# Integrated Power Controlled Rate Adaptation and Medium Access Control in Wireless Mesh Networks

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***Abstract*—In this paper, a new mathematical programming model and assignment algorithms are developed for minimizing the schedule length in adaptive power and adaptive rate link scheduling in spatial-TDMA wireless networks. The underlying problem entails the optimal joint scheduling of transmissions across multi-access communication links combined with the simultaneous allocation of transmit power levels and data rates across active links, while meeting required Signal-to-Interference-plus-Noise Ratio (SINR) levels at intended receivers. We prove that the problem can be modeled as a Mixed Integer-Linear Programming (MILP) and show that the latter yields a solution that consists of transmit power levels that are strongly Pareto Optimal. We note this problem to be NP-complete. For comparison purposes, we employ the MILP formulation for computing the optimal schedule for networks with small number of designated links and limited number of data rate levels. We proceed to develop and investigate a heuristic algorithm of polynomial complexity for solving the problem in a computationally effective manner. The algorithm is based on the construction of a Power Controlled Rate adaptation Interference Graph. The desired schedule is then derived by using a greedy algorithm to construct an independence set from this graph. Based on system analyses, we show, for smaller illustrative networks, the performance behavior realized by the heuristic algorithms to generally be in the 75 percentile of those attained by the optimal schedule. We also show that performance of our heuristic algorithm is on average 20% better than that attained under prior algorithms that were developed for use under fixed transmit power and fixed rate link scheduling.**

***Index Terms*—Graph theory, combinatorial optimization, medium access control, power control, rate adaptation.**

## I. INTRODUCTION

CONSIDER a wireless mesh network (Fig. 1) that consists of interconnected wireless Local Area Networks (LANs), a metropolitan area network and its backbone, and others that employ meshed backbones and multi-hop access nets. Assume that a scheduling based Medium Access Control (MAC) protocol such as spatial-Time Division Multiple Access (TDMA) is used. Time slots are allocated to stations to transmit their messages across their established links. To achieve high level of network throughput, it is desirable to assign a schedule that will achieve a high level of spatial reuse (i.e. high number of simultaneous transmissions). To enhance the efficiency of physical and MAC layer processes, stations employ adaptable Software Defined Radios. Such radio platform can be dynamically controlled to employ a selected Modulation/Coding Scheme (MCS), so that it can operate at a corresponding transmission data rate (R) within a time slot. It is desirable at the same time, in conjunction with the selection of the data rate level, to also adjust the level of the station's transmission power. In this paper, we study the problem of link scheduling with power control and rate adaptation in spatial-TDMA networks.

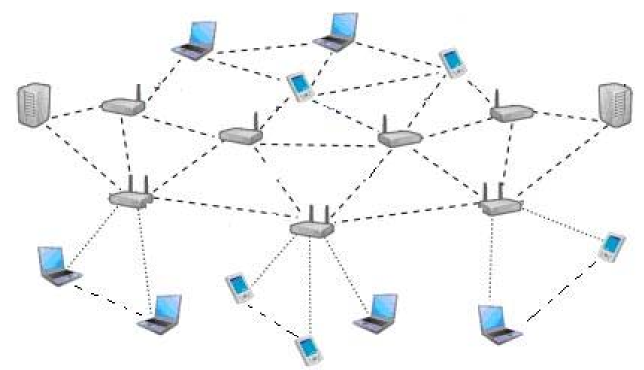

Fig. 1. A sample mesh network.

There have been many papers that study either the problem of power control or the link scheduling in isolation, but we have found no published papers that present effective algorithms that solve the link scheduling problem jointly with power control and rate adaptation.

Many publications have studied the power control problem in wireless networks. The power control problem for maximizing the network throughput for a set of simultaneously active links, whereby the data rate across each link is dictated by the chosen power level, has been modeled as a convex optimization problem in [27]. In this study, however, to make the feasible rate region a convex set, a rate function of *log(SINR)* is used instead of *log(1+SINR)*, which assumes the SINR level is high at all the receivers. Based on these assumptions, this study has proposed a gradient projection algorithm to find the optimum power vector. A simple distributed power control algorithm is presented in [1], [19], [20]. Under this algorithm, the transmitting nodes

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of a set of simultaneously active links iteratively adjust their transmission power levels by a factor that is equal to the ratio of the target SINR to the measured SINR at their intended receivers. In [29], the trade-offs involving the increase in the level of spatial reuse and the ensuing decrease in the data rates in a Carrier Sense Multiple Access/Collision Avoidance (CSMA/CA) wireless mesh network is studied. The paper shows that the network throughput is a function of the ratio of the transmit power level to the carrier sensing threshold. It proposes a decentralized method to adjust the transmit power level of each node based on measured signal interference levels. We note that the mechanisms mentioned above do not consider the link scheduling problem, as well as do not address the joint scheduling and rate adaptation problem.

Mechanisms for link scheduling at fixed power and fixed rate have also been studied extensively. In considering such a scheme in spatial-TDMA network, a heuristic algorithm identified as 'GreedyPhysical' has been proposed in [28]. The algorithm orders links based on their pair-wise interference values, and sequentially allocates to them available time-slots, during which the scheduled transmissions are feasible. The problem of scheduling active links at fixed power and fixed data rate has also been modeled and solved as an edge coloring problem in [31]. The authors introduce an efficient heuristic algorithm for the edge coloring problem that achieves a shorter schedule length compared to other edge-coloring algorithm. In their method, interference is assumed when a receiving node is in the transmission range of another node, but the aggregate physical interference is neglected. In [30], scheduling of a given traffic vector at fixed power and fixed rate in a wireless mesh network is solved as an edge-coloring problem. By mapping the given traffic vector into a weighted graph, the chromatic index of the graph is used to determine if the given traffic vector is feasible or not. An efficient coloring algorithm is proposed, achieving a schedule length that is at most twice the optimum length. The model, however, assumes transmissions to be orthogonal to each other and no mutual physical interference effects are considered. We note that the algorithms mentioned above do not consider the problem of link scheduling jointly with power control and rate adaptation.

