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Joint Power and Rate Control in Ad Hoc Networks Using a Supermodular Game Approach

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Abstract—**In ad hoc networks, reducing energy consumption and improving throughput are both important for high network performance. This paper presents a joint power and rate control adaptive algorithm to optimize the trade-off between power consumption and throughput in ad hoc networks. Each node chooses its own transmission power and rate based on limited environment information in order to achieve optimal transmission efficiency. In a fictitious game framework with strategy space transformation, our joint power and rate control adaptive algorithm can be viewed as a supermodular game. By interpreting the supermodular game using myopic best response updates, this algorithm can converge to the unique optimal transmission efficiency. Finally, the simulation results show that this supermodular game approach improves the average transmission efficiency by about 33%.**

I. INTRODUCTION

The wireless ad hoc network is a self-configuring network of mobile devices connected via wireless links. The network has a distributed and dynamic architecture and each node in the network is capable of independently adapting its actions based on the limited current environment information. Wireless ad hoc networks have gained more and more attention due to their wide applicability in many fields [1]. However, it also comes with some potential technical problems that have to be overcome. First of all, energy of mobile nodes in ad hoc networks is limited. Therefore, it is essential to minimize their energy consumption to prolong their operating time. Moreover, since throughput in ad hoc networks is restricted, it is also very important to achieve optimal overall throughput. Also some research reported in the literature focuses on the trade-off between energy consumption and throughput in ad hoc networks [7] [12].

Power control research in ad hoc networks deals with the selection of proper transmission power for each node at each link in a distributed fashion. Power control research has been raised to reduce energy consumption and improve throughput. Initial research has been reported in the literature at the physical layer with a focus on developing distributed algorithms to achieve the optimal trade-off between transmission power and signal-to-interference-plus-noise ratio (SINR). However, existing research shows a strong interconnection among all layers in ad hoc networks during the process of power control. Thus, a local layered design approach is not efficient and optimal. For instance, the transmission powers level effects not only the SINR, but also the routing by changing network topology. Link capacities in wireless ad hoc networks are not fixed. Instead, these capacities are adjusted according to power allocation, scheduling and routing to exploit network performance. Recently, cross-layer optimization for ad hoc networks has been investigated to improve the overall network performance [2-7][11].

In this paper, we focus on the problem of joint power and rate control in ad hoc networks in a game theoretic framework. A joint power and rate control adaptive algorithm is developed to balance the trade-off between power consumption and throughput. In this algorithm, each node decides its own transmission power and rate based on limited environment information in order to achieve optimal transmission efficiency. The probability of a successful transmission is taken into account to quantify the constraint of the interaction between transmission power and rate. We introduce a fictitious game to model this problem as a fictitious joint power and rate control game. Then, strategy space transformation is applied to evaluate this algorithm as a supermodular game. Following the specific properties of the supermodular game, the nodes' strategies can globally converge to optimal condition using myopic best response (MBR) updates.

The rest of this paper is organized as follows. The related works is reviewed in Section Ⅱ. The basic system model and problem formulation are described in Section Ⅲ. In Section Ⅳ, we model the problem as a fictitious joint power and rate control game (JPRG) using game theory. In Section Ⅴ, we analyze the convergence of fictitious power and rate control game (FPRG) using a supermodular game and present a joint power and rate control adaptive algorithm (JPRA). In Section Ⅵ, performance evaluation is given. Finally, Section Ⅶ gives a short conclusion.

II. RELATED WORK

Early power control research using cross-layer design schemes has been based on minimal total transmission power. The definition of power-aware routing is firstly raised in [2], using new routing metrics such as power consumption per packet, the duration of network connectivity and so on. Conditional min-max battery cost routing (CMMBCR)

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algorithm is proposed to minimize the total transmission power by maximizing the residual battery energy of the nodes on a route [3]. However, those power-aware routing algorithms cause some potential problems by placing more traffic load on some nodes, which may result in rapid energy exhaustion in some parts of the network.

