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Price-based resource allocation for wireless ad hoc networks with multi-rate capability and energy constraints

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ABSTRACT

Wireless ad hoc networks have attracted a lot of attentions recently. Resource allocation in such networks needs to address both fairness and overall network performance. Pricing is a prospective direction to regulate behaviors of individual nodes while providing incentives for cooperation. In this work, we develop some pricing strategies for resource allocation by taking account of factors like multiple transmission rates and energy consumption of nodes, which have not been well studied in former works. Multi-rate transmission capability is commonly seen in most wireless products nowadays, while energy is one of the most important resources in portable devices. We propose a clique-based model which allows us to achieve optimal resource utilization and fairness among network flows when multi-rate transmission is considered. We also show how to extend the model to dynamically adjust prices based on energy consumptions of flows. In particular, our model takes into account energy consumptions in the transmitters' side, the receivers' side, and those that are non-transmitters and non-receivers but are interfered by these activities. So our model can more accurately reflect the real energy constraint in a wireless network. Simulation results are presented to show the convergence and other properties of these strategies.

1. Introduction

In recent years, we have seen rising demand for mobile computing and communication services. The tremendous advancement in wireless network technologies has made the dream of "communication anytime and anywhere" realizable. Users can experience full mobility, while at the same time maintaining the ability to connect with others as well as the Internet. Wireless networks provide people a more durable and flexible way of communications. Successful wireless communication systems include GSM, PHS, 3G WCDMA, and WLAN (WiFi) systems.

One wireless network configuration that has become a popular subject of research is the *mobile ad hoc network (MANET)* [2,5–7,17,21–23]. A MANET is comprised of a collection of wireless nodes without a pre-existing infrastructure. Any device with a microprocessor and a wireless interface, whether highly mobile or static, may serve as a potential node in a MANET. Each node in the network acts as a router to relay data packets for others. Each flow may travel over multiple hops of wireless links from its origin to its destination. In a MANET, multi-hop routing can achieve high degree of network connectivity, but this requires the willingness of each node to forward packets for others. However, constrained by limited power and communication resources, a selfish node may be reluctant to relay packets of others, but expect others to relay its packets. Compared to wired networks, multi-hop MANETs have several special characteristics as opposed to wireline networks. For example, nodes may suffer from a higher degree of interference and energy resources are more constrained. Also, since competition is related to the geographic distribution of nodes, some flows may unfairly consume more resources (such as bandwidths and energies) than others. This raises the problem of designing proper resource allocation mechanisms to encourage cooperation among nodes in such a way that competing multi-hop flows can share scarce channel as well as battery resources in a fair way, while the whole utility of all flows is maximized.

The aim of this paper is to explore the possibility of using price as incentives in multi-hop MANETs to encourage nodes to acquire resources in a reasonable way to maximize the aggregated utility (i.e., social welfare) of flows with fairness in mind. The use of pricing as a tool for allocating resources in communication networks has drawn a lot of attention recently. Both utility and pricing are not new concepts and have been studied in economics for a long time. Utility is to reflect the level of users' satisfaction from consuming a resource and price is the cost per unit of resource charged to users. The intention is to influence users' behaviors through pricing to achieve certain desired results, such as improving the overall system utilization and maintaining fairness among users.

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In wireline networks, pricing mechanisms have been studied in [3,8–11,13]. In wireless networks, a number of works [16,19,25] have introduced pricing mechanisms to improve resource management. In the context of wireless LANs, price-based resource allocation strategies have found application in power control [19] and call admission control [4]. However, these models only concentrate on single-hop infrastructure wireless networks. Price-based approaches to bandwidth allocation in multi-hop MANETs are proposed in [18,24]. In [18], an iterative price and rate adaptation algorithm is proposed assuming that users set prices for forwarding packets to maximize their own net benefits. The result shows that using pricing to stimulate cooperation will generate a socially optimal bandwidth allocation, i.e., maximization of the total utility of all users. Ref. [24] introduces the concept of *clique* into the resource allocation problem to accommodate the unique characteristics of contention among wireless nodes. Based on this new model, they present a new pricing policy for end-to-end multi-hop flows. Their simulation results demonstrate that pricing can indeed lead to the maximization of aggregated utility of flows as well as fairness among flows.

In this work, we are interested in IEEE 802.11-based MANETs. IEEE 802.11 [12] is one of the most widely used broadband wireless access systems nowadays. In this particular domain, we observe that there are important characteristics of MANETs that have not been carefully studied in existing works. First, the transmission rate of a wireless link is in fact environment-sensitive. Most of today's wireless interfaces can support multiple modulations and thus can transmit at a wide range of rates. Second, transmitting a packet in IEEE 802.11 incurs energy consumptions not only at the transmitter and the receiver sides, but also at neighboring stations of the transmitter and the receiver. We name the latter the *idle-listening* energy cost. It follows, interestingly, that the energy cost incurred by a transmission also depends on the number of neighboring nodes. Without taking these factors into account, existing models can not accurately capture prices that should be charged to traffic flows in a MANET. Based on these observations, we then propose new pricing strategies for resource allocation in a MANET. Our contributions are twofold. First, by including the factors of multiple transmission rates and prices of idle-listening energy consumptions, our model and thus the derived results are more realistic. Second, we demonstrate that it is still feasible to use prices to control behaviors of nodes in a MANET to achieve maximal system utilization with proper fairness among nodes.

The rest of this paper is organized as follows. Some backgrounds are given in Section 2. Section 3 presents our clique-based resource allocation strategy with multi-rate constraint. Section 4 further extends our resource allocation strategy with both multi-rate and energy constraints. Section 5 reports our experimental results. Finally, Section 6 concludes the paper.

2. Backgrounds and related works

We are interested in pricing mechanisms in IEEE 802.11-based MANETs. In this particular domain, we observe that there are two important characteristics of MANETs that have been ignored in existing works. First, the transmission rate of a wireless link is environment-sensitive. Most of today's wireless interfaces can support multiple modulations and thus can transmit at a wide range of rates. For example, IEEE 802.11b can operate at rates of 1, 2, 5.5, and 11 Mbps, while with OFDM (orthogonal frequency division multiplexing), IEEE 802.11a can support a wide range of rates of 6, 9, 12, 18, 24, 36, 48, and 54 Mbps. Second, transmitting a packet in IEEE 802.11 incurs energy costs not only at the transmitter and the receiver sides, but also at the neighboring stations of the transmitter and the receiver. For example, an evaluation shows that an IEEE 802.11b card at transmit, receive, monitor, and sleep modes would cost around 280, 180, 70, and 10 mW, respectively [20]. When two nodes are communicating, a node that is within the transmitter's transmission range will overhear the wireless signal, decode the packet, and eventually drop it because it is not the intended receiver. These receiving activities do not benefit the overhearing node but would still cause significant energy consumption to the overhearing node. We name this the *idle-listening* energy cost. Experiences show that idle-listening energy cost is not much less than real receiving energy cost. It follows, interestingly, that the energy cost incurred by a transmission also depends on the number of neighbors of the transmitter. Further, because the IEEE 802.11 MAC protocol also requires extra control packets being sent by the receiver, there is also extra energy cost incurred to neighboring nodes of the receiver. This leads to an observation that the total energy consumption incurred by a multi-hop traffic flow in a MANET also depends on the number of neighboring nodes of the routing path. Based on these observations, we will propose our pricing strategies in a MANET.

Utilizing pricing as a means for fostering cooperation in a MANET has been studied in [18]. However, it assumes a simplified model, where each node k has a transmission capacity of C_k, which is disassociated with other nodes. This model ignores the unique characteristic of inter-node interference in wireless communications. In [24], it is shown that cliques (to be defined later) can better characterize the interference nature. However, it is assumed that the channel capacity for each wireless link is equal. Thus, the multi-rate nature of wireless communications is ignored. Further, in both works, the factor of energy consumptions is ignored. A comparative study of two price-based algorithms is in [15], where it is shown that the gradient projection method has a better convergence property, but at the cost of performance.

Our work will model the prices by nonlinear programming techniques [1]. We will adopt the Lagrangian Primal–Dual solution, which is summarized as follows. Consider the following nonlinear problem **P**, which is called the *primal problem*.

$$\begin{aligned}&\text{maximize } f(x)\\&\text{subject to } g_i(x) \leqslant 0 \quad \text{for } i = 1, \ldots, m\end{aligned} \tag{1}$$

Several problems, closely associated with the above primal problem, have been proposed and are called *dual problems*. Among the various dual functions, the Lagrangian dual function has perhaps drawn the most attention. The Lagrangian form of the optimization problem **P** is defined as follows:

$$L(x, \lambda) = f(x) - \sum_{i=1}^{m} \lambda_i g_i(x). \tag{2}$$

where $\lambda_i \geqslant 0$ is the Lagrange multiplier associated with the inequality constraint $g_i(x) \leqslant 0$. The *Lagrange dual function* $\theta(\lambda)$ is defined as the maximized $L(x, \lambda)$ over x, i.e.,

$$\theta(\lambda) = sup_{x \in X} L(x, \lambda), \tag{3}$$

where *sup* stands for the *least upper bound*, or the *supremum*. The *Lagrange dual problem* **D** is presented below.

$$\begin{aligned}&\text{minimize } \theta(\lambda)\\&\text{subject to } \lambda \geqslant 0.\end{aligned} \tag{4}$$

The optimal primal and dual objectives are equal. Any algorithms that find a pair of primal–dual variables (x, λ) that satisfy the KKT optimality condition would solve the primal and its dual problem. One possible approach is to use the gradient projection method [1], which updates the dual variables λ to solve the dual problem **D**:

$$\lambda(t+1) = \left[\lambda(t) - \alpha \frac{\partial \theta(\lambda(t))}{\partial \lambda}\right]^+, \tag{5}$$

where t is the iteration number and $\alpha > 0$ is the step size. Certain choice of step sizes guarantee that the sequence of dual variables $\lambda(t)$ will converge to the dual optimal λ^* as $t \to \infty$. The primal variable $x(\lambda(t))$ will also converge to the primal optimal variable x^*.