Extensive research has been performed on the joint allocation of time slots and transmit power levels in a network when a ***single transmission rate level*** is used across all the links [2] - [8]. A power control algorithm to schedule a connected set of links is proposed in [33]. The authors show that their algorithm yields better performance compared to the uniform and linear power assignment methods. Their algorithm schedules shorter links in the same time slots and avoids assigning to the same time-slot longer links that are too close to the intended receivers of the scheduled links. However, their algorithm does not take rate adaptation into account, and it assumes that each link requires only a single time-slot. A multi-rate link-scheduling problem has been studied in [9]; however, the schemes used there do not engage in combined continuous power control, data rate and disjoint time slot allocations.

In this paper, we study the problem of link scheduling with adaptive power and adaptive rate. We first model the problem as a mixed integer-linear program. We use this model to calculate the optimum solution for a network involving a small number of active links. We note the problem to be NP-hard. Hence, we present a heuristic algorithm of polynomial complexity to solve the problem efficiently. We show the performance of our algorithm to be within 75% of the optimum solutions attained for a set of illustrative small networks. We also compare the performance of our algorithm with a known fixed power and fixed rate scheduling algorithm, showing our algorithm to yield an average of 20% improvement in network throughput.

The system model is presented in Section II. In Section III, we model the problem as a mixed integer linear program. We present our heuristic algorithm in Section IV. In Section V, we compare the performance of our heuristic algorithm with the optimal solution and with an existing scheduling algorithm. Conclusions are drawn in Section VI.

## II. System Model

We consider a wireless mesh network consisting of stations that are stochastically active and wish to intercommunicate in a prescribed region of operation. We assume a multiple access channel that is shared among communicating users on a TDMA basis. The channel is divided into a control sub-channel, and a data sub-channel. A central controller is used to allocate, time-slots to stations for the transmission of their messages across the data sub-channel.

The control sub-channel is used by stations to inform the controller about their activity (i.e. their need for time slots). The controller also uses the control sub-channel to make measurements of the characteristics of the communications channels, deriving the propagation gain matrix. Often, use is made of the measurement of power losses incurred by pilot signals. The controller periodically updates these measurements. It is assumed here that such updates are performed sufficiently fast (taking into consideration channel coherence time and user mobility speeds) to be of relevance for the time period over which slot allocation is performed. It is further assumed that the control channel overhead required for updating the propagation gain matrix has been taken into account, so that it is not an additional factor in the underlying calculation of the schedule. The controller periodically performs calculation for time slot allocation. The length of this period is dynamically selected to ensure the execution of new calculations when a distinct change has taken place in the activity pattern (arrival/departure of mobile stations), in the location of users, or in the characteristics of the communications channel. The length of the calculation period is selected to be less than the coherence time of the channels; hence, in applying our mathematical model, the communication channels and user activities are assumed to remain unchanged during each calculation period.

During a calculation period, a set of nodes are identified to be active, the loading level of each node is prescribed; these network nodes are assumed to be at prescribed locations, and propagation gain values are assumed to be fixed. Each node is capable of adjusting its transmit power continuously in a given range $[0,P_{max}]$ and in a packet-by-packet fashion. Every node, when scheduled to access the communication channel, can transmit the packet at one of the data rates in the set $R = \{r_1, r_2, \cdots, r_m\}$ that is based on the use of *m* available MCS; we set $r_1 < r_2 < ... < r_m$. A single transmission is intended for exactly one receiver. All nodes are equipped with identical half-duplex radios and Omni-directional antennas. We assume every transmission to occupy the entire bandwidth of the system under consideration. Channel time is slotted into identical synchronized time slots. Slot duration $\tau_s$ is assumed to be equal to the transmission time of a packet under the lowest rate $r_1$ plus overhead. A node can successfully receive from at most one other node in the same time slot. We are concerned with the fixed assignment of transmissions for the designated links in a frame. Thus, once the optimal transmission patterns (i.e., the arrangement of transmissions and the associated data rates and transmit power levels) are determined, the frame is repeated in the time axis over the given operational period.

A directed communication link $l_{ij}$ can be established from node *i* to node *j* if there exists a power $P \in [0, P_{\max}]$, under which the *Signal-to-Noise Ratio* (SNR) at node *j* is not less than the threshold corresponding to the lowest rate $r_1$, i.e. $G_{ij}P/N \geq \gamma(r_1)$. $G_{ij}$ is the propagation gain representing the effective power loss (incorporating link loss phenomena such as fading and shadowing) incurred by direct transmission from node *i* to node *j*, and *N* is the thermal noise power [10]. It has been commonly assumed that $G_{ij}$ is equal to $G_{ji}$ [1], [11], [12], [13], [14]. The set of all designated communication links that are used for transmission of at least one packet (based on the upper layer routing considerations) is denoted by *L*. $N^{Tx}$ represents a subset of nodes that are the transmitter associated with at least one of the links in *L*. Similarly, $N^{Rx}$ denotes a subset of nodes that are the receiver associated with at least one of the links in *L*. We use $G = [G_{ij}]$ to denote the propagation gain matrix, representing the propagation gain from each of the nodes in $N^{Tx}$ to each of the nodes in $N^{Rx}$. We assume this matrix to be fixed during the underlying operational period.

Let $i \xrightarrow{r_h} j$ and $P_{ij}^{(t)} \in [0, P_{\max}]$, denote a direct transmission over link $l_{ij}$ under rate $r_h$ and the corresponding transmit power level in time slot *t*, respectively. A transmission scenario $S(t) = \{i_1 \xrightarrow{R(1)} j_1, i_2 \xrightarrow{R(2)} j_2, \cdots, i_M \xrightarrow{R(M)} j_M\}$,$R(k) \in R, k = 1, 2, \cdots, M$, is defined as a candidate set of transmissions that are considered to all take places at time slot *t*, where all transmitting and receiving nodes are distinct [15]. Fig. 2 shows a sample transmission scenario. Note that the distinction of all transmitting and receiving nodes ensures that the unicasting, half-duplexing, and receptivity constraints are satisfied in every transmission scenario.

