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Jointly rate and power control in contention based MultiHop Wireless Networks

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Abstract

This paper presents a new algorithm for jointly optimal control of session rate, link attempt rate, and link power in contention based MultiHop Wireless Networks. Formulating the problem in the framework of nonlinear optimization, we derive the required updates at end points and links to reach the optimal operating point. The proposed algorithm is a cross layer algorithm considering power control at the physical layer, attempt rate control at the Medium Access Control (MAC) layer and rate control at the transport layer of the network. The optimization variables are coordinated through two shadow prices. The first one regulates each session rate to the throughput of the links in its path, and the second one controls the attempt rates to meet maximal clique capacity constraint. Considering a model for successful transmission, the excitatory and inhibitory factors affecting each variable are derived. The proposed algorithm can be implemented in distributed fashion by message passing in the network. Simulation results at the link level verify the analytical approach and show that the algorithm converge and reach joint optimal point.

Keywords: MultiHop Wireless Network; Cross layer; Rate control; Power control

1. Introduction

Limited network resources makes the resource allocation an important problem both from engineering and economic views. Allocation of resources must be done in a dynamic manner in networks, depending on different users' utility function and demands. Considering a utility function for each user, the objective of resource allocation is efficiently and fairly use of network resources between competing sessions in the network. The utility function, defined by the application layer, depends on the session rate which is controlled at the transport layer. The session rate, itself depends on the throughput of links in the path from the source to the destination which is affected by the routing strategies at the network layer and scheduling methods at the Medium Access Control (MAC) layer. Hence, the problem involves different layers in the protocol stack. Such a problem is called a cross layer problem, i.e., a problem which needs coordination between layers to be solved efficiently [1].

In wireline networks, assuming fixed link capacities and fixed routing, the problem was formulated as a global optimization problem to maximize the total network utility subject to constraints on link capacities [2,3]. Analysis results show that a coordination is required between the end points of each session and the links which the session traversing through them. These results were used in the reverse direction, and it was proved that different existing Transmission Control Protocols (TCP) at the end points and queueing disciplines at the links can be interpreted as distributed algorithms maximizing different utility functions over the network [4,5]. This interpretation reveals that the sessions rate are regulated by explicit or implicit feedback congestion signals like packet losses or packet delays which come back from the links in the path.

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The resource allocation problem in MultiHop Wireless Networks (MHWN) gives rise to many new challenges. Among the many unique characteristics of MHWN we focus on two characteristics in our formulation. While the link capacity is fixed in wireline network, it can be adjusted in wireless networks by means of power control and other adaptive techniques like adaptive modulation. In other words, the physical layer has a higher significant role in the resource allocation problem in MHWN. Transmitter node of a link tends to increase the power to increase the capacity of the link. However, increasing the link power cause to interference for others and reducing their capacities. Therefore, transmitter power can be thought as a network resource that must be assigned by coordination between nodes. We consider power control in our optimization formulation.

Another major point in MHWN is the location dependent contention between links for the wireless channel [6,7]. In wireline networks, sessions passing a link contend for the link capacity, whiles the link capacity is independent from other links. Scheduling algorithms like Weighted Fair Queuing (WFQ) try to share fairly the bandwidth between competing sessions in time. In contrast, in MHWN, links usually use some kind of random access like slotted Aloha to access the channel. In other words links compete to access the channel with an attempt rate. The problem is that the level of contention depends on the link position in the network. In fact, there are location dependent contention regions where only one flow in any region can have successful transmission in each time slot. Regulating the attempt rate for each link, is the main problem in designing the MAC layer in MHWN. Uncontrolled increasing in attempt rates may cause to excess collisions and reduce the links throughput. We consider attempt rate control in our optimization formulation.

These characteristics have two effects on the solution of resource allocation problem in MHWN. The first is that not only the end points and links on the path for each session should have a coordination, but also a local coordination is required between links in any contention region to adjust their attempt rates. The second is that each node has two degree of freedom, power and attempt rate, for adjusting its throughput. The transmitter node of each link must decide to control these parameters jointly based on its position in the network.

The novelty of this paper is that we consider these two issues in our formulation of resource allocation problem for MHWN. Based on analytical solution of the problem we derive the required mechanisms for power and attempt rate update at the links and rate update at the sources of the network. Considering a model for successful transmission, we derive the excitatory and inhibitory factors for each of these variables. The proposed algorithm can be thought as a cross layer algorithm considering power control at the physical layer, attempt rate control at the MAC layer and rate control at the transport layer of the network. Also, it is shown that the algorithm can be implemented in distributed fashion by message passing in the network.

Related works to ours are summarized as follow.

The problem of simultaneous congestion and power control was introduced in [8] with the JOCP (Jointly Optimal Congestion and Power Control) algorithm. *The JOCP algorithm is based on perfect Code Division Multiple Access (CDMA) in MAC layer and does not consider the MAC layer contentions between nodes.*

The problem of jointly congestion and contention control is also discussed in [9,10]. Our work differs from those since we consider the attempt rate constraints in maximal cliques and consider power variables in our formulation. We use the concept of contention graph and clique capacity from [6] to express the constraints on links attempt rate in each contention region or maximal clique.

The problem of rate control at source based on capacity of maximal cliques is formulated in [11] with the association of shadow prices with maximal cliques and adapting session rates based on these prices. However, they assume perfect scheduling at the MAC layer and did not consider power in their formulation. The distributed algorithm presented by Xue in [11], indicates that clique prices can be computed with a little overhead in MHWN. We refer to [11], to show the feasibility of distributed implementation of our algorithm which depends on clique prices.

Based on our study, while the problems of congestion and power control [8], congestion control and link scheduling at the MAC layer [11], and congestion and contention control [9,10] were investigated separately, they are not considered in an optimization problem jointly. On the other hand, the link throughput, as it is discussed in Section 3.1, depends on both powers and attempt rates of links, while the sessions' rate depend on links throughput. Also, from a MAC layer design viewpoint, both power and attempt rate can be used for interference mitigation and relative assignment of these variables for links in the network is not analyzed before. Our motivation is to analyze the network utility maximization problem in the augmented space of these variables and provide insights on a power aware MAC for MHWN.

The rest of the paper is organized as follows. In Section 2, we describe the notation and system model. In Section 3, the problem is presented in the framework of nonlinear optimization. In Section 4 the solution approach based on convex optimization are presented and some discussion on them are given. The required updates and the proposed algorithm is presented in Section 5. In Section 6, we discuss about the feasibility of distributed implementation of the algorithm by message passing in the network. Simulation results of the proposed algorithm and discussion on them are presented in Section 7.

