QoS based Resources Allocation in Wireless Ad-hoc Networks

1 Introduction

To provide QoS based services, one needs to allocate his resources in an efficient and fair manner. This in turn needs to re-define allocation schemes of several QoS attributes like bandwidth, delay and packet loss etc. The allocation schemes are reasonably different for wired and wireless networks, because of the nature of the wireless networks. Wireless networks [1] are inherently limited by battery power and bandwidth constraints. They are characterized by mobility, random changes in connectivity, fluctuations in channel and interference due to neighboring nodes etc.

So, to have QoS based resource allocation in wireless networks, the allocation schemes should be adaptive to the channel variations. This is more complicated in ad-hoc networks. This is because of the need of co-operation among the users with limited resources on bandwidth, battery power etc. In this report, we have highlighted the various issues and constraints for providing QoS in wireless ad-hoc networks. We have considered a cost and incentive based approach [2] (pricing based approach) in this report. Our approach consists of:

1. Pricing based resource allocation by maximizing individual and social optimality condition.

2. Solving social optimality condition with constraints on signal to interference to noise ratio ($SINR$), delay and data rate.

3. Use of battery cost as a function of transmission power and duration of transmission of wireless nodes.

1.1 Related Work and Contribution

Few papers discuss QoS based resource allocation in wireless ad-hoc networks. Out of them, [3] discussed various issues of QoS in wireless ad-hoc networks. It focused on QoS routing and issues related to ad-hoc networks. [4] used convex optimization for QoS and resource allocation for ad-hoc networks. Though it considered delay as a constraint, it did not consider queuing delay at nodes. Queuing delay is important in the design of multi-hop ad-hoc networks. Dynamic bandwidth management based ad-hoc networks (single-hop) is discussed in network [5]. Geometric programming based power control technique for resource allocation in ad-hoc networks is discussed in [6]. Another paper [7] discussed price-based bandwidth allocation scheme for ad-hoc networks. It defined demand and utility based objective function to provide resource allocation. It is based upon the Kelly's work on "Charging and rate control for elastic traffic" [8]. Though Kelly's original work was on wired network, we modified that for wireless network with addition of various parameters like channel condition, interference, battery cost etc. Another price based resource allocation was studied by [9].

In this project, we presented a price and incentive based resource allocation scheme for wireless ad-hoc networks, with data rate, delay and $SINR$ constraints. We used Lagrangian Multipliers to solve a constraint based objective function. Our approach in this paper is based on our previous work on congestion control in wireless networks [10].

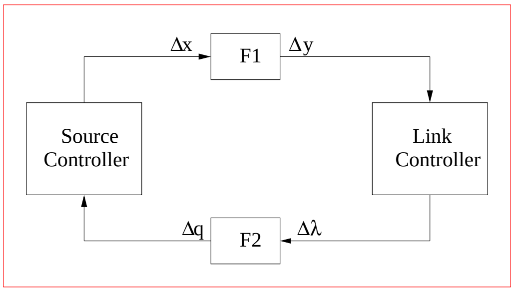

Figure 1: Feedback System Model

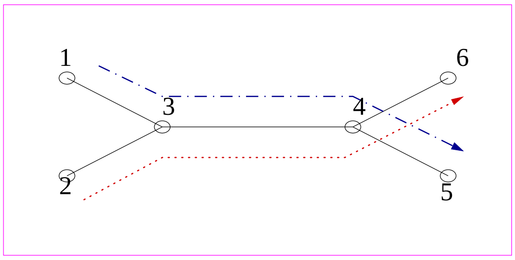

Figure 2: System Model/Topology

2 Pricing based Problem Formulation

2.1 Pricing in Wireless Networks

Price is the amount that one node needs to pay, either to an operator or to any other node for transmitting its traffic. In real sense, individual node can either charge other nodes for forwarding their traffic or use that as a debit for future (forwarding its own traffic). In this paper, we consider cost is the price that one node needs to pay to other for using their nodes for relaying. Similarly, we consider incentive is the price, one gets from other users for forwarding their traffic.