For transmission scenario *S(t)*, under power vector $P(t) = (P_{i_1 j_1}^{(t)}, ..., P_{i_M j_M}^{(t)}), 0 \leq P_{i_k j_k}^{(t)} \leq P_{\max}$,we define the transmission from $i_k$ to be successful if the SINR at $j_k$ is not less than the threshold $\gamma(R(k))$:

$$G_{i_k j_k} P_{i_k j_k}^{(t)} - \gamma(R(k)) \sum_{\substack{z=1 \\ z \neq k}}^{M} G_{i_z j_k} P_{i_z j_z}^{(t)} \geq \gamma(R(k))N \quad (1)$$

The value of the threshold $\gamma(R(k))$ depends on the acceptable Bit Error Rate (BER), MCS, and channel coding/decoding algorithm [10]. We refer to such a model for successful

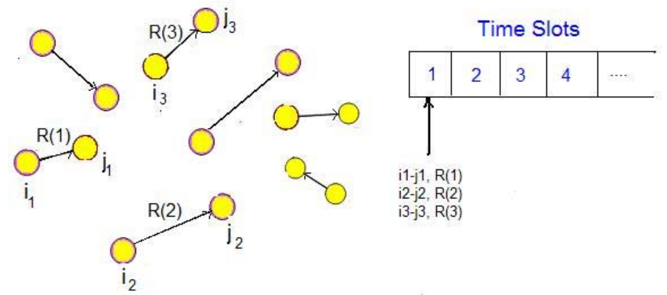


Fig. 2. A sample transmission scenario.

reception of a packet as the SINR-*based Interference Model* [16]. The power vector $P^{AP}(t) = (P_{i_1 j_1}^{(AP,t)}, ..., P_{i_M j_M}^{(AP,t)})$ that satisfies system (1) of linear inequalities in equality form is referred to as the *apex solution* of the system of linear inequalities.

**Definition 1.** We define the power vector *P(t)* to be strongly Pareto Optimal with respect to transmission scenario *S(t)*, if *S(t)* is a feasible transmission scenario under *P(t)*, and any other power vector *P'(t)* under which *S(t)* is feasible, would require at least as much power (i.e. $P'(t) \geq P(t)$ component-wise).

**Fact 1.** Based on the Perron-Frobenious theorem [17]-[20], it can be shown that if a transmission scenario *S(t)* is feasible, the apex solution of the corresponding linear inequalities is strongly Pareto Optimal with respect to *S(t)*.

The number of packets per frame required to be transmitted across the underlying links for the support of all the flows is assigned by the upper layer operations and is determined by the statistics of total offered load and the desired delay-throughput performance metrics. The above-mentioned calculations translate the offered traffic load matrix to imply the requirement of $K_{ij}$ packets to be transmitted per frame across link $l_{ij}$, for each link $l_{ij}$ in L. Using rate adaptation and power control in conjunction with link scheduling, our objective is to design a timeframe with minimum schedule length that provides for at least $K_{ij}$ successful packet transmissions across designated link $l_{ij}$, for every link $l_{ij} \in L$. Under the prescribed optimum schedule, we aim to minimize the power level employed by each of the transmitting nodes. We refer to this problem as the *Integrated Power controlled Rate adaptation Scheduling (IPRS) problem.*

## III. Mixed Integer-Linear Programming Formulation

In this section, we develop and investigate a Mixed Integer Linear Programming (MILP) formulation for the integrated power controlled rate adaptation and scheduling problem. The input for the optimization model is the set of designated links *(L)*, the traffic matrix, the associated propagation gain matrix *(G)*, maximum transmit power level *($P_{max}$)*, the set of available data rates (R) and their corresponding minimum required SINR levels($\gamma(r_k), r_k \in R$). The decision variables in our mathematical modeling are $X_{ijh}^{(t)}$'s and $P_{ij}^{(t)}$'s.

$$X_{ijh}^{(t)} = \begin{cases} 1 & \text{if at least one packet is transmitted} \\ & \text{in time slot t over link } l_{ij} \text{ at rate } r_h, \\ 0 & \text{otherwise.} \end{cases}$$

$$P_{ij}^{(t)} \in [0, P_{\max}]$$

Every solution of the IPRS can be represented as ***(X,P)***. The set of quadratic constraint:

$$G_{ij}P_{ij}^{(t)} - \gamma(r_h)(\sum_{q=1}^{m}\sum_{(f,s)} G_{fj}P_{fs}^{(t)}X_{fsq}^{(t)} - N) \geq \Phi \cdot (X_{ijh}^{(t)} - 1) \quad (2)$$

where $\Phi$ is a sufficiently large positive number, imposes the SINR requirement for a transmission over link $l_{ij}$ at time slot *t*. Note that if no transmission is scheduled to take place over link $l_{ij}$ at time slot $t(X_{ijh}^{(t)} = 0)$, the associated constraint becomes redundant.

We next prove that the IPRS problem can be modeled as the following *MILP* formulation:

$$\textit{Minimize } Z(X,P) = \sum_{t=1}^{T_{\max}}\sum_{(i,j)\in L}(c_t\sum_{h=1}^{m}X_{ijh}^{(t)} + \epsilon P_{ij}^{(t)}) \quad (3)$$

$$s.t. \quad \sum_{t=1}^{T_{\max}}\sum_{h=1}^{m}(\frac{r_h}{r_1})X_{ijh}^{(t)} \geq K_{ij} \quad (4)$$

$$\sum_{h=1}^{m}(\sum_{(i,j)\in L}X_{ijh}^{(t)} + \sum_{(j,f)\in L}X_{jfh}^{(t)}) \leq 1, j \in N^{Tx}\bigcup N^{Rx} \quad (5)$$

$$G_{ij}P_{ij}^{(t)} - \gamma(r_h)\sum_{(f,s)}G_{fj}P_{fs}^{(t)} - \gamma(r_h)N \geq \Phi(X_{ijh}^{(t)} - 1) \quad (6)$$

$$0 \leq P_{ij}^{(t)} \leq P_{\max} \quad (7)$$

$$X_{ijh}^{(t)} = 0, 1, \ (i,j) \in L, \ h = 1, \cdots, m, t = 1, \cdots, T_{\max} \quad (8)$$