2. Notation and system model

The MHWN is represented by a directed graph $G = G(N,L)$, where N is the set of nodes and L is the set of logical links. By logical link we mean two nodes that are in the transmission range of each other.

The set of sessions are represented by S. Dedicated to each session $s \in S$, there is a utility function $U_s(x_s) : \mathbb{R}^+ \mapsto \mathbb{R}^+$ which is a function of its end-to-end data rate x_s. It is assumed that the utility function is strictly increasing and strictly concave. The network utility is the sum of all users utility. The set of links that is used by session s is denoted by $L(s)$. $S(l)$ represents the subset of sessions that are traversing link l.

Dedicated to each link $l \in L$, there is an attempt rate q_l, $0 \leqslant q_l \leqslant 1$ and transmission power p_l, $p_{\min} \leqslant p_l \leqslant p_{\max}$. The attempt rate represents the rate at which the link try to access the channel and models the MAC layer behavior in our simulation. It is assumed that the system is time slotted and at the beginning of each slot, link l will attempt to access the channel with probability q_l. $\mathbf{q} = (q_1, q_2, \ldots, q_L)$ and $\mathbf{p} = (p_1, p_2, \ldots, p_L)$ are the vectors of all links attempt rates and powers.

It is assumed that the system uses CDMA at the physical layer. The Signal to Interference plus Noise Ratio (SINR) of link l is denoted by γ_l. If all links transmit in a given slot, γ_l is given by: $\gamma_l = (p_l G_{ll})/(\sum_{k \neq l} p_k G_{lk} + \eta_l)$; where G_{lk} is the path loss from transmitter of logical link k to the receiver of logical link l and η_l is the noise power at the receiver of logical link l. The simplified model for path loss as a function of distance, d, is $G = (\frac{d_0}{d})^{\alpha}$ for $d > d_0$; where d_0 is a reference distance and α is the path loss exponent [12]. We consider the spreading gain of the CDMA in G_{lk} parameters in our simulations. $c_l(\gamma_l)$ is the attainable data rate or capacity of link l which depends on the link γ_l and is given by:

$$c_l(\gamma_l) = \frac{1}{T} \log(1 + K\gamma_l) \tag{1}$$

where T is the symbol period, assumed to be one unit, and K is a constant depending on the modulation and bit error rate of the link [12]. We assume $K = 1$.

Due to the interferences, all transmissions are not successful and a fraction of each link capacity can be used effectively. In the other words, the link throughput is less than the link capacity. We use *Protocol Model* [13] to describe when a transmission is successful. The transmission of link l is successful in a time slot if no other link in the interference range of the transmitter and receiver nodes of link l sends in that time slot, i.e., when both transmitter and receiver of the link are interference free. This model is consistent with MAC protocols like 802.11 where the transmitter needs to be interference free to receive the link layer acknowledgment from the link receiver [6]. The set of links that make interference to the transmission of link l is denoted by $L^{To}_{Conf.}(l)$; where *Conf.* shows conflict in transmission. The set of links whose transmissions would be interfered with the transmission of link l, is denoted by $L^{From}_{Conf.}(l)$. Hence, the probability that the transmission of link l is successful, s_l, when it attempts to access the channel is given by $s_l = \prod_{j \in L^{To}_{Conf.}(l)} (1 - q_j)$. We also assume that there is one outgoing link for the transmitter of each link and all links carry some flow. In addition, the routing matrix of the network assumed to be fixed and known.

3. Problem statement and formulation

Fig. 1 shows the general view of a segment of MHWN with four sessions crossing a contention region consisting of three links. The parameters of link l consist of its power and attempt rate, p_l and q_l, are shown on the link. The source and destination nodes of session i are denoted by s_i and d_i, respectively, and its rate is denoted by x_{si}. The sessions flow from sources to destinations over the network links are shown by different bold lines. The objective is to regulate links and sessions parameters.

Sessions 1,2 traversing through link l and sessions 3,4 traversing through link k. The sum of rates of sessions 1,2 and 3,4 should not exceed the throughput of link l and k, respectively. Therefore, to regulate the session rates to the throughput of links, feedback congestion signals are required. Hence, congestion measures λ_l and λ_k, depicted as dashed arrows, show feedback from links l and k to sources 1,2 and 3,4 to regulate the x_{s1},x_{s2} and x_{s3},x_{s4}, respectively. To compute and apply these congestion signals, we need an estimation of link throughput which is given in Section 3.1.

The contention region denoted by ω and depicted by an oval, consists of links j, k, l. Due to the interferences, only one from three links in the contention region can have successful transmission in each time slot. Therefore, there should be a coordination between the links to access the channel. This coordination is achieved by a contention measure computed for each contention region, i.e., ϕ_ω. We apply this coordination by a constraint on attempt rates of all links in the contention region, i.e., q_j, q_k, q_l. This constraint is described in Section 3.2.

3.1. Computing the link throughput

The sum of the rates of all sessions traversing any link should not exceed the link throughput. The links around a given link named l, are divided into two groups: the first group are those which are in the contention region of l and their transmission conflict the transmission of l according to the capture model described in Section 2. We refer to this group as conflicting links. The second group are those links which are farther to link l and their transmission reduces the achievable capacity upon successful access to the channel. We refer to this group as non-conflicting links. Link l can successfully access to the channel with probability $q_l s_l$ and in that case only some links in non-conflicting links may have transmissions. We compute a constraint for the achievable average capacity in this case. Multiplying this capacity to factor $q_l s_l$ yields a constraint on achievable average throughput of the link.

Let B_k be the random variable that denotes the interference value of link k to link l.

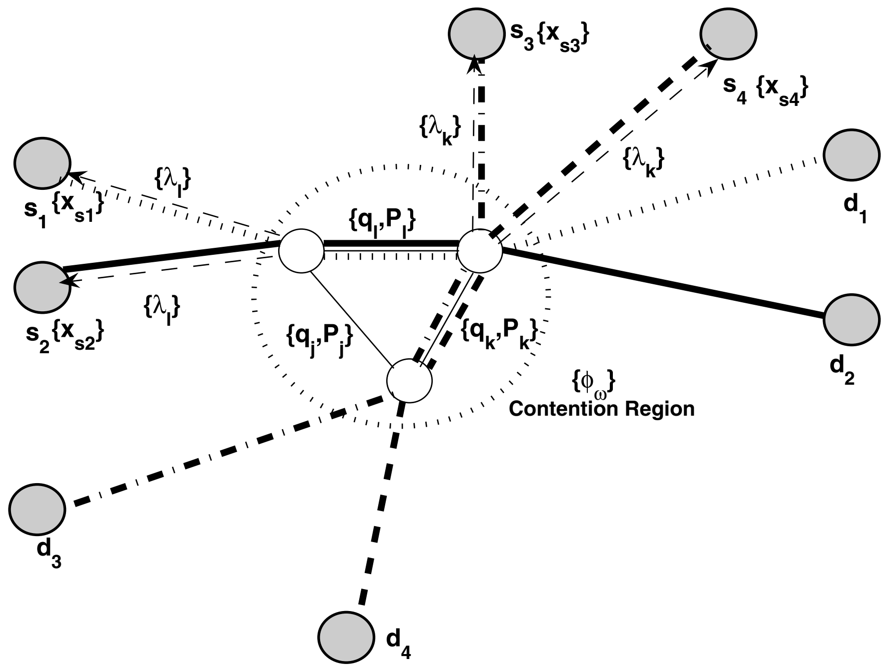

Fig. 1. General view of a segment of MHWN contains four sessions and a contention region.