2.2 System Model

We formulated our problem statement initially for a wired network, similar to [11] and [12] and then extended it to a static wireless network. We considered a feedback system model for our purpose as shown in Fig. 1, similar to [10]. The network in our discussion consists of N communicating nodes index by $n \in N$, connected by L communicating links indexed by $l \in L$ as shown in Fig. 2. The nodes are associated with maximum capacity of transmission c_n based on service level agreement (SLA) or based on some hardware constraints, or based on channel conditions. Now, we write the routing matrix R as:

$$R_{ln} = \begin{cases} 1 & \text{if, source } n \text{ uses the link } l \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Each source n has an associated individual transmission rate $x_n(t)$ in packets/sec. Node n forwards/relays other's traffic as well as transmit its own traffic. If $F(n)$ is the list of users for which node n relays traffic, and $T(n)$ is the list of users for which node n relays and transmit traffic, then, $T(n) = F(n) \cup \{n\}$. The aggregate flow $y_n(t)$ in packets/sec, at each node n is defined as:

$$y_n(t) = \sum_n R_{ln} x_n(t - \tau_{ln}^f) = x_n(t - \tau_{ln}^f) + \sum_k x_k(t - \tau_{ln}^f); \qquad k \in F(n), \tag{2}$$

where τ_{ln}^f is the forward delay between the source and sink as in [10]. The time scale of change of routing is higher than the time scale of our analysis. We assume stationary routing. Aggregate flow y_n at a node n in Eqn. (2) is the sum of one's own contribution x_n and others contribution (relayed) E_n. We call the relayed traffic as external demand E_n at node n. So, Eqn. (2) is re-written as: $y_n(t) = x_n(t) + E_n(t)$. If each link l is associated with price $\lambda_l(t)$, as a measure of cost on using that link, then the aggregate price that a node needs to pay to send to its destination is expressed as:

$$q_n(t) = \sum_l R_{ln} \lambda_l(t - \tau_{ln}^b), \tag{3}$$

where τ_{ln}^{b} is the backward delay in the feedback path. We write round trip time (RTT) as $\tau_n = \tau_{ln}^{f} + \tau_{ln}^{b}$. In vector form we write Eqns. (2) and (3) as: $y = Rx; \quad q = R^T\lambda$.

2.3 Use of Control System Equations

We use control system equations as in [12] to determine the equilibrium point (x^*, y^*, q^*) for our system with the following assumptions: (i) resource allocation is characterized by a demand curve $x_n^* = f_n(q_n^*)$, (ii) aggregate flow is less than or equal to the capacity of the link, i.e., $y_n* \leq c_n$. In our case queuing delay exists at the nodes and packets may get dropped at the forwarding nodes. This is the fundamental difference between the systems used in [10] and in this paper. The demand curve specified above is a decreasing function of price, which is equivalent to use of an utility function $U_n(x_n)$ defined by Shenker et al. [13]. This utility function is concave and continuously differentiable of x_n, in the range of $x_n \geq 0$. At equilibrium, a source chooses its maximum profit by choosing local parameters as:

$$\max_{x_n} \Big[U_n(x_n) - q_n x_n \Big], \tag{4}$$

where, $q = R^T\lambda$. Since, by relaying others traffic one will earn, the individual optimality equation in (4) is modified as:

$$\max_{x_n} \Big[U_n(x_n) - q_n(x_n + E_n) + \lambda_n E_n \Big]; \quad \text{s. t.} \qquad x_n + E_n \leq c_n \tag{5}$$

