\}$,$\{3, 6\}$
12	2	$\{1, 2\}$,$\{4, 5\}$
13	2	$\{1, 2\}$,$\{5, 3\}$
14	2	$\{2, 3\}$,$\{5, 6\}$
15	2	$\{3, 4\}$,$\{6, 1\}$
16	2	$\{3, 6\}$,$\{4, 5\}$
17	2	$\{4, 5\}$,$\{6, 1\}$
18	2	$\{5, 3\}$,$\{6, 1\}$
19	3	$\{1, 2\}$,$\{3, 6\}$,$\{4, 5\}$
20	3	$\{2, 3\}$,$\{4, 5\}$,$\{6, 1\}$

TABLE V

SCHEDULE OF OUR SINR-EC SCHEDULER UNDER VARIABLE POWER FOR THE 6-NODE NETWORK

Time-slot k	Active links $\{i, j\}$	Percentage of channel use w_k	Corresponding power $P_i^{(k)}$ (μW)
1	$\{1, 2\}$,$\{3, 6\}$	7.804%	577.30, 556.0
2	$\{1, 2\}$,$\{3, 6\}$,$\{4, 5\}$	9.091%	208.9, 21.56, 131.6
3	$\{2, 3\}$,$\{5, 6\}$	4.878%	296.9, 552.0
4	$\{3, 4\}$	4.897%	228.9
5	$\{3, 6\}$,$\{4, 5\}$	1.062%	45.00, 32.30
6	$\{5, 3\}$	5.149%	22.60
7	$\{5, 6\}$	15.073%	215.1
8	$\{2, 3\}$,$\{4, 5\}$,$\{6, 1\}$	6.707%	157.3, 84.80, 343.1

TABLE VI

PERFORMANCE OF OUR SINR-EC SCHEDULER FOR THE 20-NODE NETWORK: (I) FIXED POWER, (II) VARIABLE POWER

No. of links	(I) $\sum_{k=1}^{S} w_k$	(I) throughput gain	(I) capacity gain	(II) $\sum_{k=1}^{S} w_k$	(II) throughput gain	(II) capacity gain
10	58.31%	171.50%	1	53.80%	185.87%	1
20	55.98%	178.64%	1	50.16%	199.36%	1
30	49.12%	2.036	2	42.71%	2.341	2
40	43.76%	2.285	2	36.29%	2.756	2

TABLE VII

POWER PERFORMANCE OF OUR SINR-EC SCHEDULER FOR THE 20-NODE NETWORK: (I) FIXED POWER, (II) VARIABLE POWER

No. of links	(I) total power	(I) saved power	(II) total power	(II) saved power
10	58.31%	41.69%	24.38%	75.62%
20	55.98%	44.02%	22.69%	77.31%
30	49.12%	50.88%	19.70%	80.30%
40	43.76%	56.24%	17.18%	82.82%

TABLE VIII

COMPARISON OF THE CHANNEL EFFICIENCY BETWEEN OUR SINR-EC SCHEDULER AND SCHEMES [29] [19] FOR A 20-NODE NETWORK

Schemes	TDMA	scheme by Djukic et al [29]	scheme by Cappanera et al [19]	our SINR-EC scheduler
Channel use	100%	75.90%	64.51%	55.98%
throughput gain	100%	131.75%	155.01%	178.64%