$$B_k = \begin{cases} G_{lk}p_k & \text{with probability } q_k \\ 0 & \text{with probability } 1-q_k \end{cases} \quad (2)$$

If link l access the channel *successfully*, the received γ_l is stochastic and depends on the received interference of link l, denoted by I_l, and is given by:

$$I_l = \sum_{k:k\notin L^{To}_{Conf.}(l)} B_k$$

$$\gamma_l = \frac{G_{ll}p_l}{I_l}$$

To compute an average for achievable capacity, $\bar{c}$, on each link, we note that $\bar{c} \leqslant \log(1+\bar{\gamma})$[12]. Based on Jensen's inequality and this fact that $f(I_l) = 1/I_l$ is convex, we have:

$$\bar{\gamma} = E\left[\frac{G_{ll}p_l}{I_l}\right] \geqslant \frac{G_{ll}p_l}{E[I_l]}$$

Therefore we can find a tight constraint for the average achievable link capacity on each link given by:

$$\bar{c}_l \leqslant \log\left(1 + \frac{G_{ll}p_l}{\sum_{k:k\notin L^{To}_{Conf.}(l)} G_{lk}p_k q_k}\right)$$

3.2. Modeling the contention regions

To apply the constraint of contention regions, we use the contention graph concept from [6]. The contention graph $\tilde{G} = (\tilde{N}, \tilde{L})$ of the network represents the contention regions in the network. The vertices of $\tilde{G}$ correspond to links in G, i.e., $\tilde{N} = L$ and there exist one edge between two vertices in $\tilde{G}$ if the corresponding links contend with each other. The maximal cliques, i.e., maximal complete subgraphs of $\tilde{G}$, show the contention regions in G. At most one link in any maximal clique can transmit in each time slot successfully. Let $\Omega(l)$ be the subset of cliques that link l belongs to and $L(\omega)$ be the subset of links belonging to clique ω.

The constraint in non-contention based environment and fixed link capacities is expressed as $\sum_{l\in L(\omega)} \frac{y_l}{c_l} \leqslant 1$ where y_l is the link rate [14]. The parameter $\frac{y_l}{c_l}$ named as normalized link rate, is the fraction of time required to send y_l on a link with capacity c_l. Therefore the sum of all these fractions in a clique must be less than 1, as a necessary condition and assuming perfect scheduling between links in a clique.

In MHWN, without any centralized coordinator among nodes, this assumption is unrealistic and some capacity is wasted due to collisions. In our problem for contention based environment each transmission is successful with probability s_l. Therefor in average each transmission should be tried $\frac{1}{s_l}$ times to be successfully received by the receiver and the constraint is changed to $\sum_{l\in L(\omega)} \frac{y_l}{s_l c_l} \leqslant 1$. Since, the link rate can not exceed the link throughput, we have $y_l \leqslant q_l s_l c_l$ for each link l. In fact, as we show in Section 4.2, at equilibrium we have $y_l = q_l s_l c_l$ for each link that at least one session traversing it. Therefore the clique constraint changed to:

$$\sum_{l\in L(\omega)} \frac{y_l}{s_l c_l} \leqslant \sum_{l\in L(\omega)} q_l \leqslant 1$$

Therefore, in general the link attempt rates of all links in a clique should be less than the normalized clique capacity c_ω, i.e., $\sum_{l\in L(\omega)} q_l \leqslant c_\omega$ for each clique ω. The upper bound of c_ω is 1. In fact the $\sum_{l\in L(\omega)} q_l \leqslant 1$ is a necessary condition for a vector of attempt rates to be feasible. However, only for perfect flow contention graph the capacity of a clique, c_ω, can be normalized to 1 [15] and for general graphs it is lower than 1. It is shown that scaling the capacity of all cliques by factor 2/3, i.e., $\sum_{l\in L(\omega)} q_l \leqslant 2/3$ is sufficient to ensure the feasibility of attempt rate vector [16]. Using this lower bound can reduce the MAC layer capacity of the network. However, in all practical bandwidth allocation schemes some bandwidth is left unutilized "...to prevent buffer overflow during transients, and also to prevent excessive queueing delay at the nodes" [16]. Therefor utilization of more than 2/3 in each clique seems impractical in a real MHWN. We use $c_\omega = 2/3$ in our simulations.

Another approach for estimating the clique capacity is based on achievable bandwidth of wireless links that can be measured using the transmission history of the link [11].

3.3. Resource allocation problem

We now consider the problem of jointly rate and power control in a contention based MHWN. The objective is maximizing the total network utility with constraints on links capacity and MAC layer constraints on clique capacities. We assume that the contention matrix of the network is fixed and does not depend on nodes power. Therefore, the problem can be formulated as:

$$\mathbf{P} : \max \sum_{s\in S} U_s(x_s) \tag{3}$$

$$\text{s.t.} \sum_{s:s\in S(l)} x_s \leqslant q_l s_l \bar{c}_l \quad \forall l \in L \tag{4}$$

$$\sum_{l\in L(\omega)} q_l \leqslant c_\omega \quad \forall \omega \in \Omega \tag{5}$$

$$x_{s\min} \leqslant x_s \leqslant x_{s\max} \quad \forall s \in S \tag{6}$$

$$0 \leqslant q_l \leqslant 1 \quad \forall l \in L \tag{7}$$

$$p_{\min} \leqslant p_l \leqslant p_{\max} \quad \forall l \in L \tag{8}$$

The first constraint, Eq. (4), ensures that the total traffic of all session on each link should not exceed the throughput of the link. The second constraint, Eq. (5), is MAC layer constraint on each maximal clique of the network. Other constraints, Eqs. (6)–(8) represent the valid interval for each optimization parameter.

4. Solution approach

The objective function, Eq. (3), is strictly concave and the second constraint Eq. (5) is affine. However, due to the product terms in the first constraint, Eq. (4), this constraint is not convex. Therefore the problem is non-convex in the current form. A max optimization problem is convex if the objective function is strictly concave and the inequality constraints are convex [17]. Convexity of an optimization problem is required to ensure that the global optimal solution can be achieved using the well known convex optimization theory [17].