2.3.1 Effect of Battery Power in Optimization

The individual optimality equation in Eqn (5) is independent of power transmission, which is not true in wireless ad-hoc networks. This is because, the battery power is one of the limiting resources that needs to be properly allocated. Intuitively, the nodes will try to minimize transmission power and will charge for the amount of traffic it relayed for others. The individual optimality equation in (5) is modified as:

$$\max_{x_n} \Big[U_n(x_n) - q_n(x_n + E_n) + \lambda_n E_n - p_n(x_n + E_n) \Big]; \quad \text{s. t.} \qquad x_n + E_n \leq c_n, \tag{6}$$

where, p_n is the cost of transmission per unit traffic at node n. We assumed uniform charging (pricing) for own traffic and relaying traffic. In practice, this may be different. We considered p_n as a function of battery availability and power of transmission P_n of the node. For simplicity, we considered $p_n = e^{\kappa*\gamma*P_n}$, where κ is a constant decided by the forwarding user and γ is the amount of battery available at that particular instant (is a function of time).

2.3.2 Social Optimization

Since, all users will try to maximize their net utility as defined by Eqn. (6), the social optimality as in [14] will be possible, only when all the nodes/users get their maximum profit. So, we write the sum of all individual optimality as as:

$$\begin{aligned} \max \sum \Big[U_n(x_n) - q_n(x_n + E_n) + \lambda_n E_n - p_n(x_n + E_n) \Big]; \quad \text{s. t.} \quad X + E \leq C; \\ \text{where,} \quad X = \{x_n\}, \quad E = \{E_n\} \quad \text{and} \quad C = \{c_n\} \end{aligned} \tag{7}$$

The objective function in Eqn. (7) is re-written as:

$$\max \sum \Big[U_n(x_n) + \lambda_n E_n - (q_n + p_n)(x_n + E_n) \Big] \tag{8}$$

Now, we write the social optimality equation for the above individual optimality (Eqn. (6)) as follows:

$$\max_{X>0} \sum_n U_n(x_n) + U_n(E_n); \quad \text{s. t.,} \quad X + E \leq C, \tag{9}$$

where $U_n(E_n)$ is the utlity function of relaying traffic at node n. This is also a monotonic increasing function similar to $U_n(x_n)$. Using Karush-Kuhn-Tucker (KKT) condition [15] on the social optimal equation as in [11], constrained global maxima point[1‡] $X^* = \{x_i^*\}$ is expressed as:

$$\nabla\Big(\sum_n U(x_n) + U_n(E_n)\Big) - \sum_n \mu_n \nabla(X + E) = 0; \quad \forall \mu_n > 0, \qquad n \in N, \tag{10}$$

where, μ_n are the Lagrangian Multipliers and are used as link prices (shadow prices) as discussed in [8] and [16]. μ_n in our formulation is defined as $\mu_n = p_n + \lambda_n$. Hence, Eqn.10 is reduced to, $[U_n^{'}(x_n) + U_n^{'}(E_n)] = \mu_n^*$, at the global maximum point.

2.3.3 Modification for Wireless Network Case

As discussed in [17], power transmitted by a source is considered as a function of price and by appropriate power control of all nodes maximum aggregate throughput is attained. However, the power increase in one node has a direct impact on the data rates of other nodes due to interference. Hence, we modify the maximization Eqn (9) as follows:

$$\begin{aligned} \max_{X\geq 0} \sum_n U_n(x_n) + U_n(E_n); \quad \text{s.t.,} \quad X + E \leq C(P); \quad P = \{P_n\}, \\ P_n \leq P_{n_{Max}}, \quad \forall n; \quad P, X \geq 0, \end{aligned} \tag{11}$$

where P_n is the transmission power of n^{th} node.

2.4 Fairness Based Utility Functions

2.4.1 Proportionally Fairness

A set $X = \{x_n\}, n \in N$ is said to be proportionally [14] fair, if it feasible, and if for any other feasible set $X^* = \{x^*{}_n\}$, then the aggregate of proportional changes is zero or negative: $\sum_n \frac{x^*{}_n - x_n}{x_n} \leq 0$. As discussed in [8], the utility function for a proportional fair system is $U_n(x_n) = \log x_n$, which is strictly concave for $x_n \geq 0$.