3. Resource allocation with transmission rate constraint

3.1. Network and contention models

We are given a multi-hop MANET. Each node has a maximum transmission distance of d_{tx}. Two nodes are able to communicate with each other if their distance is no larger than d_{tx}. Wireless channels are considered as resources. When a node is transmitting a packet, any node that is within the interference distance of d_{int} can detect the carrier from its radio interface, where $d_{int} \geqslant d_{tx}$, and thus is prohibited from transmitting and receiving. We assume that each radio interface can support multiple modulations, and thus can transmit at multiple rates of $r_1, r_2, \ldots, r_m$. Without loss of generality, let $r_1 > r_2 > \ldots > r_m$. The rate that a node can transmit depends on its distance to the receiver. Let $d_1, d_2, \ldots, d_m$ be m distances such that $d_1 < d_2 < \ldots < d_m = d_{tx}$. We assume that a transmitter can successfully transmit to a receiver at the rate of r_i if the distance between them is no larger than d_i. The concept is illustrated in Fig. 1. We assume that a node can determine, from past experience, the transmission rates that it can use with each neighboring node and will always choose the best (highest) rate for use.

We are interested in solving the resource allocation problem in a MANET by modeling the power consumption incurred by a routing path by taking into account the energy cost for transmission, reception, and inter-node interference along the path. The network is modeled by a graph $G = (V, E)$, where $V(G)$ is the set of mobile nodes and $E(G)$ is the set of wireless links. For any two nodes $u, v \in V(G)$, a link (u, v) is included in $E(G)$ iff their distance $d(u, v) \leqslant d_{tx}$. For each link $e = (u, v) \in E(G)$, depending on the distance $d(u, v)$, we denote by $r(e)$ the best transmission rate for e. We are also given a set of n traffic flows F in G. Each flow $f_i \in F,\ i = 1 \ldots n$, goes from one source node to a destination node via a predefined routing path (typically a shortest path). The set of wireless links that are traversed by f_i is denoted by $E(f_i) \subseteq E(G)$. The goal is to calculate a *rate allocation vector* $A = (r(f_1), r(f_2), \ldots, r(f_n))$ such that each flow f_i can transmit at the rate of $r(f_i),\ i = 1 \ldots n$. We will formulate the objectives and constraints later on.

3.2. Clique-based rate allocation strategy

Below, we will derive our node interference model. Then we will present our rate allocation problem, followed by an iterative scheme to solve this problem. Our results are based on [14,24] with some extensions.

First, we will formulate the constraints of inter-node interference by modifying the model in [24]. Since flows in G will contend with each other for transmission, we first convert G into a *link contention graph* $G_c = (V_c, E_c)$ [14]. Each link in $E(G)$ of the original graph G is converted into a vertex in V_c. Each pair of links e_1 and e_2 in $E(G)$ with a *contention relation* is converted to a link (e_1, e_2) in E_c, where a contention relation is established if the distance between any endpoint of e_1 and any endpoint of e_2 is $\leqslant d_{int}$. The reason for such a definition is to model the behavior of the IEEE 802.11 MAC protocol, as shown in Fig. 2. For each data packet being transmitted on a wireless link, RTS/CTS/ACK control packets need to be sent. This calls for two-way communications, so we can model the contention relation without regarding the directions of flows.

With graph G_c, we define our *clique-based* rate allocation problem as follows. In a graph, a complete subgraph is called a *clique*. A *maximal clique* is a clique such that no other clique is its superset. The set of all maximal cliques, or simply cliques, in G_c is denoted by Q. Fig. 3 shows a network G and its corresponding G_c. Two example maximal cliques (marked by dotted circles) are identified in Fig. 3. For each $q \in Q$, the set of vertices of q (i.e., the set of wireless links in $E(G)$ which forms clique q) is denoted by $V(q)$. Maximal cliques (or simply called cliques below) in Q will be the units of resource allocation in our scheme. For any feasible rate allocation vector A and for each link e that is traversed by f_i, the *air time ratio* $r(f_i)/r(e)$ is the amount of air time occupied by f_i per time unit. Because no two members in a maximal clique are allowed to transmit at the same time (otherwise, collision will happen), this enforces that the sum of air time ratios seen by all links belonging to the same clique be no more than 100%. More specifically, for each clique $q \in Q$, the total of air time ratios occupied by all links of all flows that go through q at any time unit must be no more than 100%, i.e.,

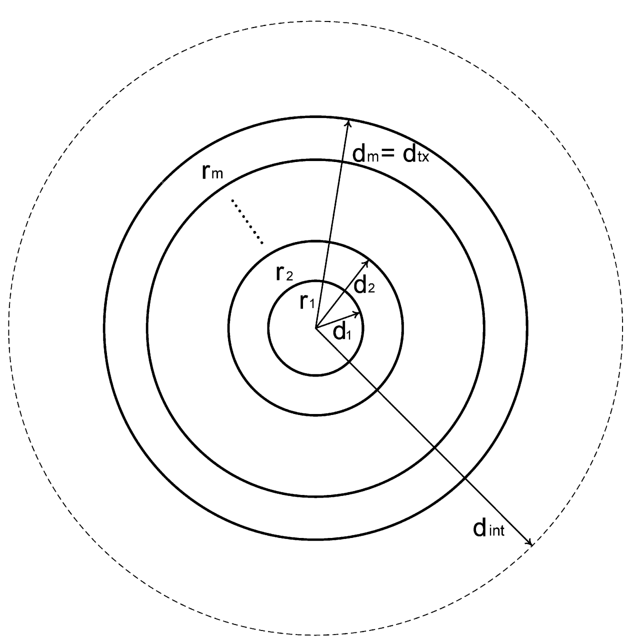


Fig. 1. Relationship of transmission distances and rates.

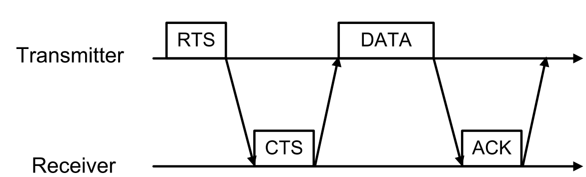


Fig. 2. IEEE 802.11 MAC protocol.

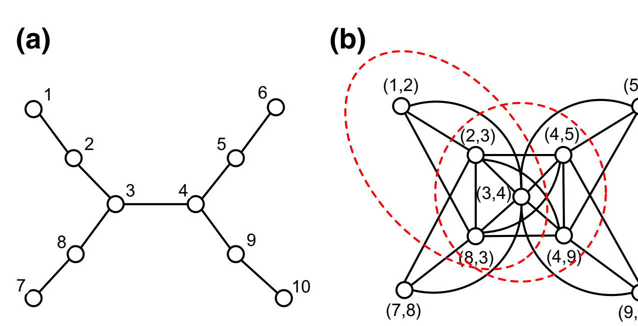


Fig. 3. (a) network G and (b) link contention graph G_c and two example maximal cliques.

$$\forall q \in Q : \sum_{\forall e \in V(q)} \left(\sum_{\forall f_i \in F: e \in E(f_i)} \frac{r(f_i)}{r(e)} \right) \leqslant 1. \tag{6}$$

For example, the total of air time ratios of members in each of the dotted circles in Fig. 3 should be bounded by 100%. We say that a rate allocation vector A is *feasible* if all inequalities in Eq. (6) are satisfied.

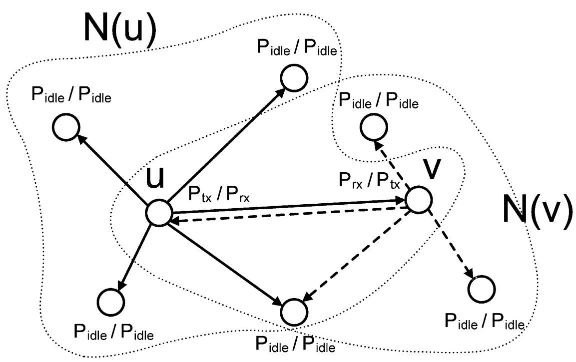


Fig. 4. Power consumption model. For each node, the corresponding P_x/P_y means the energy consumption incurred by transmissions of u/v, respectively.