In Eq. (3), $\epsilon$ is a sufficiently small positive number, and $c_t$ is a positive constants defined as

$$c_t = t.|L|.c_{t-1}, \quad t = 2, ..., T_{\max}, \quad c_1 = 1 \quad (9)$$

It can be seen that the constraints expressed by Eq. (5) guarantee that node *j* is either the transmitter or the receiver of at most one of the transmissions scheduled for time slot *t*. This feature simultaneously imposes the unicasting, half-duplexing, and receptivity constraints at every time slot *t*. Moreover, it ensures that all transmissions over link $l_{ij}$ (and link $l_{jf}$) in time slot *t* are performed under the same rate $r_h$. Note that the quadratic constraint expressed by Eq. (2) has changed into the linear constraint of Eq. (6) by excluding the $X_{fsq}^{(t)}$ variables. The use of Eq. (3) to define the objective function is performed for pure mathematical convenience. The role of the coefficients $c_t$ used in defining the objective function is to ensure that the length of the schedule corresponding to the optimal solution of the MILP formulation is minimum. The role of the coefficient $\epsilon$ in the objective function is twofold: first, the positivity of $\epsilon$ ensures the strongly Pareto optimality of the optimal transmit power levels deduced from the optimum solution of the MILP formulation. Second, the fact that $\epsilon$ is assumed to be a sufficiently small (positive) number guarantees that the addition of the power related terms to the objective function does not interfere with the role of the coefficient $\epsilon$ in inducing the minimization of the frame length.

**Lemma 1.** Every solution of the MILP formulation yields a feasible transmission scenario at each time slot.

*Proof.* Consider an arbitrary time slot *t* under a solution ***(X, P)*** of the MILP formulation. Eq. (5) guarantees that all the transmitting and receiving nodes in the time slot *t* are distinct, i.e. $S(t) = \{i \xrightarrow{r_h} j | X_{ijh}^{(t)} = 1\}$ forms a transmission scenario. Assume $S(t) = \{i_1 \xrightarrow{R(1)} j_1, i_2 \xrightarrow{R(2)} j_2, \cdots, i_M \xrightarrow{R(M)} j_M\}$. Now, we claim that transmission scenario *S(t)* under power vector $P(t) = (P_{i_1j_1}^{(t)}, P_{i_2j_2}^{(t)}, ..., P_{i_Mj_M}^{(t)})$ is feasible: Consider an arbitrary transmission $i_k \xrightarrow{R(k)} j_k$ in *S(t)*. Since $X_{i_kj_kR(k)}^{(t)} = 1$, based on Eq. (6) we have:

$$G_{i_kj_k}P_{i_kj_k}^{(t)} - \gamma(R(k))(\sum_{(f,s)\neq(i_k,j_k)}G_{fj_k}P_{fs}^{(t)} - N) \geq 0 \quad (10)$$

$$X(t) \subseteq L \rightarrow \sum_{\substack{(f,s)\in\\ L-(i_k,j_k)}}G_{fj_k}P_{fs}^{(t)} \geq \sum_{\substack{(f,s)\in\\ X(t)-(i_k,j_k)}}G_{fj_k}P_{fs}^{(t)} = \sum_{\substack{z=1\\ z\neq k}}^{M}G_{i_zj_k}P_{i_zj_z}^{(t)} \quad (11)$$

$$G_{i_kj_k}P_{i_kj_k}^{(t)} - \gamma(R(k))\sum_{\substack{z=1\\ z\neq k}}^{M}G_{i_zj_k}P_{i_zj_z}^{(t)} \geq \gamma(R(k))N \quad (12)$$

which along with Eq. (7) indicates that the arbitrary transmission $i_k \xrightarrow{R(k)} j_k$ of the transmission scenario *S(t)* under power vector *P(t)* is successful. Consequently, transmission scenario *S(t)* is feasible under power vector *P(t)*. QED

*Theorem 1.* Every optimum solution of the MILP formulation yields a strongly Pareto optimal power vector with respect to the underlying transmission scenario at each time slot.

*Proof.* Consider an arbitrary time slot *t* under an optimum solution *(X*,P*)* of the MILP formulation, $X^* = \{X_{ijh}^{*(t)}, (i,j) \in L, h = 1, 2, \cdots, m, t = 1, 2, \cdots, T_{\max}\}$, $P^* = \{P_{ij}^{*(t)}, (i,j) \in L, t = 1, 2, \cdots, T_{\max}\}$. Based on Lemma 1, the set of transmissions at time slot *t* forms a transmission scenario $S^*(t) = \{i_1 \xrightarrow{R(1)} j_1, i_2 \xrightarrow{R(2)} j_2, \cdots, i_M \xrightarrow{R(M)} j_M\}$, which is feasible under power vector $P^*(t) = (P_{i_1j_1}^{*(t)}, P_{i_2j_2}^{*(t)}, ..., P_{i_Mj_M}^{*(t)})$. To prove that the power vector *P*(t)* is strongly Pareto Optimal with respect to transmission scenario *S*(t)*, based on Fact 1, it is sufficient to show that $P^*(t) = P^{AP}(t)$ component-wise. Since cardinality of *S*(t)* is *M*, only *M* of the constraints associated with the time slot *t* in Eq. (6) are non-redundant. These active constraints can be written as the following system of *M*x*M* linear inequalities:

$$G_{i_kj_k}P_{i_kj_k}^{*(t)} - \gamma(R(k))\sum_{\substack{z=1\\ z\neq k}}^{M}G_{i_zj_k}P_{i_zj_z}^{*(t)} \geq \gamma(R(k))N \quad (13)$$

System (13) has a nonnegative solution *P*(t)*, based on Fact 1, $P^*(t) \geq P^{AP}(t)$ (component-wise). In turn, based on the optimality of *P*(t)* we have $P^{AP}(t) \geq P^{*}(t)$. Therefore, we conclude that$P^{*}(t) = P^{(AP)}(t)$. Hence, we conclude that *P*(t)* is strongly Pareto optimal with respect to transmission scenario *S*(t)*. It is noted that under the optimum solution of the MILP formulation, the total power consumption of each of the nodes are minimized over the set of all admissible power allocations for the prescribed optimum schedule. QED

*Theorem 2.* Every optimum solution of the MILP formulation is an optimum solution of the IPRS problem.