2.4.2 Max-Min and Min-Max Fairness

Max-Min fairness [18] is the most common fairness criterion used in practice. For $X = \{x_n\}, n \in N$ max-min fairness exists, if any feasible x_n can't be increased without decreasing for some other $x_n \in X$. The utility function for this kind of fairness is expressed as $U_n(x_n) = \max\{\min_{x_n}(x_n)\}$.

Min-Max fairness [18] is also another common fairness criterion used in practice, which is almost opposite of the max-min fairness. For $X = \{x_n\}, n \in N$ min-max fairness exists, if any feasible x_n can't be decreased without increasing for some other $x_n \in X$. The utility function for this kind of fairness is expressed as $U_n(x_n) = \min\{\max_{x_n}(x_n)\}$

[1‡] Since the utility functions $U(x_n)$ and $U_n(E_n)$ are concave and increasing, KKT conditions are necessary and sufficient for a global maximum

3 Inclusion of QoS Parameters

3.1 Inclusion of SINR to Maintain Minimum Data Rate

We considered a CDMA-based wireless network. Using Shannon's capacity theorem, we determine the maximum capacity attainable in link $n - j$ as:

$$c_n = \frac{1}{T} \log(1 + M.SINR_n) \qquad \text{packets/sec}, \tag{12}$$

where T is the symbol period and M is a modulation constant. To maintain a minimum capacity c_n, node n needs to maintain its $SINR$. This is equivalent to maintaining $SINR_n \geq SINR_{thresh}$; where $SINR_{thresh}$ is the minimum $SINR$ required. The requirement of $SINR$ for a successful transmission boils down to power control in wireless network.

3.1.1 Power Control to Maintain SINR

Using KKT and Lagrangian Multiplier, we solve Eqn. (11) as:

$$\phi_{system}(X, E, P, \mu) = \sum_n U_n(x_n) + U_n(E_n) - \sum_n \mu_n \Big(\sum_m x_m + E_m - c_m(P)\Big) \tag{13}$$

Maximization of $\phi_{system}(X, E, P, \mu)$ in Eqn. 13 is decomposed as:

$$\begin{aligned} \max \quad I(X, E, \mu) = \sum_n U_n(x_n) + U_n(E_n) - \sum_n \mu_n \sum_m (x_m + E_m), \\ \max \quad I(P, \mu) = \sum_n \mu_n c_n(P), \\ \text{s.t.,} \quad X \geq 0; \quad 0 \leq P_n \leq P_{n_{Max}} \end{aligned} \tag{14}$$

The $I(X, E, \mu)$ in Eqn. (14) is solved by choosing appropriate x_n and E_n for a particular μ_n. $I(P, \mu)$ is solved by choosing appropriate transmission power of wireless nodes. We used Steepest Descent Method [15] to find out the optimum P_n [10] and is expressed as:

$$P_n(t+1) = P_n(t) + \Delta \frac{\mu_n(t)}{P_n(t)} - \Delta \sum_{j \neq n} m_j(t) G_{nj}, \tag{15}$$

where Δ is a constant, called the step size in the direction of the gradient and $m_j(t)$ is the interference received from node j (similar to message passing in [17]) to the node n and is defined as: $m_j(t) = \frac{\lambda_j(t) SINR_j(t)}{P_j(t) G_{jj}}$.

3.1.2 Shadow Prices

The shadow prices μ_n is a combination of nodal prices due to buffer over flow and due to battery consumption. The nodal prices due to buffer overflow is modeled by $M/M/1/B$ queue and is expressed [10] as: $\lambda_n(t) = \frac{\max\big(0, (y_n(t) - c_n(t))\big)}{y_n(t)}$ for $y_n > 0$ and is zero otherwise. We have already discussed price due to battery consumption p_n in Section 2.3.1.

