

Rate Adaptation in Ad Hoc Networks Based on Pricing

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Abstract—Nodes in ad hoc networks are autonomous and self-configuring with no form of centralized administration such that nodes are free to selfishly optimize their individual utilities without considering utilities of other network users. This compels users to transmit at high power leading to abnormal interference in the network hence degrades network performance (i.e. low data rates, loss of connectivity among others). In this paper, we propose rate adaptation based on pricing (RAP) algorithm that incorporates penalty (pricing) obtruded to users' choices of transmission parameters to curb the self-interest behaviour. Therefore users determine their data rates and transmit power based on the perceived coupled interference at the intended receiver and the network cost charged by other network users. The proposed rate adaptation RAP is formulated as a network utility maximization (NUM) problem based on coupled interference minimization and solved using reverse engineering satisfying Karush-Kuhn-Tucker (KKT) conditions. The simulation results show that the proposed algorithm improves network performance compared to the legacy 802.11 standard.

Keywords: Coupled interference, data rates, transmit power, NUM, ad hoc network, pricing (cost), utility.

I. INTRODUCTION

Setting up wireless networks (WNs) and integrating them with existing networks is notably easy and cost effective e.g. in situations of emergency i.e., rescue missions, battle fields or in places with poor geographical terrain, hence the increase in popularity of these networks in the recent years. Owing to the success that has been realized in cellular networks, users tend to demand similar network services in WNs. This has lead to introduction of IEEE standards that supports higher data rates e.g. 802.11a/g/n. However, transmitting at these higher data rates are not always feasible due to decline in communication range that results from such data rates, and require high transmit power to sustain. Most of WN devices are portable gadgets that come with battery pre-installed. These batteries have limited life and hence need efficient power utilisation. Nevertheless, transmitting at low power results to weak received signal strength (RSS) and hence, low data rates. In addition, such scenarios are vulnerable to hidden node problem.

Consequently, to attain high data rates at low transmit power is a contradict objective that require that the sender adapt its transmission parameters depending on channel dynamics.

In this paper, we propose a distributed algorithm for rate adaptation in ad hoc networks based on pricing where users' attempt to selfishly maximize their individual utilities (data rates) is curbed by the cost function attached to their transmit power choices. In a nutshell, users are compelled to attain collective utilities due to forced cooperation such that a user increases utility of others as it increases its own utility. This is equivalent to a super-modular game [1][2], hence such a tool is used to analyse the optimality and convergence of the proposed algorithm.

Ad hoc networks are dynamic and distributed entities with no centralized controller where nodes need to adapt their transmission parameter depending on the channel status and network dynamics e.g. variation in node density, traffic, and mobility. Nodes are, therefore, free to determine their own transmission power and data rates to attain their target utility (desire). However, one of the challenges in ad hoc networks is to efficiently and fairly distribute the limited network resources (i.e. energy and bandwidth) being that users tend to selfishly maximize their utilities without considering utilities of other networks users. This often results to degradation of network performance. For instance, a user would transmit at maximum power levels possible even when lower power levels could sustain connectivity and successful transmission. Accordingly, the other users get obliged to increase their transmit powers, causing unnecessarily and abnormal interference in the network [3]. As mentioned priori, such a scenario leads to poor power efficiency, low data rates, lack of spatial reuse, and loss of connectivity. Therefore, there is need to encourage users to cooperate to attain global utility (and not only the local utility) by means of rewards (incentives) or pricing (costing).

In our approach, we propose data rate adaptation algorithm for ad hoc networks based on NUM problem formulated as a coupled interference minimization. A user selects the optimal transmission power depending on the link dynamics (i.e. coupled interference perceived at the intended receiver) and network cost attached to the selected transmit power. In a nutshell, users are aware of the current link status while determining the data rates. Due to unavoidable cost, users are obligated to cooperate such that a user maximizes utilities of other network users as it maximizes its own, thus,

improving global network performance. The formulated NUM problem is solved by localizing the global objective function and designing suitable message passing mechanism similar to approach proposed by [4][5].

The reminder of this paper is organized as follows: Section II reviews related works; Section III gives the problem formulation and the analysis of the proposed algorithm. Simulation test and results are presented in Section IV while Section V concludes this paper.