More recent research focuses on the joint power control and routing to avoid the potential problems existing in power-aware routing algorithms, and is able to achieve a better network performance. Cruz [4] uses an integrated routing, scheduling and power control policy to support high data transmission rates. It minimizes average rate per link by minimizing the total average power consumption. In contrast to the previous power control approaches, it achieves a higher throughput. Dekorsy [5] proposes a distributed routing and power control decomposition algorithm, which is designed for a combination of a joint routing, time scheduling and power control problems. As opposed to the universal dual decomposition, the authors fully exploit the combinatorial structure of the underlying optimization problem. Xi [6] presents a framework in which the power control and routing performance at the physical, MAC, and network layers can be jointly optimized. It adopts multi-commodity flow to characterize the average operation of the network and uses the appropriate scaling matrices to converge to global optimum. Zheng [7] proposes a utility-based joint power and rate adaptive algorithm which adjusts the power and rate according to the variation of channel conditions. Xiao [11] formulates the simultaneous routing and resource allocation (SRRA) problem. In the SRRA algorithm, its solution is based on exploiting problem structure via dual-decomposition method. It forms the dual problem by introducing Lagrange multipliers for the coupling constraints.

Meanwhile, in previous works, game theoretic models have been widely applied to deal with power control problems in ad hoc networks. Game theory, as a branch of applied mathematics, is used in many fields to describe and analyze interactive decision situations. It attempts to capture behavior in strategic situations, where the success decision of individual depends on the choices of others. It provides analytical tools to predict the outcome of complex interactions among rational entities that have conflict targets. As known, all nodes in ad hoc networks interact with each other in a distributed way. Thus, game theory provides useful tools to analyze and solve ad hoc network problems. For instance, the potential game is used in [7] to propose a framework for autonomous resource allocation; the repeated game is used in [8] which considers the interaction among the users' decision for power level as a repeated game; [9] uses the non-cooperate game to construct a Distributed Power and Rate Control based on Step-up Pricing Game (DPRC/SPG). However, the existing game theoretical approaches are still inefficient to adjust power and rate simultaneously.

III. SYSTEM MODEL

We consider the topology of ad hoc networks as a directed and connected graph $G = (N, E)$, where N and E are the node and edge sets. A node $i \in \{1, ..., N\}$ corresponds to an ad hoc network node, and an edge $(i, j) \in E$ corresponds to the wireless link from node i to j. We assume that the topology of the ad hoc network is fixed during each time slot. Define $\mathbf{p} = (p_1, ..., p_N)$ and $\mathbf{r} = (r_1, ..., r_N)$ as transmission power vector and rate vector of the nodes respectively. Define $\mathbf{B} = \{B_{(i,j)}\}$ as the link-route incidence matrix, which is determined by routing protocols. $\mathrm{O}_i = \{j : (i, j) \in E\}$ denotes the neighbor nodes set of i, which are reachable for node i with respect to transmission power. For node i, the transmission power and rate vectors are $p_i = \{p_{(i,j)} : j \in \mathrm{O}_i\}$ and $r_i = \{r_{(i,j)} : j \in \mathrm{O}_i\}$, where $p_i \in [P_{\min}, P_{\max}]$ and $r_i \in [R_{\min}, R_{\max}]$. The link-route incidence matrix value on link (i, j) is $B_{(i,j)}$ which equals to 1 when the route passes the link (i, j) and to 0 otherwise. The SINR at the receiver of link (i, j) is defined as:

$$SIR_i(p_i, \mathbf{p}_{-i}) = \frac{|h_{ij}|^2 p_i}{N_0 + \sum_{q \in \mathrm{O}_j, q \neq i} |h_{qj}|^2 p_q} \quad (1)$$

where h_{ij} is the path gain from node i to j. As known, the ad hoc network is interference-limited. Thus, the capacity of link (i, j) is denoted as:

$$c_{(i,j)} = \log(1 + SIR_i(p_i, \mathbf{p}_{-i})) \quad (2)$$

As a result, we estimate SINR of link (i, j) with respect to transmission rate r_i as $\gamma_{r_i} = erf(r_i)$ from (2).