4.1. Problem convexification

Fortunately, using appropriate transformation, the optimization problem can be turned to a convex optimization problem.

Using transformation $\tilde{x}_s = \log x_s$, $\tilde{p}_l = \log p_l$, $\tilde{q}_l = \log q_l$ and taking logarithm of the first constraint leads to:

$$\log\left(\sum_{s:s\in S(l)} e^{\tilde{x}_s}\right) - \log e^{\tilde{q}_l} - \log s_l - \log \bar{c}_l \leqslant 0 \tag{9}$$

Noting that if $g(x)$ is concave and positive, then $\log(g(x))$ is concave, we find that the term $\log e^{\tilde{q}_l}$ is affine and $\log s_l = \log \prod_{j\in L^{To}_{Conf.}(l)} (1 - e^{\tilde{q}_j}) = \sum_{j\in L^{To}_{Conf.}(l)} \log(1 - e^{\tilde{q}_j})$ is concave and hence $-\log s_l$ is convex. Also, noting that the log of a sum of exponentials of vector $\mathbf{x}$ is convex [17], the term $\log(\sum_{s:s\in S(l)} e^{\tilde{x}_s})$ is convex. To investigate the convexity of the term $\log(\bar{c}_l)$ we consider two cases: In high regime SINR, i.e., when $\gamma_l \gg 1$, $\bar{c}_l$ is concave and positive; considering the above note and as proved in [8]. Therefore, $-\log(\bar{c}_l)$ is convex. In low regime SINR, i.e., $\gamma_l \ll 1$, when we can approximate $\bar{c}_l = \log(1+\bar{\gamma}) \simeq \bar{\gamma}_l$, we have $\log(\bar{c}_l) \simeq \log(\bar{\gamma}_l)$ and again this term is convex. Also, the second constraint is obviously convex using the transformation.

We should note that the objective function must be strictly concave regarding this transformation. A general class of concave utility functions and their fairness properties are introduced in as [18]:

$$U_a(x_s) = \begin{cases} \log(x_s) & \text{if } a = 1 \\ (1-a)^{-1} x^{1-a} & \text{otherwise} \end{cases} \tag{10}$$

Using transformation $\tilde{x}_s = \log x_s$ we have:

$$\tilde{U}_a(\tilde{x}_s) = \begin{cases} \tilde{x}_s & \text{if } a = 1 \\ (1-a)^{-1} e^{\tilde{x}_s(1-a)} & \text{otherwise} \end{cases} \tag{11}$$

which is strictly concave assuming $a > 1$. Therefore, using the log transformation and appropriate choose of utility function the problem is a convex optimization problem.

4.2. Optimality conditions

The Lagrangian function for problem $\mathbf{P}$, considering $\Lambda = (\lambda_1, \ldots, \lambda_{|L|})$ and $\Phi = (\phi_1, \ldots, \phi_{|\Omega|})$ as lagrange multipliers for the first and second constraint we have:

$$\begin{aligned} L(\tilde{\mathbf{x}}, \tilde{\mathbf{p}}, \tilde{\mathbf{q}}, \Lambda, \Phi) = &\sum_{s\in S} \tilde{U}_s(\tilde{x}_s) \\ &- \sum_l \lambda_l \left[\log\left(\sum_{s:s\in S(l)} e^{\tilde{x}_s}\right) - \log(e^{\tilde{q}_l} s_l \bar{c}_l)\right] \\ &- \sum_\omega \phi_\omega \left[\sum_{l\in L(\omega)} e^{\tilde{q}_l} - c_\omega\right] \end{aligned} \tag{12}$$

Applying Karush–Kuhn–Tucker (KKT) theory [17] to problem and doing some simplification we can find the required conditions at optimal solution.

$$\frac{\partial L}{\partial \tilde{x}_s} = 0 \;\Rightarrow\; \tilde{U}'_s(\tilde{x}_s) - \sum\nolimits_{l:l\in L(s)} \lambda_l \frac{x_s}{\sum\limits_{s:s\in S(l)} x_s} = 0 \tag{13}$$

$$\begin{aligned} \frac{\partial L}{\partial \tilde{q}_l} &= 0 \\ &\Rightarrow \frac{\lambda_l}{q_l} - \frac{1}{1-q_l}\sum\nolimits_{k:k\in L^{From}_{Conf.}(l)} \lambda_k \\ &\quad - p_l \sum\nolimits_{k:k\notin L^{From}_{Conf.}(l)} \frac{\lambda_k p_k G_{kl}}{\bar{c}_k \sum\limits_{j:j\notin L^{To}_{Conf.}(k)} p_j q_j G_{kj}} \\ &\quad - \sum\nolimits_{\omega:\omega\in\Omega(l)} \phi_\omega = 0 \end{aligned} \tag{14}$$

$$\begin{aligned} \frac{\partial L}{\partial \tilde{p}_l} &= 0 \\ &\Rightarrow \frac{\lambda_l}{\bar{c}_l p_l} - q_l \sum\nolimits_{k:k\notin L^{From}_{Conf.}(l)} \frac{\lambda_k p_k G_{kl}}{\bar{c}_k \sum\nolimits_{j:j\notin L^{To}_{Conf.}(k)} p_j q_j G_{kj}} = 0 \end{aligned} \tag{15}$$

And at equilibrium we have:

$$\begin{cases} \text{if} \quad \lambda_l > 0 \;\Rightarrow\; \sum\limits_{s:s\in S(l)} x_s = q_l s_l \bar{c}_l \\ \text{if} \quad \sum\limits_{s:s\in S(l)} x_s < q_l s_l \bar{c}_l \;\Rightarrow\; \lambda_l = 0 \end{cases} \tag{16}$$

$$\begin{cases} \text{if} \quad \phi_\omega > 0 \;\Rightarrow\; \sum\limits_{l:l\in L(\omega)} q_l = c_\omega \\ \text{if} \quad \sum\limits_{l:l\in L(\omega)} q_l < c_\omega \;\Rightarrow\; \phi_\omega = 0 \end{cases} \tag{17}$$

We interpret these equations as follows. Each session should regulate its rate based on Eq. (13). There are two terms that affect the final rate of the session. An excitatory term and an inhibitory term appear with positive and negative sign, respectively. The excitatory term tends to increase the session rate according to the utility function. The inhibitory term which should be feedback from the links on session path, tends to decrease the session rate. Denoting the total load on link l by $y_l = \sum_{s:s\in S(l)} x_s$, we see that each session observes the sum of all congestion signals on its path, multiplied by the session rate to the total rate of the link. At equilibrium these terms are equal.