We now present our price-based resource allocation scheme with the above air time constraints. Our derivation will be based on a *social welfare* model to calculate a rate allocation vector A such that the total utility of all flows is maximized and fairness among flows is maintained. We will associate with the rate $r(f_i)$ of each f_i a *utility function* $U(r(f_i))$, which represents the degree of satisfaction of f_i given rate $r(f_i)$. Following typical definitions of utility, we assume that the function $U(\cdot)$ is strictly increasing, concave, and twice continuously differentiable. The *primal problem* **P** can be formulated by a nonlinear optimization problem as follows:

$$\text{maximize} \sum_{\forall f_i \in F} U(r(f_i))$$

$$\text{subject to } \forall q \in Q : \sum_{\forall e \in V(q)} \left(\sum_{\forall f_i \in F: e \in E(f_i)} \frac{r(f_i)}{r(e)} \right) \leqslant 1. \tag{7}$$

The goal is to maximize the total of all flows' utilities. However, because of the way that utility functions are defined, it also has a sense of fairness behind. Since traffic flows have to compete with each other, they have to share the resources provided by cliques.

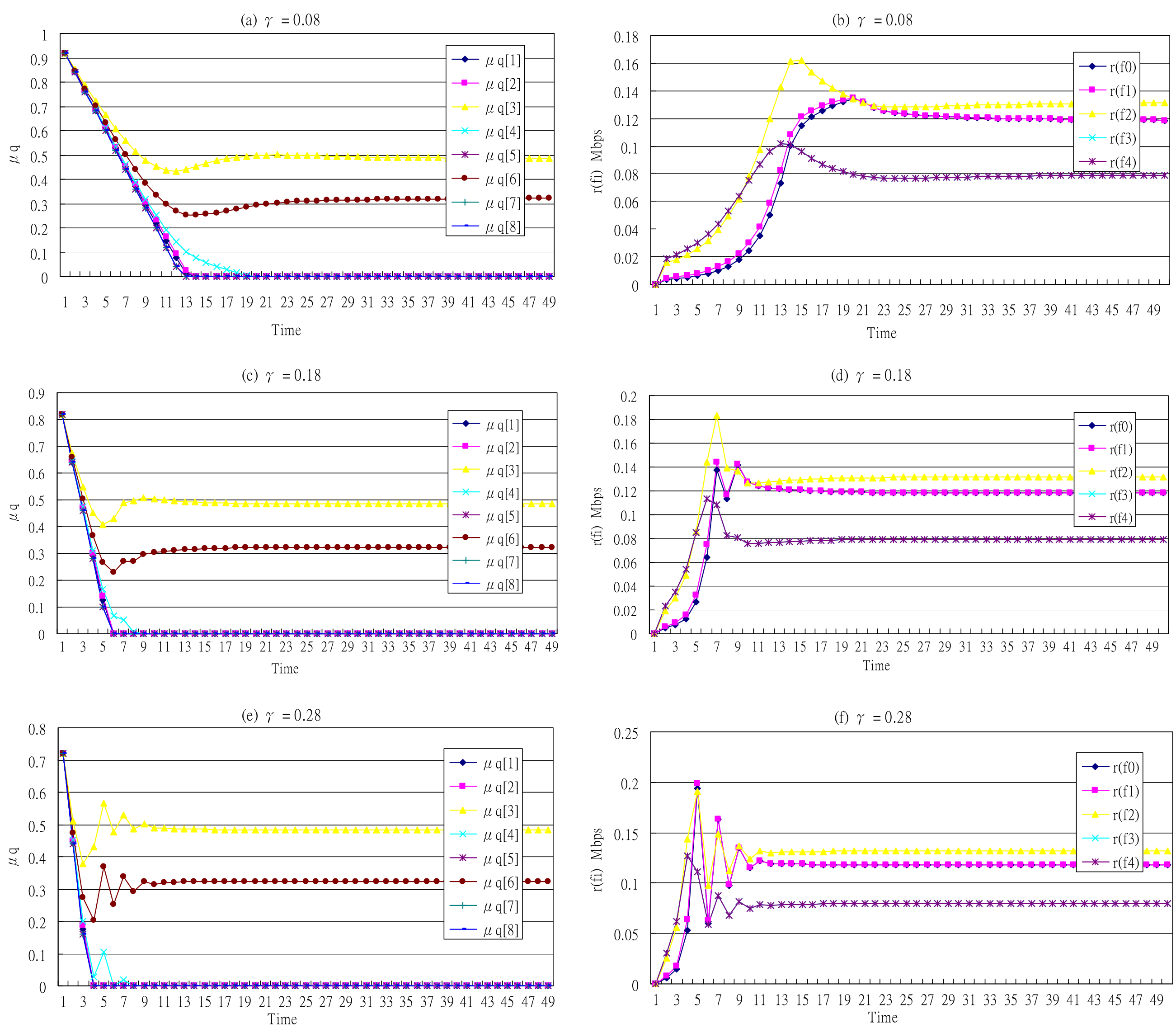


Fig. 5. Test of convergence with different step sizes.

The way utility functions are defined will enforce a flow's utility to gradually saturate as more and more resources are taken by it. Intuitively, when approaching the saturation point, it would be better to reduce its traffic rate and give the saved resource to other traffic flows, which may generate higher utility margins. This is what we mean by social welfare. Also, utility functions are based on users' psychological feelings to prices and can be defined differently. Several examples of utility functions can be found in our simulations.

In order to solve problem **P**, we turn our attention to the *dual problem* **D** of **P** defined as follows. For each $q \in Q$, let μ_q be the cost of the usage of one air time unit charged by clique q. Problem **D** is defined as the following min–max problem:

$$\min_{\forall \mu_1,\mu_2,\ldots,\mu_{|Q|}} \left\{ \max_{\forall r(f_1),r(f_2),\ldots,r(f_n)} \{D(r(f_1),r(f_2),\ldots,r(f_n);\mu_1,\mu_2,\ldots,\mu_{|Q|})\} \right\},$$

where

$$D(r(f_1),r(f_2),\ldots,r(f_n);\mu_1,\mu_2,\ldots,\mu_{|Q|}) = \sum_{\forall f_i \in F} \left(U(r(f_i)) - \sum_{\forall e \in E(f_i)} \left(\sum_{\forall q \in Q: e \in V(q)} \frac{r(f_i)}{r(e)} \cdot \mu_q \right) \right) + \sum_{\forall q \in Q} \mu_q, \qquad (8)$$

under the same constraints as in **P**, where the expression inside the first summation can be considered as the net benefit of flow f_i and the second term can be considered as the total value of the potential capacities of all cliques that can be offered to flows. Eq. (8) can be rewritten as

$$D(r(f_1),r(f_2),\ldots,r(f_n);\mu_1,\mu_2,\ldots,\mu_{|Q|}) = \sum_{\forall f_i \in F} \left(U(r(f_i)) - r(f_i) \sum_{\forall q \in Q} \mu_q \left(\sum_{\forall e \in E(f_i): e \in V(q)} \frac{1}{r(e)} \right) \right) + \sum_{\forall q \in Q} \mu_q, \qquad (9)$$

which satisfies the Lagrangian form of the optimization problem **P**, where $(\mu_1,\mu_2,\ldots,\mu_{|Q|})$ is a vector of Lagrange multipliers. In Eq. (9), the term

$$\sum_{\forall q \in Q} \mu_q \left(\sum_{\forall e \in E(f_i): e \in V(q)} \frac{1}{r(e)} \right) \qquad (10)$$

can be regarded as the unit path cost charged to flow f_i. From Eq. (10), we see that the difference between our formulation and that of [24] is that we take into account the *actual* air time occupied for a flow in each clique, while [24] only counts the number of links appearing in each clique. This does matter when two links belong to the same clique, one transmitting at a higher speed and the other transmitting at a lower speed; although they may transmit the same amount of information, the occupied air time ratios should be differentiated. Thus, our formulation can more accurately model the cost charged to each flow.

Next, we develop an iterative algorithm to determine the rate allocation vector A. Intuitively, each clique can be regarded as a provider and each flow can be regarded as a buyer. Clique q may gradually adjust its unit price μ_q depending on the demands of buyers. On the other hand, each buyer f_i may gradually adjust its flow rate $r(f_i)$ depending on its current utility value and the accumulated price charged by all cliques that it will go through. More specifically, the algorithm goes in a sequence of steps. At step t, the unit cost of each clique q is denoted by $\mu_q(t)$, and the rate of each flow f_i is denoted by $r(f_i,t)$. In each iteration, the clique costs will be updated first, followed by updates of flow rates. The algorithm is a distributed one executed by individual cliques and sources of flows.

A1. For each clique q, one node L_q is pre-elected as the leader of that clique. L_q then collects the rate $r(f_i,t)$ of each f_i such that $E(f_i) \cap V(q) \neq \emptyset$. (How to elect a leader is trivial, so we omit the details.)