Due to the dependency between transmission power and rate, only when the SINR on link (i, j) is equal to or larger than γ_{r_i}, node i will succeed in data transmission. Here, we also consider the probability of a successful transmission f_i on link (i, j). In [10], the ad hoc network channel condition was considered to vary according to the random-walk model. In a similar manner, we model the variation pattern of SINR as a lognormal distribution [7]. For node i with transmission power p_i and rate r_i, the probability of a successful transmission is represented by:

$$f_i(\lambda_i) = f_i(SINR_i, r_i) = \frac{1}{2}\left\{1 + erf\left[\frac{\ln(SINR_i / \gamma_{r_i})}{\sigma\sqrt{2}}\right]\right\} \quad (3)$$

where $\lambda_i(r_i, p_i, \mathbf{p}_{-i}) = \frac{W}{r_i} SINR_i$, and σ is the average of the channel condition.

Then we can obtain the data transmission efficiency on link (i, j), which is defined as successful transmission data consumed per joule energy as $\frac{r_i f_i(\lambda_i)}{p_i}$, to present the trade-off between energy consumption and throughput. As a result, the utility function of node i is represented as.

$$U_i(r_i, p_i, \mathbf{p}_{-i}) = \frac{\sum_{j\in O_i} B_{(i,j)} r_i f_i(\lambda_i)}{p_i} \quad (4)$$

IV. JOINT POWER AND RATE CONTROL GAME

In the ad hoc network discussed in this paper, each node tries to achieve its own optimal transmission efficiency by jointly adjusting its transmission power and rate based on limited environment information. There is no central control node and all the nodes behave in a selfish manner in order to maximize their own utilities. Therefore, the problem of joint power and rate control in ad hoc networks can be formulated as a non-cooperative game.

Let $G_{JPRG} = [A, \{S_i\}, \{U_i\}]$ denotes a joint power and rate control game (JPRG) in ad hoc networks. $A = \{1, ..., N\}$ is a set of players corresponding to all the nodes in ad hoc networks. $\{S_i = [P_{\min}, P_{\max}] \times [R_{\min}, R_{\max}]\}$ is the strategy space of all players, where $S_i = \{p_i, r_i\}$ denotes the transmission power and rate decision of player i. The utility of players in this game is represented by transmission efficiency of each node in (4). In this game, each player jointly chooses its p_i and r_i in such a way that its utility is maximized. Thus, the JPRG is formally expressed as:

$$\max_{p_i \in [P_{\min}, P_{\max}], r_i \in [R_{\min}, R_{\max}]} U_i(r_i, p_i, \mathbf{p}_{-i}) \quad (5)$$

In this game, given the transmission powers and rates of the other nodes, node i tends to select its optimal neighbor node j to achieve maximum utility. Data transmission efficiency of node i to its optimal neighbor node j represents the utility of node i. Each node jointly adjusts its transmission power and rate based on limited environment information, as well as on its optimal neighbor.

Definition 1: The transmission power vector $\mathbf{p}^* = (p_1^*, ..., p_N^*)$ and rate vector $\mathbf{r}^* = (r_1^*, ..., r_N^*)$ are Nash equilibrium (NE) of the JPRG, such that no node can unilaterally improve its own utility, that is

$$U_i(r_i^*, p_i^*, \mathbf{p}_{-i}^*) \ge U_i(r_i, p_i, \mathbf{p}_{-i}^*),$$

$$\text{for } \forall i \in A \text{ and } \forall (r_i^*, p_i^*) \in S_i.$$

It is obvious that no node has the motivation to change its strategy unilaterally in the NE of the JPRG.

In game theory, the best response is the strategy which produces the most favorable utility for a player, taking other players' strategies as given. What's more, players only choose the best response that would give them the highest payoff in the next round, without considering the effect this would have in following play of the game. This update rule is called a myopic best response (MBR).

V. CONVERGENCE ANALYSIS OF JOINT POWER AND RATE CONTROL ADAPTIVE ALGORITHM

In this section, we characterize the convergence of joint power and rate control adaptive algorithm by introducing a supermodular game model. We first consider a fictitious game similar to the JPRG. Later, strategy space transformation is applied so that this fictitious game is equivalent to a supermodular game. Finally, a joint power and rate control adaptive algorithm is derived for the supermodular game.