Each link should regulate its attempt rate based on Eq. (14). To simplify the description of this equation we adopt the notation of messages like that used in [8]. Let m_k be the message information that broadcasted by link k as:

$$m_k = \frac{\lambda_k p_k}{\bar{c}_k \sum\nolimits_{j:j\notin L^{To}_{Conf.}(k)} p_j q_j G_{kj}} \tag{18}$$

The excitatory term is the current congestion measure of the link divided by the current attempt rate. The first two inhibitory terms show the effect of conflicting links and non-conflicting links. The sum of congestion measure for all conflicting links divided by $1 - q_l$, tends to decrease the attempt rate of link explicitly. However, non-conflicting links tend to decrease the link attempt rate based on current power level of the link. Upon receiving the messages broadcasted by non-conflicting links, the message content multiplied by the factor G_{kl} and take part in attempt rate regulation. The larger the transmission power of the link, the more is the effect of non-conflicting links. This term, shows the tradeoff of links on choosing between their options: a higher attempt rate or a higher power transmission. The third inhibitory term ensures that the capacity of each clique does not exceed the clique capacity. Since, the sum of all clique contention measures which this link belongs to is used as an inhibitory term to regulate the link attempt rate.

Each link should regulate its transmission power based on Eq. (15). The excitatory factor is based on current congestion level divided by the current power and current average capacity. The inhibitory term is based on non-conflicting links messages which their contents multiplied by link attempt rate q_l. The larger the attempt rate the more is the effect of the received messages to decreases the transmission power of the link.

Eqs. (16) and (17) show the required conditions on shadow prices at equilibrium. To find the required formula to update these values, we may solve the dual problem of **P**.

The dual function is:

$$\begin{aligned} D(\Lambda,\Phi) &= \max\nolimits_{\tilde{\mathbf{x}},\tilde{\mathbf{p}},\tilde{\mathbf{q}}} L(\tilde{\mathbf{x}},\tilde{\mathbf{p}},\tilde{\mathbf{q}},\Lambda,\Phi) \\ &\quad \text{s.t. constraints (4–8)} \end{aligned} \tag{19}$$

To solve the dual problem we should solve:

$$\begin{aligned} \mathbf{D} &: \min D(\Lambda,\Phi) \\ &\quad \text{s.t. } \Lambda > 0, \Phi > 0 \end{aligned} \tag{20}$$

Since the dual problem is also convex, we can use gradient projection to find the required update equations for shadow prices. Therefore, we have:

$$\frac{\partial D(\Lambda,\Phi)}{\partial \lambda_l} = q_l s_l \bar{c}_l - \sum_{s:s\in S(l)} x_s \quad \forall l \in L \tag{21}$$

$$\frac{\partial D(\Lambda,\Phi)}{\partial \phi_\omega} = c_\omega - \sum_{l:l\in L(\omega)} q_l \quad \forall \omega \in \Omega \tag{22}$$

The interpretation of shadow prices, i.e., λ_l for the first constraint (Eq. (4)) and ϕ_ω for the second constraint (Eq. (5)), is based on the rule of supply and demand. If the demand by source nodes on a link is higher than the link throughput, the link shadow price λ_l is increased indicating sessions which use this link, to reduce their rate. By the same way, if the sum of attempt rate in a maximal clique is grater than the clique capacity, the shadow price ϕ_ω is increased indicating the links in the clique to reduce their attempt rate. To satisfy Eqs. (16) and (17) and according to Eqs. (21) and (22), the shadow prices for the first constraint are defined as:

$$\lambda_l = \left[\frac{\sum_{s:s\in S(l)} x_s - q_l s_l \bar{c}_l}{q_l s_l \bar{c}_l}\right]^+ \tag{23}$$

where $[x]^+ = \max\{x,0\}$. λ_l can be interpreted as the backlog at link l assuming first-in-first-out service discipline at the link [4]. In the same way, we defined the shadow price for the second constraint as:

$$\phi_\omega = \left[\frac{\sum_{l:l\in L(\omega)} q_l - c_\omega}{c_\omega}\right]^+ \tag{24}$$

Based on this analysis we find the required updates for the resource allocation problem variables and the shadow prices. Our algorithm is presented in the next section.

Before closing this section, we note that at the equilibrium, the first inequality constraint is active for each link that one or more sessions cross it, i.e., $\sum_{s:s\in S(l)} x_s = q_l s_l \bar{c}_l$. The reason is that all utility functions are strictly increasing functions and any available throughput, no matter how much low, could provide marginal improvement in the objective function.

5. The proposed algorithm

The following algorithm should be executed in sources and links simultaneously until the convergence. For now it is assumed that each link can do the required clique computations. In the next section we discuss about feasibility of distributed implementation of the algorithm.

Algorithm
In each time slot $t = 1,2,\ldots$

1 Computations at links
The transmitter of each link:

(1a) Estimates an average of the link congestion measure $\lambda_l(t+1)$ based on current load and capacity.

$$\lambda_l(t+1) = \left[\lambda_l(t) + \gamma\left(\frac{\sum_{s:s\in S(l)} x_s(t) - q_l(t)s_l\bar{c}_l}{q_l(t)s_l\bar{c}_l}\right)\right]^+ \tag{25}$$

where $0 < \gamma < 1$ is a constant.

(1b) Broadcasts its message vector $\mathbf{M}_l(t)$. The message vector contains the link current congestion measure $\lambda_l(t)$, current attempt rate q_l, and its current computed message information, $m_l(t)$, to other nodes, i.e., $\mathbf{M}_l(t) = (\lambda_l(t), q_l(t), m_l(t))$. Where

$$m_l(t+1) = \frac{\lambda_l(t)p_l(t)}{\bar{c}_l \sum_{j:j\notin L^{To}_{Conf.}(l)} p_j q_j G_{lj}}$$

(1c) Estimates the contention measure, ϕ_ω, of all cliques it belongs to, based on the attempt rate of the links in the clique and assuming fix clique capacity, i.e., $c_\omega = 2/3$.

$$\phi_\omega(t+1) = \left[\phi_\omega(t) + \xi\left(\frac{\sum_{l:l\in L(\omega)} q_l(t) - c_\omega}{c_\omega}\right)\right]^+ \tag{26}$$

where $0 < \xi < 1$ is a constant.