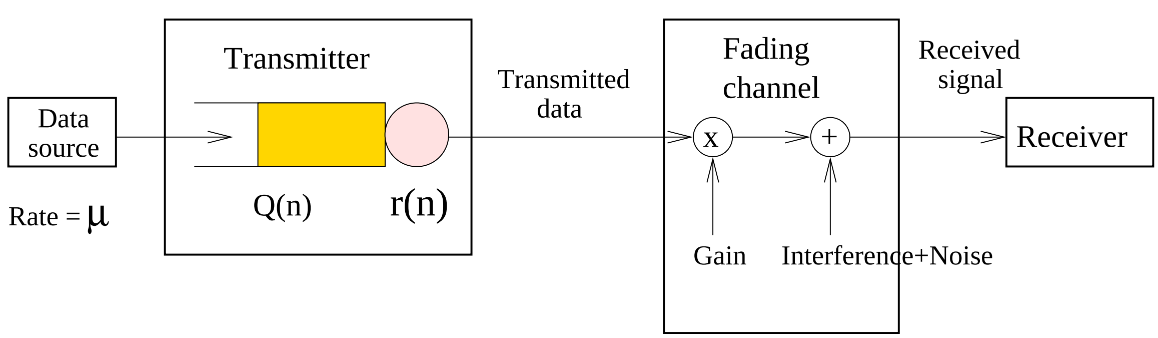

Fig. 1. Queueing system model used in our simulation.

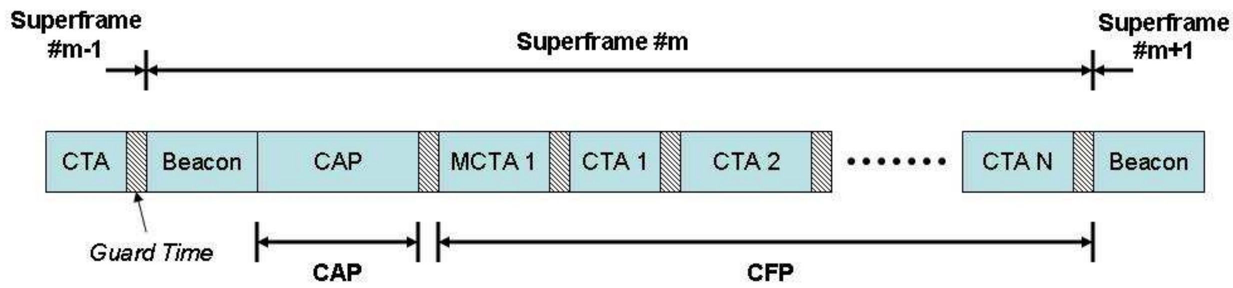

Fig. 2. Superframe structure of the proposed MAC protocol.

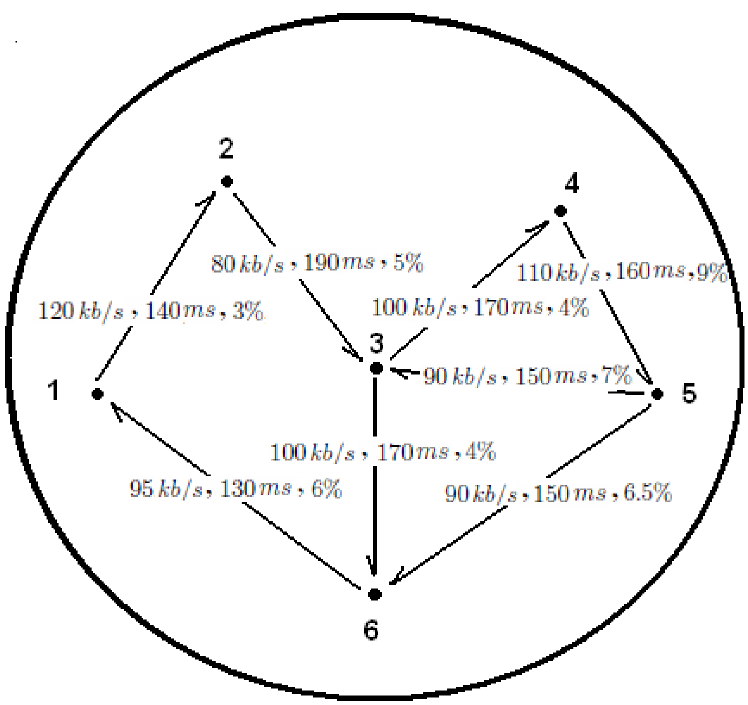

Fig. 3. Topology and traffic load of the 6-node network