*Proof.* Let *(X',P')* and *T'* represent an optimum solution of the IPRS problem and the associated minimum frame length (in terms of number of time slots) respectively. We have:

$$\begin{aligned} Z(X', P') &= \sum_{t=1}^{T'} \sum_{(i,j)\in L} (c_t \sum_{h=1}^{m} X_{ijh}^{'(t)} + \epsilon P_{ij}^{'(t)}) \\ &\leq \sum_{t=1}^{T'} (c_t|L| + \epsilon \sum_{(i,j)\in L} P_{ij}^{'(t)}) \qquad (14) \\ &\leq c_{T'}|L|T' + \epsilon \sum_{t=1}^{T'} \sum_{(i,j)\in L} P_{ij}^{'(t)} \end{aligned}$$

where inequality (14) is deduced by the fact that there cannot be more than $|L|$ simultaneous transmissions in every time slot. Since $\epsilon$ is a sufficiently small number, we have:

$$\epsilon \sum_{t=1}^{T'} \sum_{(i,j)\in L} P_{ij}^{'(t)} \leq c_{T'}|L| \quad {}^{1} \qquad (15)$$

By considering relations (9), (14), and (15), we conclude

$$Z(X', P') \leq c_{T'+1}. \qquad (16)$$

Now, suppose there is an optimum solution of the MILP formulation *(X*,P*)* that yields a frame length of *T** slots, where *T** > *T'*. We have:

$$\begin{aligned} Z(X^{*}, P^{*}) &= \sum_{t=1}^{T*} \sum_{(i,j)\in L} (c_t \sum_{h=1}^{m} X_{ijh}^{*(t)} + \varepsilon P_{ij}^{*(t)}) \\ &\geq \sum_{t=1}^{T'} \sum_{(i,j)\in L} (c_t \sum_{h=1}^{m} X_{ijh}^{*(t)} + \varepsilon P_{ij}^{*(t)}) + c_{T'+1} \qquad (17) \end{aligned}$$

Considering relations (16) and (17), we have

$$Z(X', P') < Z(X^{*}, P^{*}). \qquad (18)$$

which contradicts the optimality of *(X*,P*)* for the MILP formulation. Therefore, *T** cannot be strictly greater than *T'*. Consequently, we conclude that every optimum solution of the MILP formulation is an optimum solution of the IPRS problem. QED

The edge-coloring problem is known to be NP-complete [21]. The IPRS problem presented above can be reduced to an edge coloring problem to show that it is NP-hard. To show this equivalence, we must go through considerable simplification of the original problem. Such modifications include assumptions that all the links operate at a fixed rate, ignoring aggregate physical interference effects, and assuming that each link only requires a single time-slot. The use of known bounds for heuristic edge-coloring algorithms (e.g., the square of the maximum nodal degree [32]) is therefore too loose in providing an effective measure of computational complexity. We thus conclude the need for a heuristic algorithm to provide an acceptable solution to the IPRS problem in a computationally efficient manner for networks with a large number of active links to be scheduled.

[1]For instance $\epsilon$ can be any positive number less than $[|L|^2 P_{\max}]^{-1}$

## IV. Heuristic Algorithm for the Adaptive Rate, Power and Slot Assignment Problem

### A. The Power Controlled Rate Adaptation Interference Graph

In this section, we introduce the notion of the *Power Controlled Rate Adaptation (PCRA) Interference Graph*, which is used as the basic building block of the heuristic algorithm that we present in the subsequent section. We use the following result to derive a simple mathematical formalism for the construction of the links of the interference graph:

Transmission scenario $S(t) = \{i_1 \xrightarrow{R(1)} j_1, i_2 \xrightarrow{R(2)} j_2\}$ is feasible if and only if the components of the apex solution of the following linear inequalities are in the range [0, $P_{max}$]:

$$\begin{cases} G_{i_1 j_1} P_{i_1 j_1}^{(t)} - \gamma(R(1)) G_{i_2 j_1} P_{i_2 j_2}^{(t)} \geq \gamma(R(1))N \\ -\gamma(R(2)) G_{i_1 j_2} P_{i_1 j_1}^{(t)} + G_{i_2 j_2} P_{i_2 j_2}^{(t)} \geq \gamma(R(2))N \end{cases} \qquad (19)$$

The *PCRA Interference Graph* is defined as an undirected weighted graph *G(V,E,w)*, in which *V* and *E* are the set of vertices and set of edges of graph *G*, respectively, and *w* is a nodal weight function, $w : V \rightarrow R^{+}$, where $R^{+}$ is the set of positive real numbers. Every vertex in *V* is represented by an ordered triplet$(i, j, r_h)$, considering only active links $l_{ij}$ in *L* and rates that are not excessively high with respect to the residual load $K_{ij}$. Thus, the set of vertices is presented as: $V = \{v_{ij}, l_{ij} \in L\}$, $v_{ij} = \{v_{ijh} = (i, j, r_h), h = 1, 2, \cdots, m_{ij}'\}$. The parameter $m_{ij}'$ represents the index of the highest rate considered for active link $l_{ij}$. We thus have:

$$m_{ij}' = \begin{cases} m & k_{ij} > r_m/r_1,\ G_{ij}P_{\max}/N \geq \gamma(r_m) \\ h+1 & r_h < r_1 K_{ij} \leq r_{h+1}, G_{ij}P_{\max}/N \geq \gamma(r_{h+1}) \\ 0 & \text{otherwise} \end{cases} \qquad (20)$$

The weight of each vertex $(i, j, r_h)$in the interference graph is set to $r_h/r_1$, which is the number of packets that can be transmitted over link $l_{ij}$ in a single time slot operating at rate $r_h$.