A2. L_q will determine the price of q in the next step $t+1$ based on its current price at step t using the gradient projection method [1] as follows:

$$\mu_q(t+1) = \left[\mu_q(t) - \gamma \frac{\partial D(\cdot)}{\partial \mu_q} \right]^+, \qquad (11)$$

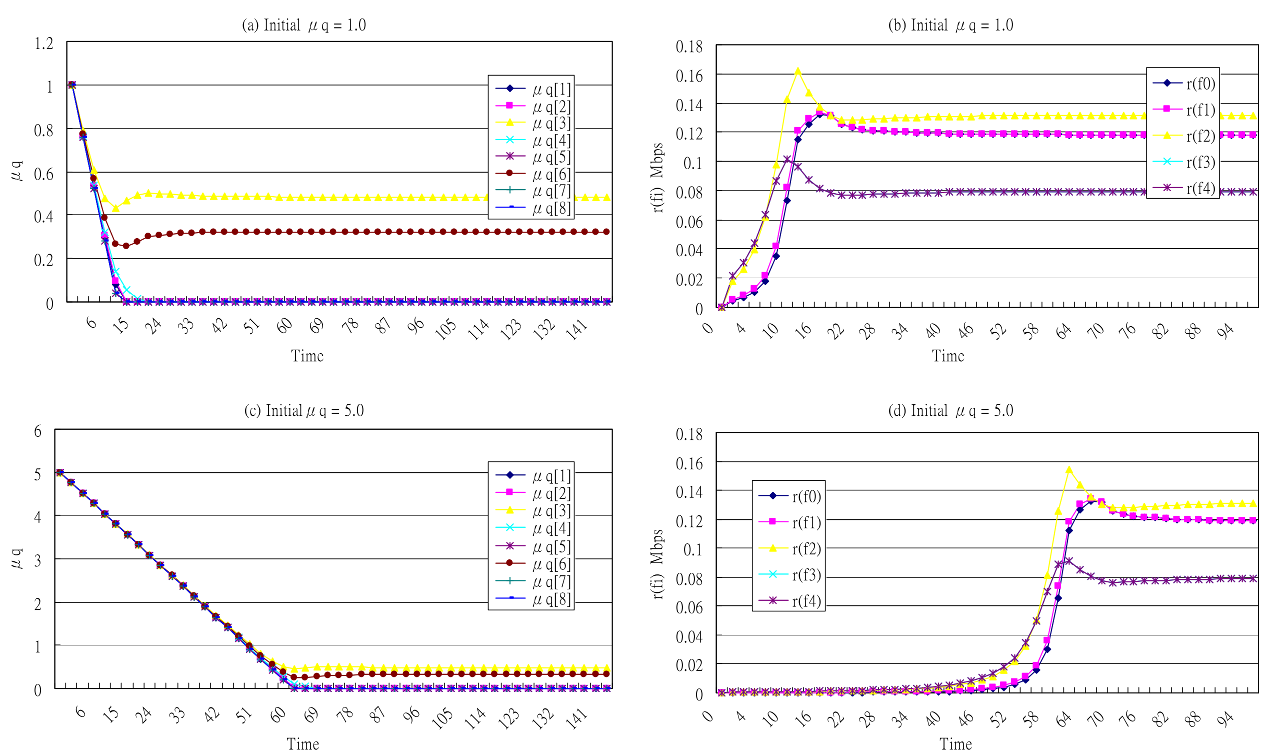


Fig. 6. Test of convergence with different initial clique unit prices.

where γ is a small step size and $[\cdot]^+$ will return 0 when the value inside the brackets is negative. Since the utility function is strictly concave, $D(\cdot)$ is continuously differentiable. From Eq. (8), L_q can derive that

$$\frac{\partial D(\cdot)}{\partial \mu_q} = 1 - \sum_{\forall f_i \in F}\left(\sum_{\forall e \in E(f_i): e \in V(q)} \frac{r(f_i)}{r(e)}\right). \tag{12}$$

Plugging Eq. (12) into Eq. (11), L_q determines its unit price in step $t+1$ as

$$\mu_q(t+1) = \left[\mu_q(t) - \gamma\left(1 - \sum_{\forall f_i \in F}\left(\sum_{\forall e \in E(f_i): e \in V(q)} \frac{r(f_i)}{r(e)}\right)\right)\right]^+. \tag{13}$$

Then L_q sends the updated price $\mu_q(t+1)$ to all members in $V(q)$.

A3. On receiving $\mu_q(t+1)$, each $e \in V(q)$ notifies the updated price to each flow that goes through it. Each flow should forward the new price to its source node.

A4. When the source of f_i collects all updated prices at step $t+1$, it derives its updated net benefit function as

$$B(r(f_i)) = U(r(f_i)) - \sum_{\forall e \in E(f_i)}\left(\sum_{\forall q \in Q: e \in V(q)} \frac{r(f_i)}{r(e)} \cdot \mu_q(t+1)\right) \tag{14}$$

and takes the first derivative of $B(r(f_i))$ by setting it to 0

$$\frac{\partial B(r(f_i))}{\partial r(f_i)} = U'(r(f_i)) - \sum_{\forall e \in E(f_i)}\left(\sum_{\forall q \in Q: e \in V(q)} \frac{1}{r(e)} \cdot \mu_q(t+1)\right) = 0. \tag{15}$$

The next injection rate that would maximize its net benefit is

$$r(f_i, t+1) = \arg_{r(f_i)}\left\{\frac{\partial B(r(f_i))}{\partial r(f_i)} = 0\right\}. \tag{16}$$

A5. The source of f_i then communicates its updated rate $r(f_i, t+1)$ to all cliques flowed by it by piggybacking the value with its data packets. The above procedure then loops back to step A2 and repeats in each time step.

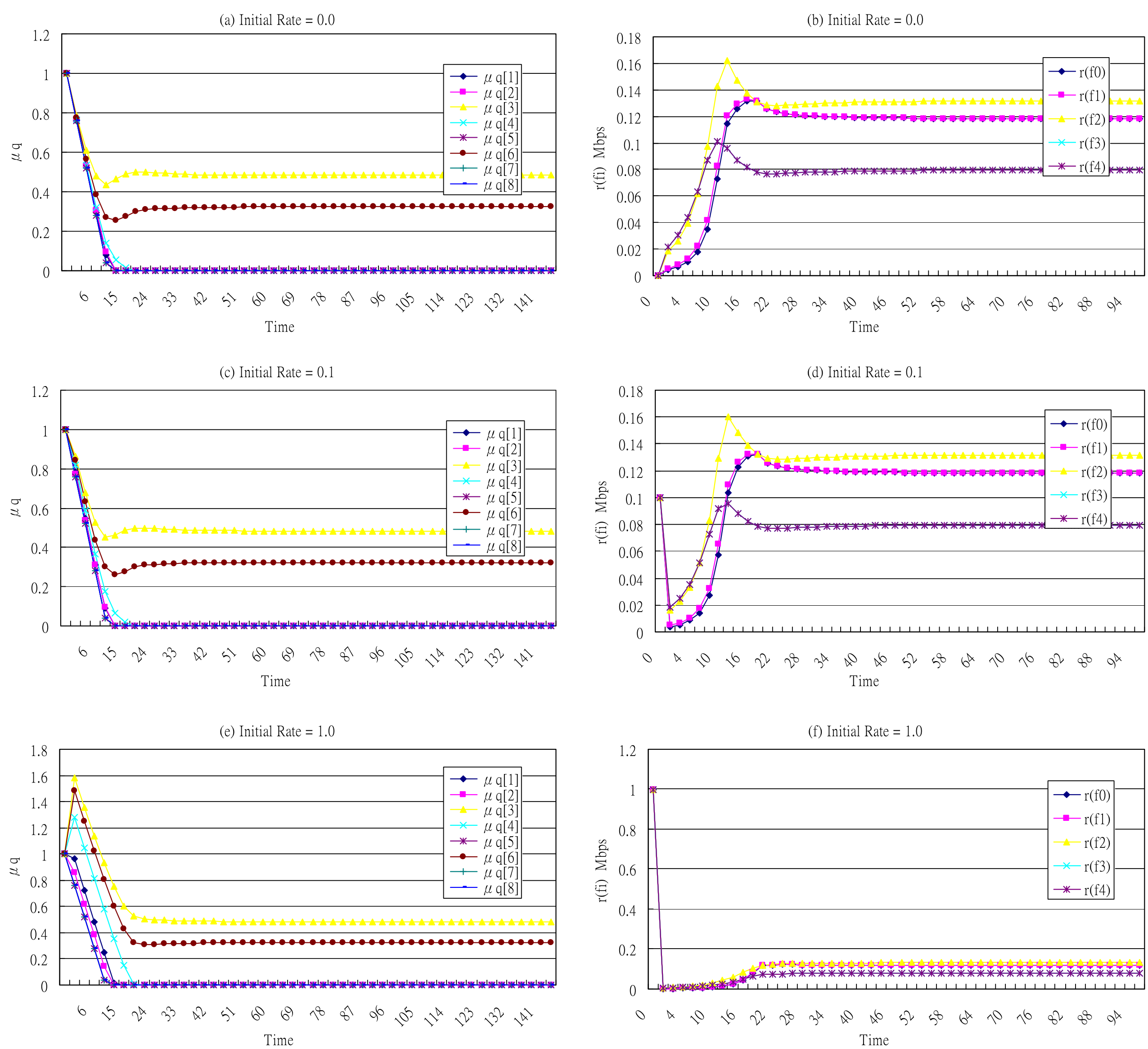


Fig. 7. Test of convergence with different initial flow rates.