3.2 Maintaining Minimum Delay

In ad-hoc networks the delay is mainly due to queuing delay at nodes, as the propagation delay and transmission delay are negligible. So, we consider queuing delay only in our discussion using an $M/M/1/B$ queuing model as in [19].

$$E(T) = \frac{E(N)}{\Lambda(1 - P_B)}, \tag{16}$$

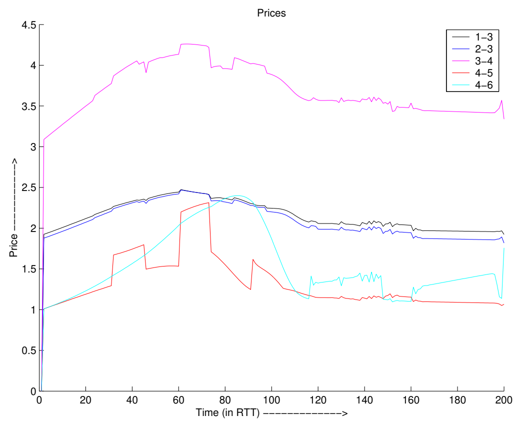

Figure 3: Price Variation - with Power Control

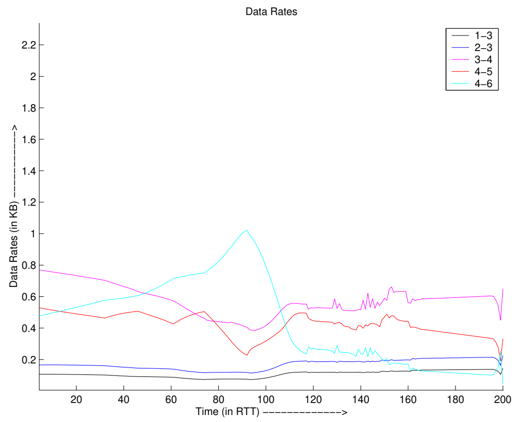

Figure 4: Data Rate - with Power Control

where $E(T)$ is the average delay, Λ is the arrival rate and P_B is the steady state loss probability of the system. P_B and $E(N)$ are defined as

$$P_B = \frac{(1-\rho)\rho^B}{1-\rho^{B+1}}; \quad E(N) = \frac{\rho}{1-\rho} - \frac{(B+1)\rho^{B+1}}{1-\rho^{B+1}} \tag{17}$$

where $\rho = \frac{\Lambda}{\nu}$ and ν is the departure rate. So, to calculate the total end-to-end delay, one needs to take a sum of all nodal delays, which depends upon the arrival as well as the departure rate (E_n and c_n in our case) and the buffer level. So, a node can decide, whether to accept a particular route or not in advance. Which is equivalent to optimize c_n.

4 Numerical Results

We considered a simple topology as shown in Fig. 2 for our simulations. The transmitter receiver pairs in our case are 1-5 and 2-6. Both forward and reverse channel characteristics are same in our case. The channel gains are randomly chosen with a log-normal shadowing of $\sigma = 8dB$. The path loss factor γ is assumed to be 4. The utility function we used is for proportional fairness criterion. We simulated this using Matlab software [20].

4.1 Results

Figure 3 and 4 shows the variation of data rates and price respectively with respect to time. Parameter p_n is dominant at low battery stage and hence is increased as duration of activeness of the node increases. But, as time goes on, both price and data rates stabilized to a point, where social optimality is achieved. If node increases it's data rate further, then that will result in paying more as both p_n and q_n will increase.

5 Discussion

We have considered minimum $SINR$, minimum data rate in our simulation. The resource allocation in our model satisfies the social optimality condition with both $SINR$ and minimum data rate constraints. We have considered a simple topology for our simulation. A complex topology can be used to study other issues. Also, one can see the delay requirements during resource allocation.

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