Vertices $(i_1, j_1, R(1))$ and $(i_2, j_2, R(2))$ are connected to each other by an edge in the interference graph *G* if and only if nodes $i_1$, $j_1$, $i_2$, and $j_2$ are not mutually distinct, or transmission scenario $S(t) = \{i_1 \xrightarrow{R(1)} j_1, i_2 \xrightarrow{R(2)} j_2\}$ is not feasible (does not satisfy constraint (19)). Consequently, every edge in the PCRA Interference Graph has the property that successful simultaneous transmissions of the network links represented by the end nodes of this interference graph edge at the prescribed data rates under any power allocation is impossible.

The weight of a nodal subset $S, S \subseteq V$, in a graph *G* is defines as$W(S) = \sum_{u\in S} w(u)$. A *weighted independent set I* of *G* is defined to be *maximum* if there is no other independent set *I'* of *G* such that $W(I') > W(I)$. Moreover, a weighted independent set $I$ of $G$ is said to be *maximal* if for every vertex $u, u \in (V-I), I \bigcup u$is not independent anymore [22]. We define a maximal weighted independent set of the PCRA Interference Graph to be *super-maximal* if an increase of the rate across any single link will make the set non-independent.

*Theorem 3.* Let $MWIS = \{(i_1, j_1, R(1)), \cdots, (i_M, j_M, R(M))\}$ denote a maximal weighted independent set of the PCRA Interference Graph. Then, $S(t) = \{i_1 \xrightarrow{R(1)} j_1, \cdots, i_M \xrightarrow{R(M)} j_M\}$ is a transmission scenario that it is not a proper subset of any feasible transmission scenario.

*Proof.* First, we note that all the nodes $i_1, j_1, \cdots, i_M, j_M$ are mutually distinct. Now, assume that $S'(t) = \{i_1 \xrightarrow{R(1)} j_1, \cdots, i_{M+\Delta} \xrightarrow{R(M+\Delta)} j_{M+\Delta}\}$ is a feasible transmission scenario. By definition of a feasible transmission scenario, then there exists a power vector $P'(t) = (P^{'(t)}_{i_1 j_1}, \cdots, P^{'(t)}_{i_{M+\Delta} j_{M+\Delta}})$, under which simultaneous transmission of every transmissions in *S'(t)* at the prescribed data rates is successful. Consequently, the set $\{(i_1, j_1, R(1)), \cdots, (i_{M+\Delta}, j_{M+\Delta}, R(M+\Delta))\}$ is also a weighted independent set of the PCRA Interference Graph. But, the latter contradicts the maximality of the weighted independent set $MWIS = \{(i_1, j_1, R(1)), \cdots, (i_M, j_M, R(M))\}$ which completes the proof. QED

### *B. Integrated Power Controlled Rate adaptation Scheduling Algorithm*

We have noted that the derivation of an algorithm that achieves an optimal solution of the IPRS problem for networks with large number of designated links in a reasonable time is an NP-hard problem. This motivates the need for a computationally efficient heuristic algorithm that provides an acceptable solution to any instance of the problem in polynomial time. Based on the notion of the PCRA Interference Graph, we introduce in this section a novel heuristic algorithm that solves the IPRS problem in a polynomial efficient manner.

An efficient greedy heuristic algorithm, identified as GWMIN, has been developed for solving the Maximum Weighted Independent Set problem [23]. At each iteration of the GWMIN algorithm, one vertex is selected from the residual graph for inclusion into the weighted independent set; then, the selected vertex and all its neighbors are removed from the graph. This process is repeated until the set of vertices *V(G$_i$)* of the residual graph $G_i$ at the *i*-th iteration is null. In selecting a vertex in each step, vertex *v* is selected if:

$$w(v)/(d_{G_i}(v)+1) = \max_{u \in V(G_i)} \{w(u)/(d_{G_i}(u)+1)\}, \quad (21)$$

It is noted that the nodal selection process takes into account the weight of a node, which represents the underlying rate. In the interference graph, the nodal degree is indicative of the level of interference imposed by a transmission conducted along this link on other links. Based on using the greedy algorithm in the interference graph we define the following algorithm:

***The Integrated Power Controlled Rate adaptation Scheduling (IPRS) Algorithm***:

1) Generate the PCRA Interference Graph.
2) Using the GWMIN algorithm, obtain a maximal weighted independent set of the PCRA Interference Graph.
3) Check feasibility of the selected set in step 2 and remove links until it becomes feasible.
4) Try to add links to make the selected set super-maximal.
5) Update the load and go to step 1 if there is residual load.

The set selected at the completion of Step 2, say *S*(1), has the property that it satisfies the half-duplexing, unicasting, and receptivity constraints. Furthermore, based on Theorem 3, transmission scenario *S*(1) is not a proper subset of any feasible transmission scenario. Moreover, based on the definition of the PCRA Interference Graph, every subset of *S*(1) with cardinality equal to two is a feasible transmission scenario, which, in turn, implies that there is a good chance that *S*(1) (or a large subset of *S*(1)) is also a feasible transmission scenario. The IPRSA algorithm utilizes transmission scenario *S*(1) as a suitable initial point for its search for a super-maximal feasible transmission scenario for allocation to time slot 1. This search consists of two consecutive steps (i.e., Feasibility and Super-Maximality). After these two steps, the resulting super-maximal feasible transmission scenario *S'*(1) is allocated to the first time slot.

After scheduling the first time slot, the values of $K_{i'_k j'_k}$ are updated and subsequently the PCRA Interference Graph is trimmed. The algorithm then iterates the same procedure for the next time slot. IPRSA terminates when the residual PCRA Interference Graph becomes a trivial graph or equivalently when $K_{ij} = 0$ for all the communication links $l_{ij}$ in *L*.

In the following, we explain the Feasibility and Super-Maximality stages in more detail.