(1d) Updates its power and link attempt rate.

$$q_l(t+1) = \left[q_l(t) + \xi\left(\frac{\lambda_l(t)}{q_l(t)} - \frac{\sum_{j:j\in L^{From}_{Conf.}(l)} \lambda_j(t)}{1-q_l(t)} - p_l(t)\sum_{k:k\notin L^{From}_{Conf.}(l)} G_{kl}m_k(t) - \sum_{\omega:\omega\in\Omega(l)} \phi_\omega(t)\right)\right]_0^1 \tag{27}$$

$$p_l(t+1) = \left[p_l(t) + \kappa\left(\frac{\lambda_l(t)}{\bar{c}_l p_l(t)} - q_l(t)\sum_{k:k\notin L^{From}_{Conf.}(l)} G_{kl}m_k(t)\right)\right]_{p_{\min}}^{p_{\max}} \tag{28}$$

where $0 < \kappa < 1$ is a constant and $[x]_b^a = \max\{b, \min\{a,x\}\}$.

2 Computations at sources
Each session:

(2a) Estimates its congestion on all links in its path based on link shadow prices feedback to it.

(2b) Updates its rate based on estimate (2-a) and its utility function. Assuming utility function in (10) we have: $\tilde{U}'(\tilde{x}_s) = e^{\tilde{x}_s(1-a)} = x_s^{1-a}$

$$x_s(t+1) = \left[x_s(t) + \gamma\left(x_s^{1-a} - \sum_{l:l\in L(s)} \lambda_l \frac{x_s}{\sum_{s:s\in S(l)} x_s}\right)\right]_{x_{s\min}}^{x_{s\max}} \tag{29}$$

where $0 < \gamma < 1$ is a constant.

The constants γ, ξ, κ should be selected small enough to ensure the convergence of the algorithm [19]. As the simulation results show, the power update constant κ should be selected about an order of magnitude larger than the two other constants.

6. Feasibility of distributed implementation

The algorithm presented in the previous section can be implemented in distributed fashion by message passing in the network. Suppose that the transmission range and interference range are equal and the same for all nodes.

Distributed implementation of the algorithm, requires coordinations between each session and the links it is traverses through them, and a local coordination between links in each congestion region.

At each source, s, we need to find $\sum_{l\in L(s)} \lambda_l w_l^s$, where $w_l^s = \frac{x_s}{\sum_{s\in S(l)} x_s}$ is the contribution of session s on the congestion of link l. To feedback this values we need an explicit or implicit congestion notification at the transport layer, i.e., in TCP protocol. In an explicit scenario, each link may add the session contribution to its congestion measure to a specified variable provided in the TCP header. This variable is cleared at the session's source, and piggy backed to the source, by the session's destination, to regulate the session rate. In an implicit case, the session's source can infer the required feedback if the Adaptive Queue Management (AQM) is such that the loss or delay of the sessions' packets in the links queue is proportional to the weight of the session.

At the links, the first requirement of the algorithm is that each link must be able to characterize neighboring conflicting and non-conflicting links. If $G_{lj}\ \forall l,j$ parameters can be estimated at the transmitter of link l through the training sequences, each node is able to discriminate conflicting and non-conflicting neighbors. Therefore, it is possible to decide which filed of received message vector should be used depending on the identity of the message transmitter.

The second requirement is that each link must be able to do its required clique computations. It is shown in [11] that for a given link l, the knowledge of neighboring links up to three hops away from the transmitter and receiver of l is sufficient to construct all maximal cliques which contain l. Therefore, when all message vectors are available, each link can construct the around cliques and compute $\sum_{\omega:\omega\in\Omega(l)}\phi_{\omega}$.

It is clear that to update powers and attempt rates, we need all other links information. This can lead to excessive overhead for message passing on the network. As it is explained in [8] and according to Eqs. (27) and (28), for a given transmitter node, the farther the distance is from a neighboring non-conflicting node k, i.e., less G_{kl}, the less is the effect of its message. Therefore, the messages of far away links have negligible effect on final equilibrium powers and attempt rates. We can do some tradeoff between the complexity of message passing and the optimality of the result. Specifically, for each link we may restrict the transmission of messages, to the neighboring nodes up to H hops away from the transmitter and receiver of the link.

7. Simulation results

The simulation results for algorithm evaluation are done at the link level. Results of simulation for two network topologies are presented. The first topology is a simple chain network topology that contains all aspects of the algorithm and is used as an illustrative example. The second topology is a bit complex.

7.1. Network topology 1, illustrative example

The network topology 1 and its link flow contention graph is shown in Fig. 2. In this figure, the distance between adjacent nodes are the same and equal $d = 2d_0$; where d_0 is the reference distance in path loss model. The spreading gain is 20. The transmission range and interference range are also equal to d. There are four end-to-end sessions denoted by $S_1,\ldots,S_4$ on the figure. The utility function of all sessions and their weights are alike in the objective function. The link flow contention graph shows that there are two maximal cliques in this topology, i.e., $\omega_1 = \{1,2,3\}$ and $\omega_2 = \{2,3,4\}$. Other simulation parameters are summarized in Table 1.

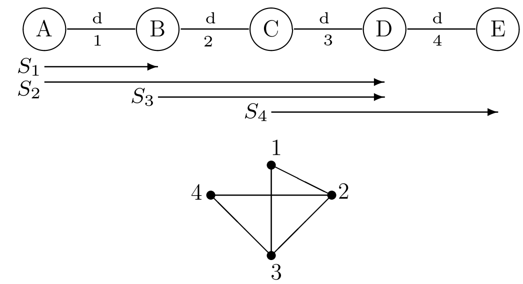

Fig. 2. Network topology 1, end to end sessions, and link flow contention graph.

Figs. 3a–d show the variations of links power, sessions rate, links attempt rate and links success probability, respectively, until the convergence of the algorithm to the optimal point. The final equilibrium values of links are summarized in Table 2.

According to Table 2, links 2,3 use the maximum possible power at equilibrium. This is reasonable since according to contention graph, all other links conflicted if these links have transmission. Therefore, the best choice is that we use maximum allowable power to get the maximum capacity if access to the channel is successful. Links 1,4 adjust their power based on other factors. Link 1 chooses a higher power (3.55 vs. 0.21) and attempt rate (0.28 vs. 0.20) compared to link 4. The reason is that the interference of link 4 transmission on the link 1 is more destructive than that from link 1 on link 4, i.e., $G_{14} > G_{41}$.

The success probability of links 1 and 4 are the same as it expected because they have the same condition in the contention graph. We also note that at equilibrium all links use their full throughput, as expected and explained in Section (4.2). The clique prices at equilibrium are $\phi_{\omega_1} = 1.39$ and $\phi_{\omega_2} = 0$, indicate that only the constraint on first clique is active at equilibrium.

The sessions' rate at equilibrium using the proposed algorithm are given in Table 3. We note that link l congestion measure, i.e., λ_l, can be interpreted as the average delay that will be encountered when a flow traverses this link. Therefore, adding the total delay for each session on its path, we can find the session end to end delay. These delays are also shown in Table 3.