We consider the following fictitious power and rate control game (FPRG):

$$G_{FPRG} = [A^p \cup A^r, \{S_i^p, S_i^r\}, \{U_i^p, U_i^r\}].$$

In this fictitious game, each node $i \in \{1, ..., N\}$ in the original ad hoc network splits into two fictitious players, one is the fictitious power player in set $A^p = \{1, ..., N\}$ who controls the transmission power p_i by a strategy from set $S_i^p = [P_{\min}, P_{\max}]$, and the other is the fictitious rate player in set $A^r = \{1, ..., N\}$ who controls transmission rate r_i by a strategy from set $S_i^r = [R_{\min}, R_{\max}]$. There are 2N fictitious players in set $A^p \cup A^r$, and each of them chooses a strategy from set $\{S_i^p, S_i^r\}$ to maximize its own utility function in a selfish manner.

In order to analyze the convergence of FPRG, we first introduce some definitions.

Definition 2: The game $G = [A, \{S_i\}, \{U_i\}]$ is a supermodular game if for all $i \in A$:

- S_i is a compact subset of $\Re$;
- U_i is upper semi-continuous in (S_i, S_{-i});
- U_i has increasing differences in (S_i, S_{-i}), satisfies $\frac{\partial^2 U_i}{\partial S_i \partial S_{-i}} \ge 0$.

There are several important properties in the supermodular game [13]:

1) There is at least one NE. In case of multiple NEs, there always exist a smallest one and a largest one.

2) Each player starts from the smallest (largest) element of the strategy space and uses MBR updates, then the strategies monotonically converge to the smallest (largest) NE.

3) If there are positive spillovers, then the largest NE is the Pareto Optimal.

Next we show that with an appropriate strategy space transformation, FPRG is equivalent to a supermodular game. The supermodular game is characterized by "strategic complementarities". In other words, this means that when one player takes a higher action, the others want to do the same.

First of all, we prove that the utility function of the fictitious power player has increasing differences between its own transmission power and other players' transmission power. The first-order partial derivative of U_i^p with respect to p_i is given as:

$$\frac{\partial U_i^p}{\partial p_i} = \sum_{j\in O_i} B_{(i,j)} r_i \left[\frac{1}{p_i^2}\left(p_i \frac{\partial f_i(\lambda_i)}{\partial \lambda_i}\frac{\partial \lambda_i}{\partial p_i} - f_i(\lambda_i)\right)\right]$$
$$= \sum_{j\in O_i} B_{(i,j)} r_i \left[\frac{1}{p_i^2}\left(\lambda_i \frac{\partial f_i(\lambda_i)}{\partial \lambda_i} - f_i(\lambda_i)\right)\right]$$

Then we can continue to obtain:

$$\frac{\partial^2 U_i^p}{\partial p_i \partial \mathbf{p}_{-i}} = \sum_{j\in O_i} B_{(i,j)} r_i \left[\frac{1}{p_i^2}\left(\lambda_i \frac{\partial^2 f_i(\lambda_i)}{\partial \lambda_i^2}\frac{\partial \lambda_i}{\partial \mathbf{p}_{-i}} + \frac{\partial \lambda_i}{\partial \mathbf{p}_{-i}}\frac{\partial f_i(\lambda_i)}{\partial \lambda_i} - \frac{\partial f_i(\lambda_i)}{\partial \lambda_i}\frac{\partial \lambda_i}{\partial \mathbf{p}_{-i}}\right)\right]$$
$$= \sum_{j\in O_i} B_{(i,j)} r_i \left[\frac{1}{p_i^2}\left(\lambda_i \frac{\partial^2 f_i(\lambda_i)}{\partial \lambda_i^2}\frac{\partial \lambda_i}{\partial \mathbf{p}_{-i}}\right)\right]$$

As mentioned before, $f_i(\lambda_i)$ is a cumulative distribution function of the lognormal distribution, so it is a sigmoid function which satisfies the following:

$$\frac{\partial f_i(\lambda_i)}{\partial \lambda_i} > 0\ ,\quad \frac{\partial^2 f_i(\lambda_i)}{\partial \lambda_i^2} \le 0\ .$$

At the same time, it is obvious that:

$$\frac{\partial \lambda_i}{\partial p_i} > 0\ ,\quad \frac{\partial \lambda_i}{\partial \mathbf{p}_{-i}} < 0 \text{ and } \frac{\partial \lambda_i}{\partial r_i} < 0$$

according to the definition of λ_i.