II. RELATED WORK

Rate adaptive WLAN stations select data transmission modulation scheme that maximizes the throughput for a given signal to interference plus noise ratio (SINR) such that if the RSS is high, data rate of the modulation scheme is equivalently increased and vice versa but maintaining certain bit or packet error probability. The basic idea of rate selection is to estimate the channel condition and adaptively select the best rate out of multiple available transmission rates [6]. A number of rate adaptation algorithms are considered in the literature e.g. auto rate fall-back mechanism that follows a trial and error approach to select the optimum modulation scheme. The data transmission is first tried with a high bit rate modulation scheme and reduced in cases of transmission errors. However, such schemes may not perform well in rapidly fluctuating channel since performance and efficiency of rate adaptation depend on the rate control parameters such as up/down thresholds. For example, fast-fading channels require a small value of up-threshold in order for the rate adaptation to keep up with the channel variations. Conversely, for slowly changing channels, the use of a large value of up-threshold can prevent excessive rate-increasing attempts [7].

Most practical rate adaptations focus on the time-varying characteristics of wireless channels, ignoring the impact of link-layer collisions. As a result, they may respond to frame collisions (that cannot be distinguished from channel errors based on missing acknowledgements (ACKs) alone) resulting in unnecessary rate down shift even when channel noise is low. This can significantly decrease throughput when transmission failures are caused by collisions [8].

The main objective is to find a solution (modulation adaptation) that dynamically adjust up or down thresholds that copes with channel dynamics [9] and [10] with minimal (if any) overhead to request-to-send/clear-to-send (RTS/CTS) control packets since as the number of contending stations increases, the number of collisions is also likely to increase triggering unnecessary - in fact, detrimental - rate-down shifts.

The classical way of performing link adaptation is to rely on feedback from the receiver. In such approach, the channel quality is estimated from SINR, RSS, or packet error rate measurements which is used to determine transmit rate or power for the subsequent transmissions [11][12]. Channel-driven rate and power adaptation algorithm in the generalized Nakagami fading channel considered by the authors of [13] adaptively adjust the transmission rate and power according to RSS (E_b/N_o) of CTS frame on an open-loop control

basis. The channel quality fluctuation is derived as a transition probability that is used to determine and evaluate the goodput and energy efficiency in a Nakagami fading channel. Transmit power and data rate are jointly adjust in [7] by considering link adaptation depending on the radio channel conditions based on the information available at the transmitter. However, in this approach the transmitter may unnecessarily adjust data rates when ACK may have not been received due to other reasons e.g. packet collision and not strictly changes in channel condition.

In [14] and [15], energy-efficient rate adaptation that dynamically selects a suitable modulation schemes based on channel state and network traffic is considered. The algorithms in [13][16] considers joint energy minimization and throughput maximization in the context that users are able to determine their power-rate combination depending on their interest. This approach is likely to result into selfish behaviours where individual users strive for their own utility maximization at the expense of others. In a nutshell, performing link adaptation involves estimating channel condition and selecting feasible data rate out of the multiple available transmission rates taking into account interference minimization and link quality [3][6].

In these algorithms, the NUM problem is formulated as a function of power and rate control strategy to optimize network performance without considering coupled interference minimization (reduction). The schemes assume that the power choices would always be optimal in terms of interference reduction.

Motivated by aforementioned properties of ad hoc networks and need to mitigate interference in such networks, we propose a rate adaptation algorithm based on link dynamics. In the proposed approach, coupled interference NUM problem formulated optimizes network performance by allowing users to determine data rates based on their local observations (i.e., channel condition). Therefore, a user's choice of data rate is a function of link dynamics and coupled interference that is controlled by attaching cost function to users transmission power choices. This obligates users to transmit at the least power that can sustain the intended transmission. Moreover, network users are obliged to cooperate thus maximizing both their local and global network utility.

III. SYSTEM MODEL

A. Background Information

Designing a distributed algorithm that attains global optimal NUM solutions is a challenge in ad hoc networks owing to the distributed and heterogeneous nature of these networks. Most of utility problem formulations considered in the literature ([16]-[19] and citations therein) concern uncoupled utilities where the local variables corresponding to one node do not directly affect the utilities of the other nodes. Systems with competition or cooperation, however, do not satisfy this assumption and the utilities are indeed coupled [20]. Solving these coupled utilities require that the coupling in the objective function be transferred to coupling in the constraints by introducing auxiliary variables and then

decoupled by dual/primal decomposition, and solved using consistency pricing [20][21]. However, consistency pricing employs significant message passing, hence, increases channel overhead. Moreover, it depends on convexity of the NUM problem. An intuitive and flexible approach that does not require convexity in NUM is considered in [4][5]. In this approach, the global objective function is localized (reverse-engineering) and limited message passing used. Thus such approach is adopted in our algorithm.