4. Resource allocation with both transmission rate and energy constraints

A radio channel is a kind of replenishable resource in the sense that in every time unit, the same amount of resource can be provided again. On the contrary, it is not so for battery energy in a mobile node because after each usage, the remaining energy decreases until the battery is exhausted. Below, we will develop an extension to our model to include energy price.

We first develop the energy consumption model in IEEE 802.11 MAC, where each transmission of a data packet is accompanied by RTS/CTS/ACK control packets, as illustrated in Fig. 2. Let the amounts of energy consumption per time unit for transmission, reception, and idle-listening be P_{tx}, P_{rx}, and P_{idle}, respectively. For each directional wireless link $\vec{e} = (u, v) \in E(G)$, the amount of energy required to transmit one data bit from u to v can be written as

$$P(\vec{e}) = (1 + \delta_{tx}) \times \frac{1}{r(e)} \times (P_{tx} + P_{rx} + (|N(u)| - 1)P_{idle}) + \delta_{rx} \times \frac{1}{r(e)} \times (P_{tx} + P_{rx} + (|N(v)| - 1)P_{idle}), \tag{17}$$

where the first term is the cost incurred by the transmission activities at u and the second term is the cost incurred by the transmission activities at v. $N(u)$ and $N(v)$ are the sets of neighbors of u and v in G, respectively. The terms δ_{tx} and δ_{rx} are to account for the ratios of extra control overheads per data bit incurred for u and v, respectively. Note that since $\vec{e}$ is directional, $P((u, v))$ may not be equal to $P((v, u))$. Fig. 4 shows an example.

We utilize energy price $P(\vec{e})$ in two ways. First, $P(\vec{e})$ will be sent to each clique leader L_q to differentiate the unit price of q charged to each flow. More specifically, the unit cost μ_q will be extended to $\mu_{q,\vec{e}}$ to account for the energy cost of link $\vec{e}$. Second, the energy price will also be sent to each source node to be included in its net benefit function. The detail procedure is shown below.

B1. Each directional link $\vec{e}$ will calculate its energy cost $P(\vec{e})$. At step t, the leader L_q of each clique q will collect the rate $r(f_i, t)$ of each f_i such that $E(f_i) \cap V(q) \neq \emptyset$ and the energy cost $P(\vec{e})$ of each link $\vec{e} \in V(q)$.

B2. To reflect the difference in energy cost of each link, we modify Eq. (13) such that L_q assigns a different step size $\gamma_{\vec{e}}$ to each link $\vec{e} \in V(q)$. We intentionally let links with higher

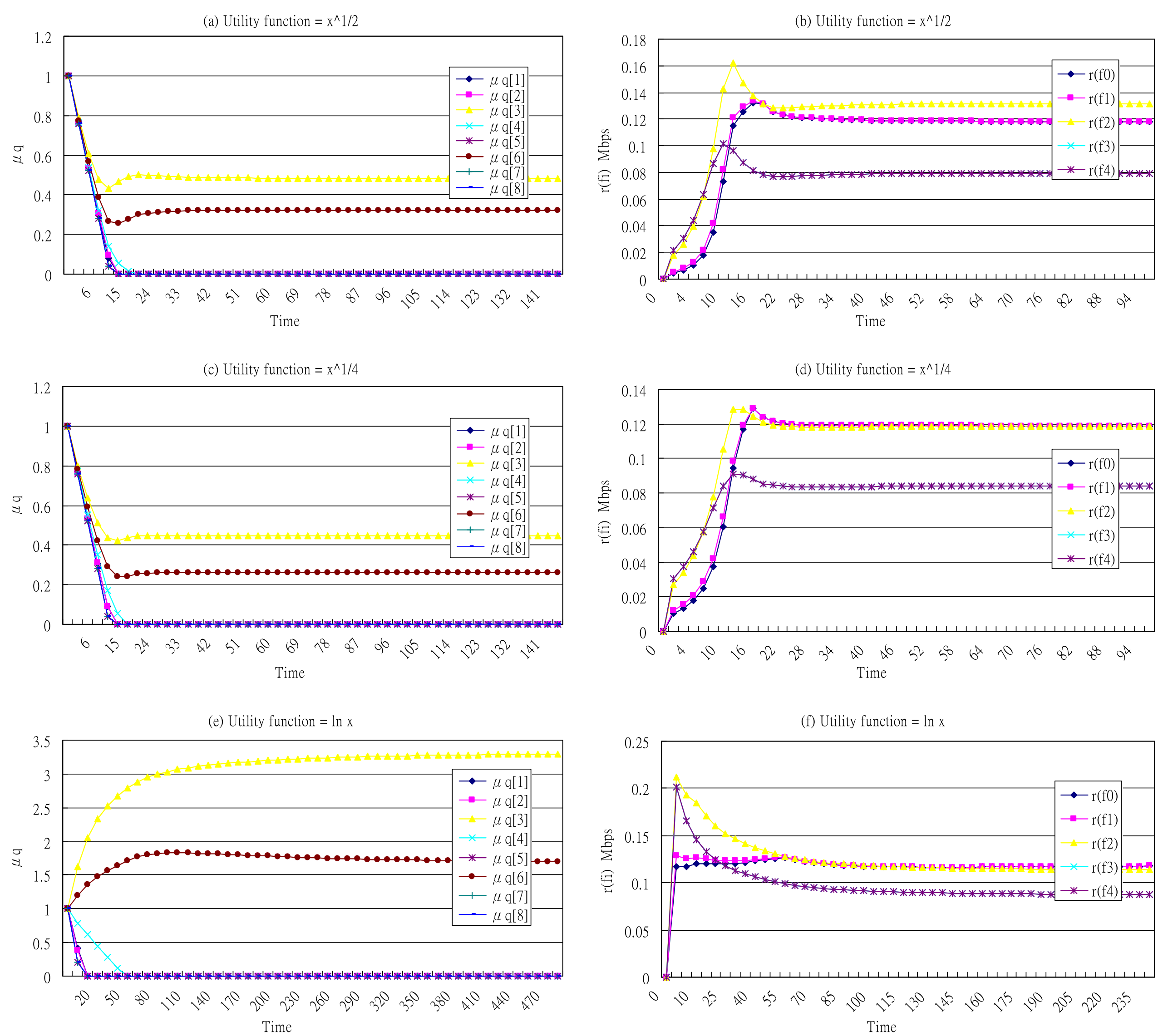


Fig. 8. Changes of clique unit prices and flow rates by varying the utility functions.

energy costs get larger step sizes, and vice versa. The intuition is to let links with higher energy costs adjust prices more quickly. So flows passing high energy consumption areas will be more sensitive to price changes. Specifically, L_q sets the unit price of link $\vec{e}$ in step $t+1$ as

$$\mu_{q,\vec{e}}(t+1) = \left[\mu_{q,\vec{e}}(t) - \gamma_{\vec{e}}\left(1 - \sum_{\forall f_i \in F}\left(\sum_{\forall e \in E(f_i): e \in V(q)} \frac{r(f_i)}{r(e)}\right)\right)\right]^{+}, \tag{18}$$

where $\mu_{q,\vec{e}}(t)$ is the unit price charged by each link $\vec{e}$ in step t. Then L_q sends the updated price to all members in $V(q)$. The value of $\gamma_{\vec{e}}$ is defined as follows. Let *step size variance* β be a positive constant such that $\beta < \gamma$ (for example, if $\gamma = 0.01$, then β can be 0.005). Let $P_{avg} = \frac{1}{2|V(q)|}\sum_{\forall \vec{e} \in V(q)} P(\vec{e})$. For link $\vec{e}$, we let

$$\gamma_{\vec{e}} = \gamma + \beta \cdot h\left(\frac{P(\vec{e}) - P_{avg}}{P_{avg}}\right), \tag{19}$$

where

$$h(y) = \begin{cases} y & \text{if } -1 \leqslant y \leqslant 1 \\ -1 & \text{if } y < -1 \\ 1 & \text{if } y > 1 \end{cases}. \tag{20}$$

Function $h(y)$ is to constrain the returned value within $[-1, 1]$ when y is outside that range.

B3. On receiving $\mu_{q,\vec{e}}(t+1)$, each $\vec{e} \in V(q)$ notifies the updated price to each flow that goes through it. Each flow should carry the new price to its source node.