So we can easily get that: $\frac{\partial^2 U_i^p}{\partial p_i \partial \mathbf{p}_{-i}} \ge 0$.

Therefore, all fictitious power players are equivalent to ones in a supermodular game. It means that when one fictitious power player takes a higher power, the others want to do the same. At time slot t, all fictitious power players' strategies are given as $(p_i(t), \mathbf{p}_{-i}(t))$. Then at time slot $t+1$, the best response function of the fictitious power player i^p is represented as:

$$\rho_i^p(t+1) = \arg \max_{p_i\in[P_{\min},P_{\max}],r_i\in[R_{\min},R_{\max}]} U_i(p_i, \mathbf{p}_{-i}(t)) \qquad (6)$$

However, for the fictitious rate player, it is easily found that the increasing differences condition does not hold with the original definition. The first-order partial derivative of U_i^r with respect to r_i is given as:

$$\frac{\partial U_i^r}{\partial r_i} = \frac{\sum_{j\in O_i} B_{(i,j)}}{p_i}\left[f_i(\lambda_i) + r_i \frac{\partial f_i(\lambda_i)}{\partial \lambda_i}\frac{\partial \lambda_i}{\partial r_i}\right]$$
$$= \frac{\sum_{j\in O_i} B_{(i,j)}}{p_i}\left[f_i(\lambda_i) - \lambda_i \frac{\partial f_i(\lambda_i)}{\partial \lambda_i}\right]$$

Then we can continue to obtain:

$$\frac{\partial^2 U_i^r}{\partial r_i \partial \mathbf{p}_{-i}} = \frac{\sum_{j\in O_i} B_{(i,j)}}{p_i}\left[\frac{\partial f_i(\lambda_i)}{\partial \lambda_i}\frac{\partial \lambda_i}{\partial \mathbf{p}_{-i}} - \left(\frac{\partial \lambda_i}{\partial \mathbf{p}_{-i}}\frac{\partial f_i(\lambda_i)}{\partial \lambda_i} + \lambda_i \frac{\partial^2 f_i(\lambda_i)}{\partial \lambda_i^2}\frac{\partial \lambda_i}{\partial \mathbf{p}_{-i}}\right)\right]$$
$$= \frac{\sum_{j\in O_i} B_{(i,j)}}{p_i}\left[-\lambda_i \frac{\partial^2 f_i(\lambda_i)}{\partial \lambda_i^2}\frac{\partial \lambda_i}{\partial \mathbf{p}_{-i}}\right]$$

It is obvious that: $\frac{\partial^2 U_i^r}{\partial r_i \partial \mathbf{p}_{-i}} \le 0$. This means higher strategy of one fictitious rate player leads to decreasing strategies of other players.

In order to model the fictitious joint power and rate control problem as a supermodular game, it is necessary to apply strategy space transformation on the original one. Firstly we define $r_i' = -r_i$ and let each fictitious player choose r_i' from the strategy space $[-R_{\max}, -R_{\min}]$. It is easy to prove that $\frac{\partial^2 U_i^r}{\partial r_i' \partial \mathbf{p}_{-i}} \ge 0$, which means the utility function of the fictitious rate player has increasing differences between its own transmission rate and other players' transmission power. At the time slot t, all fictitious rate players' strategies are given as $r_i'(t)$. Then at time slot $t+1$, the best response function of the fictitious rate player i^r is represented as:

$$\rho_i^r(t+1) = \arg \max_{p_i\in[P_{\min},P_{\max}],r_i'\in[-R_{\max},-R_{\min}]} U_i(r_i', \mathbf{p}_{-i}(t)) \qquad (5)$$

If we can prove that all the fictitious player's utility function have increasing differences between their own transformed strategy and any other player's transformed strategy, then FPRG is equivalent to a supermodular game. Therefore, all fictitious rate players are also equivalent to the ones in a supermodular game by an appropriate strategy space transformation. In conclusion, FPRG can be viewed as a supermodular game with the strategy set $(r_i^{'}, p_i, \mathbf{p}_{-i})$.