Table 1
Parameter values in simulations

Parameter	Value
α, path loss exponent	2
p_0, initial links power value	2.5 mW
$p_{\max}$, maximum allowed power	5 mW
γ, constant in (25)	0.02
ξ, constant in (26,27)	0.02
κ, constant in (28)	0.2
c_ω, clique capacity	0.67

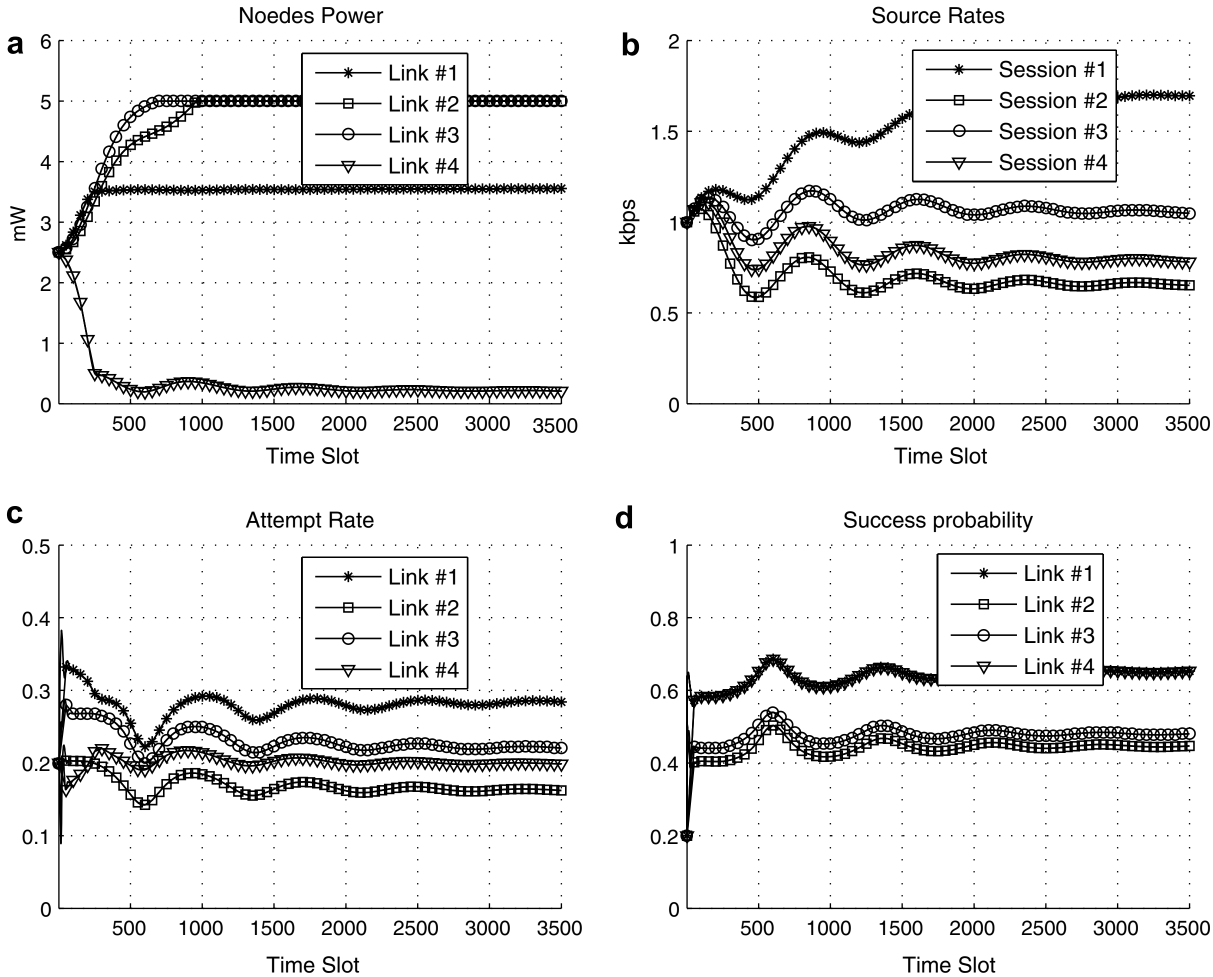

Fig. 3. Variation of problem variables until convergence for network topology 1. (a) link power, (b) session rate, (c) link attempt rate, (d) link success probability.

Table 2
The value of link parameters at equilibrium for network topology 1

Link number	Power p_l [mW]	Attempt rate q_l	Success prob. s_l	Congestion measure λ_l	Throughput $q_l s_l \bar{c}_l$ [kbps]
1	3.55	0.28	0.65	1.27	2.36
2	5.00	0.16	0.45	0.80	1.71
3	5.00	0.22	0.48	1.06	2.50
4	0.21	0.20	0.65	0.61	0.78

Table 3
The value of sessions rate and delay at equilibrium for network topology 1 using the proposed algorithm and without adjusting the attempt rates

Session number	Using the proposed algorithm		Without adjusting attempt rate	
	Session rate [kbps]	Session delay	Session rate [kbps]	Session delay
1	1.69	1.28	0.35	1.53
2	0.65	3.13	0.21	3.26
3	1.05	1.85	0.52	1.73
4	0.78	1.66	0.21	2.30

In the next experiment and to investigate the effect of adjusting the attempt rate on the performance improvement, the links' attempt rate are kept fixed and only powers and sessions' rate are adjusted. The sessions' rate and delay for this experiment are also given in Table 3. According to this table the total network throughput increases by a factor more than 2.2, while the average session delay decreases about 11.3%. Also, using the proposed algorithm the network utility increases about 21%, compared to the case where attempt rates are fixed.

7.2. Network topology 2

Fig. 4 shows network topology 2 and its flow contention graph.

The notations in this figure are alike those used in Fig. 2 for topology 1. According to the contention graph, this topology contains three maximal cliques, i.e., $\omega_1 = \{1,2,3,5\}$, $\omega_2 = \{2,3,4\}$, $\omega_3 = \{3,4,6\}$. It is assumed that the weight of session 1 utility function is two and the weight of other three sessions is one in the objective

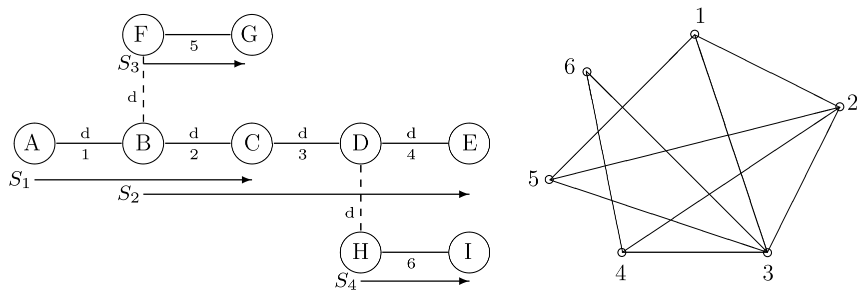

Fig. 4. Network topology 2, end to end sessions, and link flow contention graph.