B4. When the source of f_i collects all updated prices at step $t+1$, it derives its updated net benefit function as

$$B(r(f_i)) = U(r(f_i)) - \sum_{\forall e \in E(f_i)}\left(\sum_{\forall q \in Q: e \in V(q)}\left(\frac{r(f_i)}{r(e)} \cdot \mu_{q,\vec{e}}(t+1) + w_{eng} \cdot r(f_i) \cdot P(\vec{e})\right)\right), \tag{21}$$

where w_{eng} is a constant representing the weight of the price of energy, considering that one may give more or less empha-

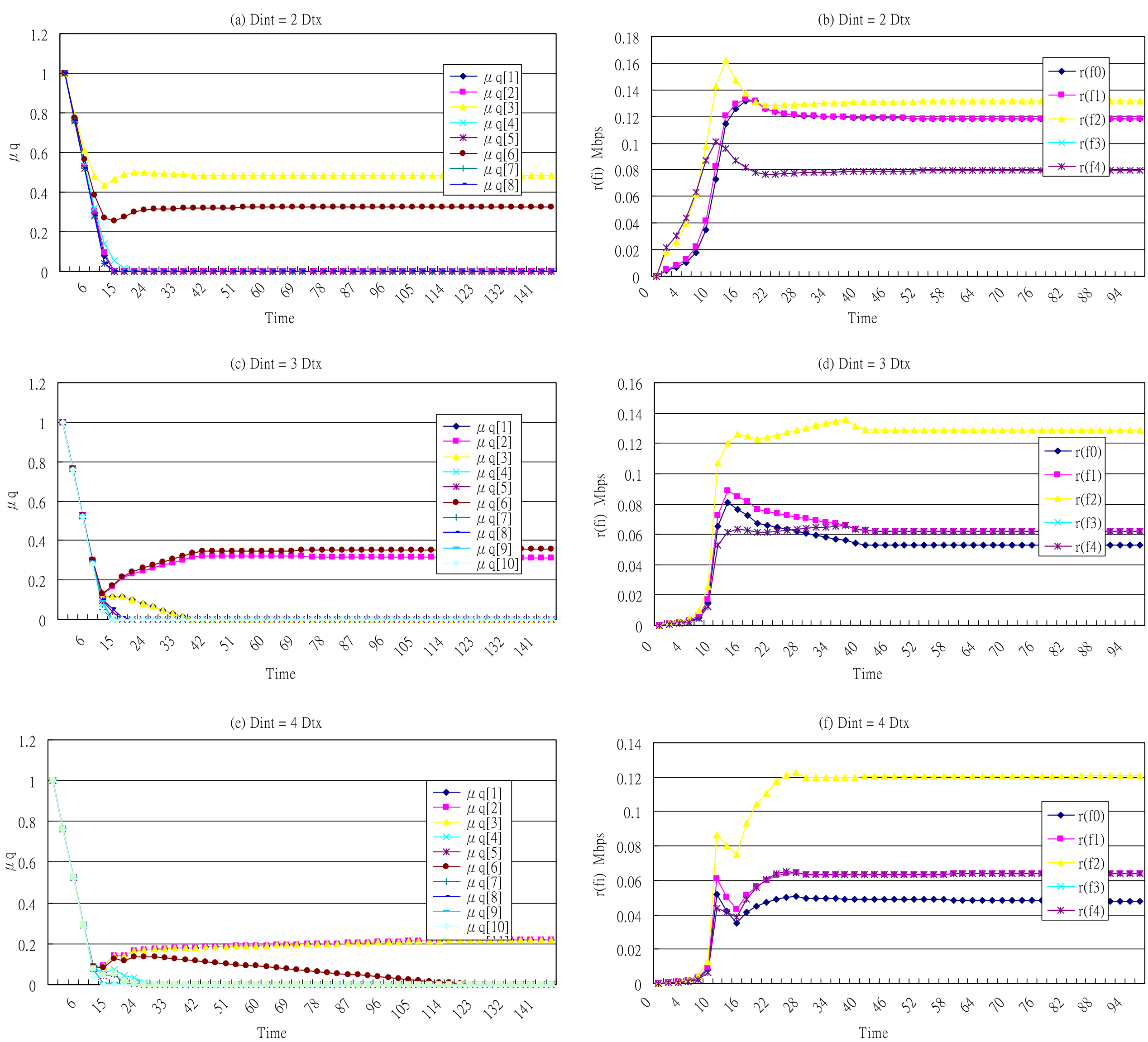


Fig. 9. Varying the network density by changing the interference range.

sis on the cost of energy consumption. Taking the first derivative of $B(r(f_i))$ by setting it to 0, we have

$$\frac{\partial B(r(f_i))}{\partial r(f_i)} = U'(r(f_i)) - \sum_{\forall e \in E(f_i)} \left(\sum_{\forall q \in Q: e \in V(q)} \left(\frac{\mu_{q,\vec{e}}(t+1)}{r(e)} + w_{eng} \cdot P(\vec{e}) \right) \right) = 0. \quad (22)$$

The next injection rate that would maximize its net benefit is

$$r(f_i, t+1) = \arg_{r(f_i)} \left\{ \frac{\partial B(r(f_i))}{\partial r(f_i)} = 0 \right\}. \quad (23)$$

B5. The source of f_i then communicates its updated rate to all cliques flowed by it by piggybacking the value of $r(f_i, t+1)$ with its data packets. The above procedure then loops back to step B2 and repeats in each time step.

5. Experimental results

To understand the convergence property and performance of the proposed protocols, we have developed a simulator. We consider the effect of multi-rate transmission, without the effect of energy price. A network area of size 1500 m × 1500 m is simulated, on which 50 nodes are randomly generated. We assume that the IEEE 802.11b wireless interface cards are used, which support four transmission rates of $r_1 = 11$ Mbps, $r_2 = 5.5$ Mbps, $r_3 = 2$ Mbps, and $r_4 = 1$ Mbps, with transmission distances of $d_1 = 30$ m, $d_2 = 50$ m, $d_3 = 80$ m, and $d_4 = 145$ m, respectively. Therefore, $d_{tx} = 145$ m. Unless stated otherwise, we set $d_{int} = 2 \times d_{tx}$ and initial price $\mu_q(0) = 1.00$ for each q. For each flow, the initial rate is set to 0. The step size γ is set to 0.05. In the following simulations, we first assume $w_{eng} = 0$ (i.e., no energy price). At the end, we will evaluate the impact of w_{eng}.

(A) Convergence test: First, we inject different initial values to verify the convergence property of our scheme. We adopt the utility function $U(x) = x^{1/2}$. There are $n = 5$ flows each with an initial flow rate of 0 Mbps. The initial unit price for each clique is 1.0. We test different step sizes $\gamma = 0.08$, 0.18, and 0.28. The results are in Fig. 5, which shows that in all step sizes, the clique unit prices and flow rates will converge to the same values. A smaller step size will lead to slower convergence, which is reasonable. We also conduct simulations with different initial clique unit prices, under a fixed $\gamma = 0.08$. As Fig. 6 shows, initial unit prices do affect the speed of convergence. However, all cases converge to the same flow rates. A similar test of convergence using different initial flow rates are shown in Fig. 7.

(B) Impact of utility functions: Next, we test on different utility functions: $U(x) = x^{1/2}, x^{1/4}$, and $\ln x$. Five traffic flows are injected. Then we observe the changes of unit prices of some cliques (Fig. 8(a), (c), (e)) and changes of rates of some flows (Fig. 8(b), (d), (f)). It can be seen that in all cases, flow rates will converge within short times. The convergence speed of $U(x) = \ln x$ is relatively slower. Overall, we see that when $U(x) = x^{1/2}$ or $x^{1/4}$, the flow rates converge at faster speeds than the case $U(x) = \ln x$. This is because the degree of satisfaction is less sensitive to rate change in the latter case. Interestingly, we also see that even after all flow rates have converged, some cliques' unit prices will converge quickly, but some may keep on increasing or decreasing. Decreasing ones are due to the corresponding cliques are not 100% saturated yet. So their prices will keep on decreasing. However, flow rates may not be increased any more (observe that some cliques may be saturated already and become the bottlenecks of these flows). This causes such cliques drop their unit prices gradually to 0. This can also explain why some flows will keep on increasing their prices. As a flow sees a dropping path price, it will try to increase its rate. However, since no more increase is possible, this only causes those already saturated cliques to become over-saturated and thus increase their unit prices.