Theorem 1: In FPRG, there is at least one NE, and all the players start from the largest element of the strategy space and use MBR updates, then the strategies monotonically converge to the Pareto Optimal.

The Pareto Optimal of FPRG means that any change to make any player better off is impossible without making someone else worse off. The network has the global optimal data transmission efficiency when each node converges to its equilibrium situation and achieves its own optimal data transmission efficiency.

According to Theorem 1, the joint power and rate control adaptive algorithm can be described as follows:

1) Initially, t=0, each fictitious player chooses the largest element from strategy space, $S_i^p = P_{\max}$ and $S_i^r = -R_{\min}$; each node has its neighbor node set $\mathrm{O}_i = \{j : (i, j) \in E\}$ and get its optimal neighbor, as well as its utility.

2) At time slot t, for the fictitious power player $i^p \in A^p$, with the given strategies of the other players as $S_{-i}^p(t-1)$, we can compute the best response of i^p as $\rho_i^p(t) = \arg \max_{p_i \in [P_{\min}, P_{\max}], r_i \in [R_{\min}, R_{\max}]} U_i(p_i, \mathbf{p}_{-i}(t-1))$; for the fictitious rate player $i^r \in A^r$, with the given strategies of the other players as $S_{-i}^r(t-1)$, we can get $\rho_i^r(t) = \arg \max_{p_i \in [P_{\min}, P_{\max}], r_i^{'} \in [-R_{\max}, -R_{\min}]} U_i(r_i^{'}, \mathbf{p}_{-i}(t-1))$.

3) If all power vectors and rate vectors converge, then stop. Let $t = t+1$, and go to (2).

VI. Performance Evaluation

A. Numerical Evaluation for two scenarios

In this section, we consider a simple ad hoc network shown in Fig. 1. This ad hoc network is randomly generated by drawing node positions from a uniform distribution on the space $[0,5]\times[0,5]$. The ad hoc network has $N = 10$ nodes. The maximum transmission power allowed is $P_{\max} = 1W$, and the minimum transmission power allowed is $P_{\min} = 0.01W$. The path gain h_{ij} is modeled as $h_{ij} = A_{ij} / d_{ij}^4$, where d_{ij} is the distance between the transmitter of node i and the receiver of node j, and A_{ij} is the attenuation factor due to fading, following the lognormal distribution. We also assume that the maximum transmission rate allowed is $R_{\max} = 100kbps$, and the minimum rate is $R_{\min} = 10kbps$.

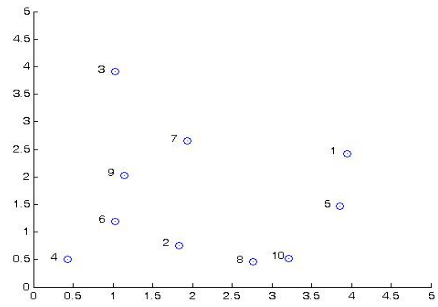

Figure 1. The distribution of the ad hoc network

We firstly observe the convergence of all the nodes' behaviors by only power control in terms of several iterations in one time slot. In this scenario, each node follows a policy of transmitting with the maximum feasible transmission rate, aiming to maximize the amount of total transmission data.

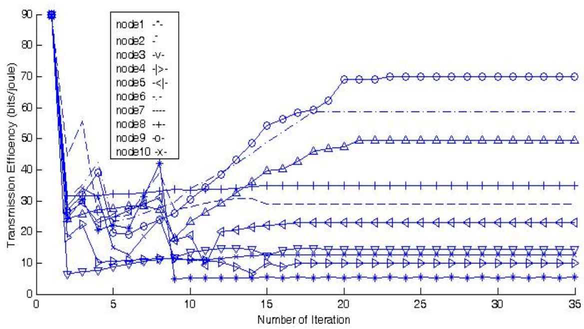

Figure 2. The evolution of behaviors by only power control

In Fig. 2, the evolution of the all nodes' behaviors is demonstrated by several iterations. After 20 iterations, the transmission efficiency of each node converges to a stable level.