Table 4
The value of link parameters at equilibrium for network topology 2

Link number	Power p_l [mW]	Attempt rate q_l	Success prob. s_l	Congestion measure λ_l	Throughput $q_l s_l \bar{c}_l$ [kbps]
1	3.39	0.18	0.58	0.85	1.18
2	3.75	0.24	0.56	1.24	1.44
3	5.00	0.05	0.24	0.31	0.26
4	0.28	0.11	0.39	0.41	0.26
5	2.58	0.19	0.59	0.93	1.21
6	0.18	0.46	0.84	0.92	1.73

Table 5
The value of sessions rate and delay at equilibrium for network topology 2 using the proposed algorithm and without adjusting the attempt rates

Session number	Using the proposed algorithm		Without adjusting attempt rate	
	Session rate [kbps]	Session delay	Session rate [kbps]	Session delay
1	1.17	2.09	0.34	2.74
2	0.26	1.95	0.18	2.72
3	1.21	0.93	0.44	1.42
4	1.73	0.92	0.15	0.94

function. Other simulation parameters are the same as those used in the first experiment.

Table 4 shows link parameters at equilibrium. From table 4 we see that link 3 uses the maximum allowable power at equilibrium which is reasonable since it belongs to all maximal cliques. Other links adjust their powers to maximize total network utility. Again, we note that each link adjust its power and attempt rate according to its location in the network. Links that are located in regions with less contention, like link 6, use higher attempt rate and lower power. However, links that are located in regions with high contention, like link 3, use higher power and lower attempt rate. Also, we note from these table that at equilibrium all constraints on links throughput are active as expected, i.e., for all links $\lambda_l > 0$.

The clique prices at equilibrium are $\phi_{\omega_1} = 1.2$, $\phi_{\omega_2} = 0.0$, $\phi_{\omega_3} = 0.0$, indicate that the constraint on first clique is active at equilibrium.

The session's rate and end to end delays are summarized in Table 5. This table also shows these parameters when the links attempt rate are not adjusted. The total network throughput is increased by a factor of 2.9 while the average session's delay decreases about 32.7%. The total network utility is also increased 21.5%.

These results show that considerable gain can be achieved in increasing the network throughput and decreasing the delay by using the proposed algorithm in MHWN.

8. Conclusion

Efficient use of MultiHop Wireless Networks needs coordination between layers. We consider the jointly control of session rate at the end points and link attempt rate and power at the links in this paper. Based on a analytical solution, the required coordinations are extracted and a new algorithm for updating these variables is proposed. The algorithm suggests that links which are located in regions with high contention, should use higher power and lower attempt rate. However, links which are located in regions with low contention, should use lower power and higher attempt rate. Simulation results of the algorithm verify the convergence of the algorithm to the joint optimal solution. It is shown that Considerable gain can be achieved in terms of increasing the network throughput and decreasing the session's end to end delay. We also discuss about distributed implementation of the algorithm and show its feasibility in the network.

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References

[1] A.J. Goldsmith, S.B. Wicker, Design challenges for energy-constrained ad hoc wireless networks, IEEE Wireless Commun. Mag. 9 (4) (2002) 8–27.
[2] S.J. Golestani, S. Bhattacharyya, A class of end-to-end congestion control algorithms for the Internet, in: IEEE Proceedings of the Sixth International Conference on Network Protocols, ICNP, 1998.
[3] F.P. Kelly, A.K. Maulloo, D.K.H. Tan, Rate control in communication networks: shadow prices, proportional fairness and stability, J. Oper. Res. Soc. 49 (1998) 237–252.
[4] S.H. Low, L. Peterson, L. Wang, Understanding Vegas: a duality model, J. ACM 49 (2) (2002) 207–235.

[5] S.H. Low, A duality model of TCP and queue management algorithms, IEEE/ACM Trans. Networking 11 (4) (2003) 525–536.
[6] T. Nandagopal, T.-E. Kim, X. Gao, V. Bharghavan, Achieving MAC layer fairness in wireless packet networks, in: Proc. ACM Mobicom Conf., pp. 87–98, 2000.
[7] K. Jain, J. Padhye, V. Padmanabhan, L. Qiu, The impact of interference on multi-hop wireless network performance, in: Proceedings of ACM MOBICOM, 2003.
[8] M. Chiang, Balancing transport and physical layers in wireless multihop networks: jointly optimal congestion control and power control, IEEE J. Select. Areas Commun. Special Issue on Wireless Ad-Hoc Networks 23 (1) (2005) 104–116.
[9] J.W. Lee, M. Chiang, R.A. Calderbank, Jointly optimal congestion and contention control in wireless ad hoc networks, IEEE Commun. Lett. 10 (3) (2006) 216–218.
[10] X. Wang, K. Kar, Cross-layer rate control for end-to-end proportional fairness in wireless networks with random access, in: Proceedings of ACM MobiHoc'05, May 2005.
[11] Y. Xue, B. Li, K. Nahrstedt, Optimal resource allocation in wireless ad hoc networks: A price-based approach, IEEE Trans. Mobile Comput. 5 (4) (2006) 347–364.
[12] A. Goldsmith, Wireless Communications, Cambridge Univ. Press, 2005.
[13] P. Gupta, P.R. Kumar, The capacity of wireless networks, IEEE Trans. Inform. Theory 46 (2) (2000) 388–404.
[14] L. Chen, S.H. Low, J.C. Doyle, Joint congestion control and media access control design for wireless ad hoc networks, in: Proceedings of IEEE INFOCOM, Miami, FL, March 2005.
[15] Z. Fang, B. Bensaou, Fair bandwidth sharing algorithms based on game theory frameworks for wireless ad-hoc networks, in: Proceedings of IEEE INFOCOM 2004.
[16] L. Tassiulas, S. Sarkar, Maximum fair scheduling in wireless networks, in: Proceedings of IEEE INFOCOM 2002.
[17] S. Boyd, L. Vandenberghe, Convex Optimization, Cambridge Univ. Press, 2004.
[18] J. Mo, J. Walrand, Fair end-to-end window-based congestion control, IEEE/ACM Trans. Network 8 (5) (2000) 556–567.
[19] D.G. Luenberger, Linear and Nonlinear Programming, Addison-Wesley, Reading, MA, 1989.

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