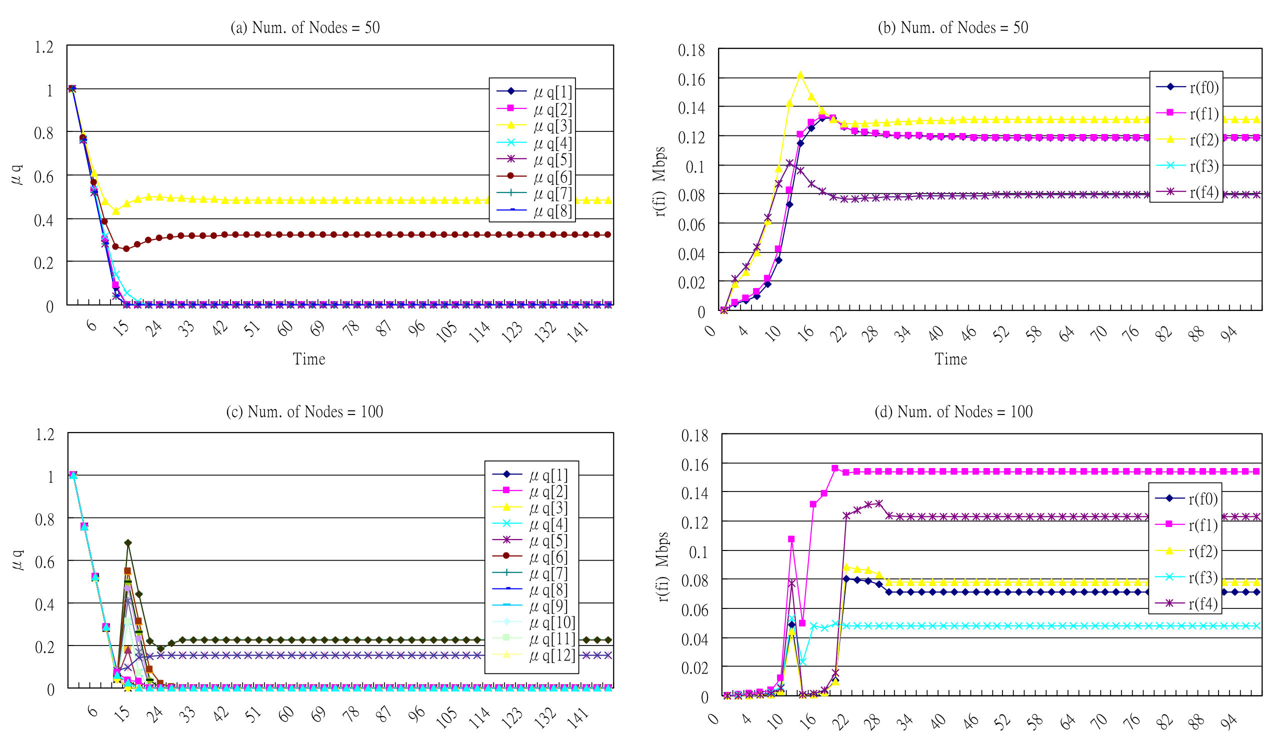


Fig. 10. Varying the network density by changing the number of nodes.

(C) Varying the network density: In the next set of simulations, we fix the utility function at $U(x) = x^{1/2}$ and vary the network density. The network density can be changed by varying the interference range or the number of nodes. The results in Fig. 9 are obtained by setting $d_{int} = 2 \times d_{tx}, 3 \times d_{tx}$ and $4 \times d_{tx}$. The convergence property remains true. However, since the definitions of cliques will change as the interference ranges change, the convergence speeds and the final flow rates are not necessarily the same. The results in Fig. 10 are obtained by setting the numbers of nodes to 50 and 100. While the convergence is guaranteed, the speed of convergence is slower as there are more nodes, which is reasonable.

(D) Impact of number of flows: Finally, we fix the utility function at $U(x) = x^{1/2}$ and the interference range at $d_{int} = 2.0 \times d_{tx}$ and vary the number of flows among 5, 10, and 25. The results are in Fig. 11. The convergence speeds are not sensitive to the number of flows, so the proposed protocol should be quite scalable to the number of flows.

(E) Impact of energy price: The above results assume no energy price (i.e., steps A1-A5 are adopted). In this simulation, we set $U(x) = x^{1/2}, d_{int} = 2.0 \times d_{tx}$, and vary the weight w_{eng} (i.e., steps B1-B5 are adopted). The results are in Fig. 12. We see both the convergence property and the impact of energy cost. Flows 1 and 3 consume the most energy, so their stable rates decrease as w_{eng} increases. On the contrary, flows 2 and 4 consume relatively less energy, so their stable rates, benefiting from the channel resources released by flows 1 and 3, increase as w_{eng} increases. Fig. 13 shows the impact of w_{eng} by varying it between 0.1 and 2.0. As can be seen, the cost of energy can suppress the rates of flows 1 and 3 effectively. As some channel resources are released by flows 1 and 3, flows 2 and 4 will first benefit from these new resources. However, as w_{eng} keeps on increasing, flows 2 and 4 will eventually see higher overall prices, enforcing them to reduce their rates. This explains why we see increment followed by decrement in stable rates for them as w_{eng} keeps on increasing.

6. Conclusions

We have addressed the resource allocation problem in MANETs by using pricing to regulate individual flows' behaviors. Two pric-

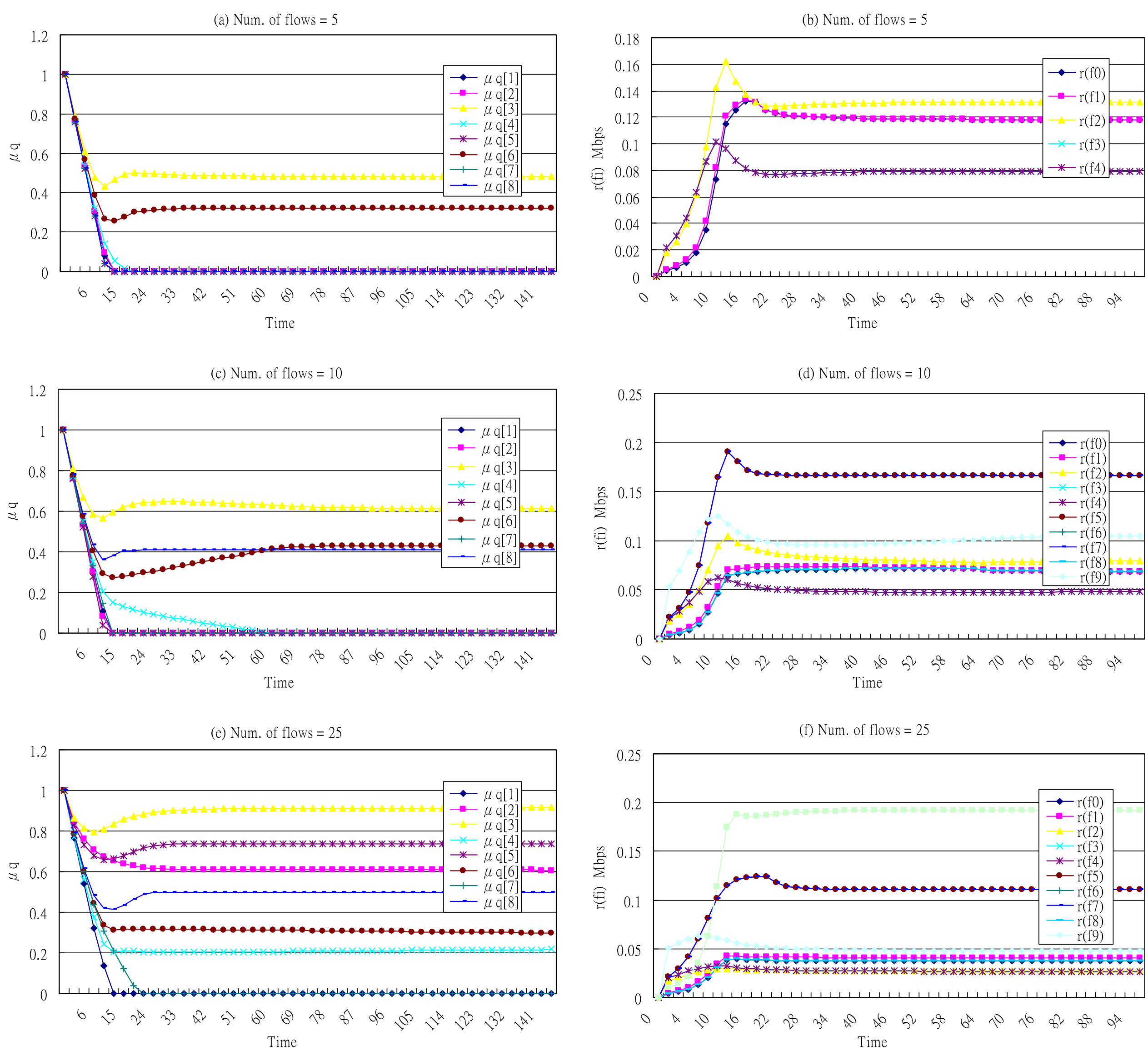
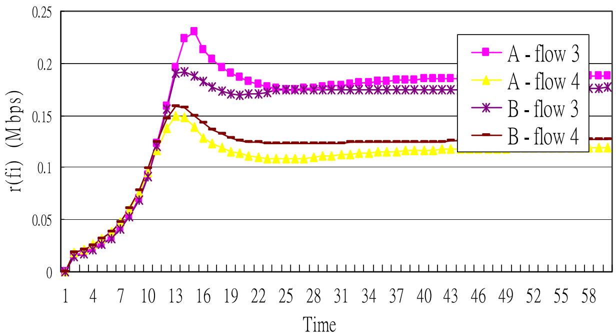


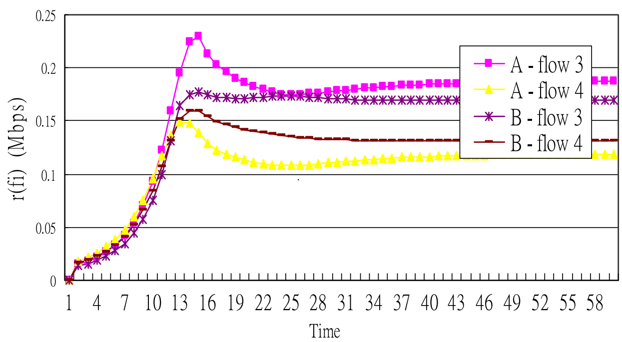
Fig. 11. Changes of clique unit prices and flow rates by varying the number of flows.