In the second scenario, each node splits into two fictitious players that behave as a supermodular game. According to the previously analyzed operation of the joint power and rate control adaptive algorithm, at each time slot, all nodes will take part in a fictitious player supermodelar game to choose their transmission power and rate jointly. The results for the second scenario are presented in Fig. 3. We can see that all the nodes quickly achieve an optimal overall transmission efficiency.

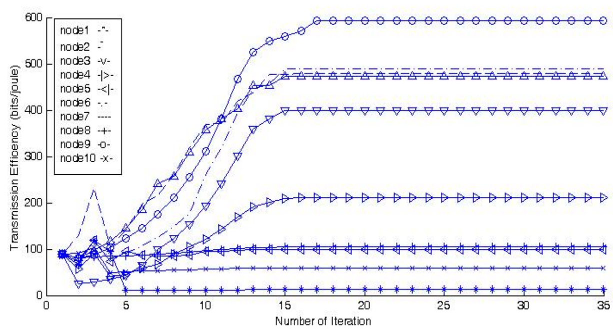

Figure 3. The evolution of joint power and rate control

The results show that the policy that forces nodes to transmit with the maximum feasible transmission rate would not necessarily increase the transmission efficiency. In Fig. 2 it achieves lower transmission efficiency because separate adjustment brings a decrease in the probability of successful transmission.

Moreover, we can see in Fig. 3 that node 9, 6, 7 and 2 achieve the top 4 transmission efficiency. It means that the nodes in the center of the network usually have higher transmission efficiency and also afford higher loads. It may therefore be necessary to design special routing mechanisms to balance these loads.

B. Simulation Results

In order to illustrate the advantage show the performance of the proposed algorithm in this paper, we compare the JPRA algorithm with the SRRA algorithm presented in [11]. We consider 50 nodes randomly located in the area $[0,50]\times[0,50]$, following a uniform distribution. Both algorithms run for 10 time slots.

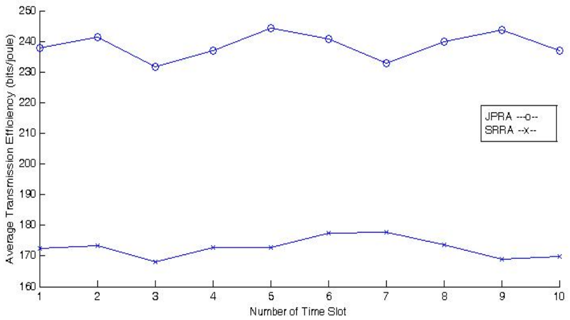

Figure 4. Transmission Efficiency in 10 Time Slots

The results show that the JPRA algorithm achieves an obvious improvement on network average transmission efficiency over the SRRA algorithm. SRRA algorithm is based on exploiting problem structure via the dual-decomposition method. It forms the dual problem by introducing Lagrange multipliers for the coupling constraints. However, in the JPRA algorithm, joint power and rate adjusting with a supermodular game approach is more agile, and there may emerge quasi-cooperation situation which achieves higher transmission efficiency. As a result, the JPRA algorithm with a supermodular game approach improves the transmission efficiency by about 33%.

VII. CONCLUTIONS

In this paper, we have presented a joint power and rate control adaptive algorithm (JPRA) for ad hoc networks. Each node chooses its own transmission power and rate based on limited environment information in order to achieve its own optimal transmission efficiency. We prove that this algorithm can be viewed as a supermodular game after a strategy space transformation in a fictitious game framework and it converges to the unique globally optimal transmission efficiency. Finally, the simulation results show that JPRA algorithm achieves a significant improvement over the SRRA algorithm in the transmission efficiency by about 33%.

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