***Feasibility Stage.*** The Feasibility Stage aims to find a maximum feasible transmission scenario over all the subsets of transmission scenario $S(t) = \{i_1 \xrightarrow{R(1)} j_1, \cdots, i_M \xrightarrow{R(M)} j_M\}$. This problem is known to be an NP-complete problem [24]. We modify the *Stepwise Maximum Interference Removal Algorithm* (SMIRA) that was originally introduced for the downlink connection removal of the cellular radio systems [25] to be used in a network where nodes are transmitting at different rate. In the SMIRA algorithm, at every step a transmission is removed from the group of potential transmissions, which on average causes most interference to other receivers (i.e., the non-intended receivers) or is most sensitive to interference from other transmissions. SMIRA iterates this process until the resulting transmission scenario is feasible.

***Super-Maximality Stage.*** The feasible transmission scenario *FS* induced by the Feasibility Stage is not necessarily maximal with respect to the underlying residual PCRA Interference Graph. To ensure that the set of transmissions allocated to every time slot forms a maximal feasible transmission scenario, the Super-Maximality stage iteratively considers the other remaining transmissions for possible inclusion in the transmission scenario *FS*. Also, the Super-Maximality stage iteratively assigns the maximum possible rate to each transmission in the resulting maximal feasible transmission scenario to ensure that the resulting feasible transmission scenario is super-maximal.

*Theorem 4.* The computational complexity of the IPRS Algorithm is $O(m^2\alpha^3|L|^2)$.

*Proof.* The number of available data rates is equal to *m*, the size of the maximum independent set of the PCRA Interference Graph is set equal to $\alpha$, and |L| is the number of links to be scheduled. Note that $\alpha$ is typically much smaller than |L|. The selection of a maximal independent set from the PCRA Interference Graph (using GWMIN) requires an order of $m^2|L|^2$ computations. To check the feasibility of an independent set, the algorithm has to solve a system of linear inequalities with a size of at most $\alpha$x$\alpha$, which requires an order of $\alpha^3$ computations. The super-maximality stage checks for feasibility and maximality as it considers links for possible inclusion into the feasible transmission scenario. Hence, it requires an order of at most $m^2\alpha^3|L|^2$ computations. We note that the complexity of the algorithm is dominated by the super-maximality stage. QED

The complexity of the heuristic algorithm scales in a manner that is proportional to the square of the number of links in the network, so it is able to perform the scheduling rapidly even for a network with a large number of active links. Hence, our approach is effective as long as the coherence time of the channel (based on the rate of channel quality fluctuations and user mobility) is longer than the computation time of our heuristic algorithm.

## V. Numerical Illustrations

We have compared the performance of our IPRS algorithm with the optimal solution by running extensive computer simulations. We have also compared the performance of our IPRS algorithm with that of a scheduling algorithm identified as 'Greedy Physical', which was presented in [28]. The latter algorithm was developed for spatial-TDMA network, where nodes transmit at a fixed power and a fixed rate. We uniformly distribute 500 nodes in a square area of dimensions 5000m x 5000m. Each node can select for the transmission across each link, one out of three transmission rates $\{r_1 =$ 1Mbps, $r_2 =$ 2Mbps, $r_3 =$ 5.5Mbps$\}$. At rate $r_k$, a node can transmit $2^k$ packets in a time-slot. We have used the rates and the corresponding SINR thresholds according to the 802.11b standard [34]. Each node can adjust its transmit power continuously in the range [0,$P_{max}$], where $P_{max}$ is set to be 100 mW. The propagation gain is modeled as $G_{ij} = 1/{d_{ij}}^{2.5}$ where $d_{ij}$ is the distance between the transmitter and receiver.

The complexity of the optimum solution obtained through the MILP model grows exponentially with the number of active links. Hence, to compare the performance of the heuristic algorithms with that of the optimum solution, we had to pick a small number of active links. We examined 6 different scenarios. Scenarios are differentiated by using distinct noise power levels. The selected noise power level affects the maximum length of a realizable link (a link that satisfy the lowest SINR threshold at its receivers, when the transmit power is $P_{max}$). A higher noise power level results in

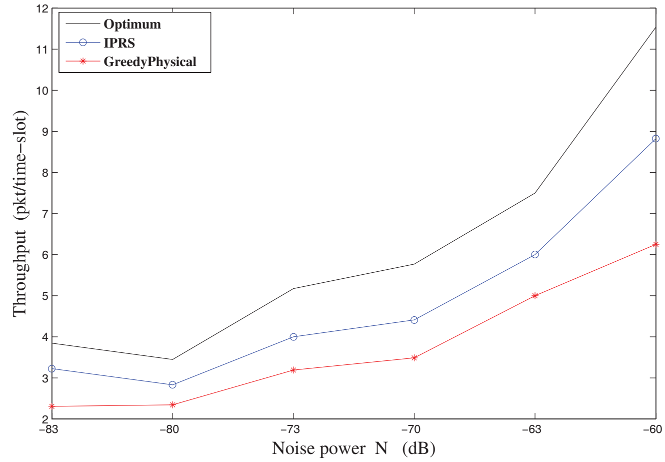


Fig. 3. Throughput of 6 different network scenarios with 15 links.

the selection of shorter links, which in turn leads to a higher spatial reuse factor. For each scenario, the underlying noise power level is fixed. We, however, proceed for each scenario to examine different sets of active links by selecting 15 links at random from the set of realizable links. For each scenario, the demand is for 20 packets to be transmitted across each one of the selected links. Considering 6 different scenarios, we show in Fig. 3 the network throughput attained under the use of the optimum method, the IPRS algorithm, and the GreedyPhysical algorithm. For each scenario, each data point is the average throughput obtained from 10 simulation runs. As it can be seen from Fig. 3 the throughput under the IPRS algorithm is (on average) 20% better than that attained by the use of the GreedyPhysical algorithm which assumes a fixed data rate ($r_1$) and fixed power ($P_{max}$). Noticeable performance improvement is realized as the network offers higher spatial reuse levels. The throughputs attained under the IPRS algorithm are noted to be within 75% of the optimum throughput values for the set of illustrated scenarios. Of course, the computational complexity of the optimal scheme becomes prohibitively high as the number of links and rates increases to even a moderate level. For the illustrated scenarios, using a 1 GHz PC computer, typical calculation time required by the optimum MILP method to assign data rate and power values in a time-slot was about 25 sec while the required time by the heuristic IPRS algorithm was about 6 msec.