(a) Weng = 0.1



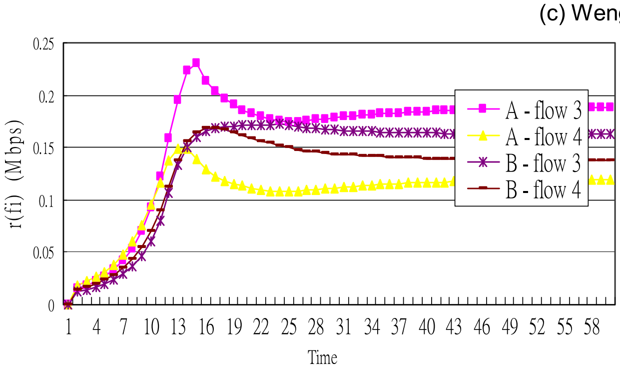
Rate & Power \ Flow No.		flow 1	flow 2	flow 3	flow 4
A	Stable Rate (Mbps)	0.11577	0.11577	0.18765	0.11918
	Power Consumption / Sec.	0.06941	0.05959	0.07097	0.06189
B	Stable Rate (Mbps)	0.11465	0.11795	0.17660	0.12694
	Power Consumption / Sec.	0.06873	0.06072	0.06679	0.06591

(b) Weng = 0.4



Rate & Power \ Flow No.		flow 1	flow 2	flow 3	flow 4
A	Stable Rate (Mbps)	0.11577	0.11577	0.18765	0.11918
	Power Consumption / Sec.	0.06941	0.05959	0.07097	0.06189
B	Stable Rate (Mbps)	0.11064	0.12203	0.17012	0.13201
	Power Consumption / Sec.	0.06633	0.06282	0.06434	0.06854

(c) Weng = 0.75



Rate & Power \ Flow No.		flow 1	flow 2	flow 3	flow 4
A	Stable Rate (Mbps)	0.11577	0.11577	0.18765	0.11918
	Power Consumption / Sec.	0.06941	0.05959	0.07097	0.06189
B	Stable Rate (Mbps)	0.10608	0.12688	0.16251	0.13776
	Power Consumption / Sec.	0.06360	0.06531	0.06146	0.07153

Fig. 12. Impact of energy price. (Set A considers only channel cost, while set B considers both channel and energy costs.)

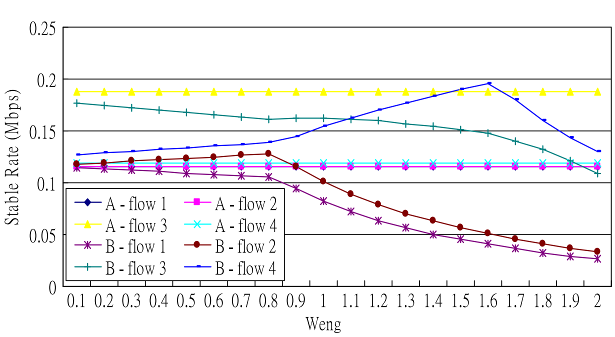


Fig. 13. Impact of weight w_{eng} when energy price is considered. (Set A considers only channel cost, while set B considers both channel and energy costs.)

ing strategies have been proposed, which take the factors of multiple transmission rates and energy consumptions into account. These two factors are critical ones for MANETs, but have not been well studied in former works. Therefore, our results can more closely reflect realistic wireless network environments under current technologies. Our schemes do not rely on global network information. Each clique will run as an individual to adjust its unit price. Similarly, each flow will run as an individual to adjust its flow rate depending on its current utility value and the external charges. As shown by our simulations, the system will gradually reach a balance point. Our simulation results have verified the convergence properties of the proposed clique-based and clique-plus-energy-based models. Various factors have been studied in our simulation experiments.

References

[1] D. Bertsekas, Nonlinear Programming, Athena Scientific, 1999.
[2] S.-M. Chen, S.-P. Kuo, Y.-C. Tseng, A quorum-based mechanism as an enhancement to clock synchronization protocols for IEEE 802.11 MANETs, IEEE Communications Letters 11 (4) (2007) 313–315.

[3] R. Gibbens, F. Kelly, Resource pricing and the evolution of congestion control, Automatica 35 (12) (1999) 1969–1985.
[4] J. Hou, J. Yang, S. Papavassiliou, Integration of pricing with call admission control for wireless networks, in: Vehicular Technology Conference, vol. 3, 2001, pp. 1344–1348.
[5] C.-F. Huang, Y.-C. Tseng, On topology improvement of a packet radio network by power control, IEEE Transaction on Vehicular Technology 52 (4) (2003) 985–998.
[6] C.-F. Huang, H.-W. Lee, Y.-C. Tseng, A two-tier heterogeneous mobile ad hoc network architecture and its load-balance routing problem, Mobile Networking and Applications 9 (4) (2004) 379–391.
[7] J.-R. Jiang, Y.-C. Tseng, C.-S. Hsu, T.-H. Lai, Quorum-based asynchronous power-saving protocols for IEEE 802.11 ad hoc networks, ACM Mobile Networking and Applications 10 (1/2) (2005) 169–181.
[8] K. Kar, S. Sarkar, L. Tassiulas, A simple rate control algorithm for maximizing total user utility, in: Proceedings of IEEE INFOCOM, 2001.
[9] F. Kelly, Charging and rate control for elastic traffic, European Transactions on Telecommunications 8 (1997) 33–37.
[10] F. Kelly, A. Maulloo, D. Tan, Rate control for communication networks: shadow prices, proportional fairness and stability, Journal of Operational Research Society 49 (3) (1998) 237–252.
[11] R. La, V. Anantharam, Utility-based rate control in the internet for elastic traffic, IEEE/ACM Transactions on Networking 10 (2) (2002) 272–286.
[12] LAN MAN Standards Committee of the IEEE Computer Society, IEEE Std 802.11-1999, Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) specifications, IEEE, 1999.
[13] S. Low, D. Lapsley, Optimization flow control: basic algorithm and convergence, IEEE/ACM Transactions on Networking 7 (6) (1999) 861–874.
[14] H. Luo, S. Lu, V. Bharghavan, A new model for packet scheduling in multihop wireless networks, in: ACM Mobicom, 2000.
[15] M. Luthi, S. Nadjm-Tehrani, C. Curescu, Comparative study of price-based resource allocation algorithms for ad hoc networks, in: Proceedings of IEEE IPDPS, 2006.
[16] P. Marbach, R. Berry, Downlink resource allocation and pricing for wireless networks, in: Proceedings of IEEE INFOCOM, 2002.
[17] C.E. Perkins, Ad Hoc Networking, Addison-Wesley, 2001.
[18] Y. Qiu, P. Marbach, Bandwidth allocation in ad hoc networks: a price-based approach, in: Proceedings of IEEE INFOCOM, 2003.
[19] C.U. Saraydar, N.B. Mandayam, D.J. Goodman, Efficient power control via pricing in wireless data networks, IEEE Transactions on Communications 50 (2) (2002) 291–303.
[20] Y.-C. Tseng, T.-Y. Hsieh, An architecture for power-saving communications in a wireless mobile ad hoc network based on location information, Microprocessors and Microsystems 28 (8) (2004) 457–465.
[21] Y.-C. Tseng, Y.-F. Lee, Y.-C. Chang, On the lifetime of routing paths in multi-hop mobile ad hoc networks, IEEE Trans. on Mobile Computing 2 (4) (2003) 366–376.
[22] Y.-C. Tseng, S.-Y. Ni, E.-Y. Shih, Adaptive approaches to relieving broadcast storms in a wireless multihop mobile ad hoc network, IEEE Transactions on Computer 52 (5) (2003) 545–557.
[23] Y.-C. Tseng, S.-L. Wu, W.-H. Liao, C.-M. Chao, Location awareness in ad hoc wireless mobile networks, IEEE Computer 34 (6) (2001) 46–52.
[24] Y. Xue, B. Li, K. Nahrstedt, Optimal resource allocation in wireless ad hoc networks: a price-based approach, IEEE Transactions on Mobile Computing 5 (4) (2006) 347–364.
[25] H. Yaiche, R.R. Mazumdar, C. Rosenberg, A game theoretic framework for bandwidth allocation and pricing in broadband networks, IEEE/ACM Transactions on Networking 8 (5) (2000) 667–678.