To test the performance of our heuristic IPRS algorithm in networks that involve a larger number of active links, we ran another set of simulations under which we have compared the performance of our IPRS algorithm with that of the GreedyPhysical algorithm. Considering a network of 500 nodes, we randomly select a specified number of links (*L*). We display the attained network throughput versus *L*, under the use of the IPRS algorithm and the GreedyPhysical algorithm. We have studied the performance of these algorithms by examining three different sets of active links. Under the first set, each selected link must be able to transmit at a minimum rate $r_1$. Under the second and third sets, each selected link must be able to transmit at a minimum rate $r_2$ and $r_3$, respectively. Under the GreedyPhysical algorithm, when the k-th set of active links is used, the fixed transmit rate at each node is

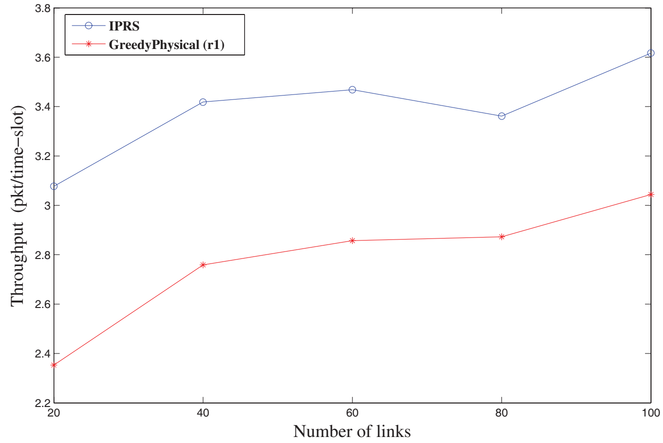


Fig. 4. Throughput versus number of links.

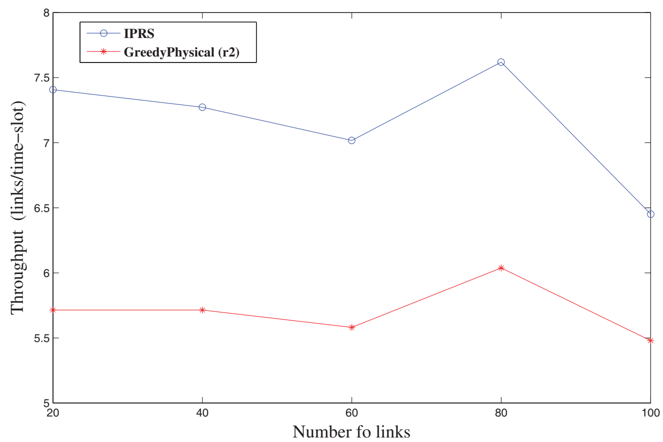


Fig. 5. Throughput versus number of links.

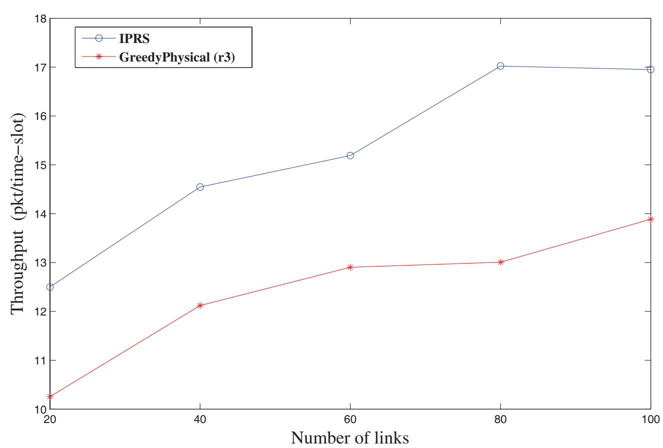


Fig. 6. Throughput versus number of links.

set equal to $r_k$. Figs. 4,5, and 6 show the network throughput vs. the number of active links ($L$) under the IPRS algorithm and under the GreedyPhysical algorithm, whereby nodes under the latter algorithm use fixed power $P_{max}$ and fixed rate $r_1$, $r_2$ and $r_3$, respectively. Note that each data point corresponds to a random placement of the nodes and a random selection of $L$ links among these nodes. Consequently, network throughput levels are expected to fluctuate from case to case as the $L$ level changes. We observe that for each case, the network throughput attained under the IPRS algorithm is on average 20% higher than that attained under the fixed power and fixed rate GreedyPhysical algorithm.

## VI. Conclusion

Many wireless networks that serve telecommunications infrastructures employ TDMA based medium access control protocols. Due to the variable and stochastic nature of traffic processes and interference patterns, the channel quality of communication links tends to fluctuate. The introduction of Software Defined Radios, coupled with the use of intelligent cross-layer scheduling mechanisms can go a long way towards improving the network throughput. In this paper, we develop models and algorithms that are used for the implementation of efficient spatial-TDMA based adaptive power and adaptive rate cross-layer scheduling schemes.

We model this optimum cross-layer scheduling problem as a Mixed Integer Linear Program (MILP) and show that it can be solved for a system that involves a small number of links and data rate levels. We note the optimum method to be NP hard. Hence, we proceed to develop and present a heuristic algorithm for solving the problem. Under our heuristic method, we derive a feasible super-maximal independent set in the PCRA Interference Graph.

We have carried out performance analyses for a wide multitude of networking scenarios. By considering networks that involve smaller set of active links, our simulation results demonstrate the performance of our heuristic method to be in the 75 percentile of the optimum solution for the investigated networking scenarios. When considering networks that involve larger set of active links, we have shown our heuristic algorithm to yield a throughput that is (on the average) 20% higher than that attained by a fixed rate and fixed power link scheduling algorithm. Future extensions of this work include the derivation and study of distributed methods for allocation of time-slot, power level, and data rate levels, as well as the incorporation of such adaptations that are performed jointly with the selection of end-to-end routes.

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