B. Problem Formulation

Consider an ad hoc network with I nodes where a given node i transmits to a node j on single hop in an environment where all the nodes can hear each other's transmissions and hence can interfere with the transmission. Normally, the link ij is subject to path loss, shadowing and multi path fading dynamics estimated using transmit power p_i at i and received power p_j at j as $p_j = h_{ij}p_i$ where h_{ij} is the channel gain (path loss) [3]. Notably, h_{ij} is not necessarily equal to h_{ji} since the channel condition is time variant. Further, transmit power p and data rate r are bounded by p_{min} , p_{max} and r_{min} , r_{max} values respectively. Half duplex model is assumed i.e., a user can either receive or transmit but not both simultaneously.

We formulate coupled interference minimization NUM problem where users determine transmit power to optimize their utilities based on local observations as in (1) given that every user's utility function $u_i(\gamma_i(p))$ is concave, differentiable and increasing function of the received SINR [5][21].

$$\max \sum_{i \in I} u_i(\gamma_i(p)) \quad (1)$$

such that

$$r_{min} \leq r \leq r_{max} \quad (2)$$

$$p_{min} \leq p \leq p_{max} \quad (3)$$

where $\gamma_i(p)$ is SINR on link ij given by $\gamma_{ij} = \frac{h_{ij}p_i}{\sum_{k \neq i,j} h_{kj}p_k + \eta_o}$.

In this expression, $\sum_{k \neq i,j} h_{kj}p_k$ is the sum of interference power I_{ij} at j due to transmissions of other network users other than the intended transmitter i while η_o is the thermal noise.

Due to existence of mutual interference, network users have coupled utility function that depends on both the user's local decision and that of other network users. Hence, we derive the NUM problem that attains global optimality from (1) as follows:

$$\max_{\{p: p_i \in p^{\forall i}\}} \sum_{i=1}^I u_i(\gamma_i(p)) \quad (4)$$

such that (2) and (3)

Since $U_i(\cdot)$ in (4) is concave in γ_i , we adopt reverse-engineering based on KKT conditions to solve the coupled objective function (4)[4][5][20][21]. Such approach localizes the NUM function (4) and uses limited message passing to inform users of their neighbour's utility choices.

C. Interference Cost Minimization

Define a power profile p such that $p \in \{p_i; p_{-i}\}$, power profile of user i as p_i and power profile for user i 's opponents as p_{-i} i.e., $p_{-i} = (p_1, \dots, p_{i-1}, p_{i+1}, \dots, p_I)$. The NUM can be modelled as a power control game $G = [I, \{p_i\}, \{u_i\}]$ where all the players, selects transmit power p_i that maximize their utilities u_i given that $u_i(i)$ represents user i 's pay-off (or reward/satisfaction). Then $i \in I$ maximizes its response (utility) as in (5) (ref.[17][18]).

$$\beta_n(p_{-i}) = \arg \max_{p_i \in p} u_i(\gamma_i(p_i, p_{-i})) \quad (5)$$

Assuming that p_{-i} is fixed, the reward $u_i(\gamma_i(p_i, p_{-i}))$ in (5) is strictly increasing with p_i .

Consider a non cooperative game (NCG) where users selfishly determine transmit power to maximize their utilities without considering other networks users' utilities, then a fixed point $p = p^*$ defined in (6) is the best operating point, Nash Equilibrium (NE)[13][19].

$$u_i(\gamma_i(p_i^*; p_{-i}^*)) \geq u_i(\gamma_i(p_i'; p_{-i}^*)) \quad (6)$$

where $p_i' \in p$ is any power chosen by i other than p^* in view of the fact that each user's reward $u_i(\gamma_i(p_i, p_{-i}))$ is strictly increasing with p_i for fixed p_{-i} [1][2][5].

Since pricing has effect of discouraging users' selfish behaviours but promoting cooperation, introduce penalty (cost) function to users' choices would improve the NE in (6). If the reward(utility) is defined as $f_i(\gamma_i)$ in (7), then users will be prompted to minimize the cost c in (7) attached to power choice p_i .

$$u_i(p_i, p_{-i}) = f_i(\gamma_i) - cp_i \quad (7)$$

Considering (7) as cost function penalized on user i for generating interference to other network users, i has to minimize the cost to maximize its utility. Since c depends on h_{ij} and network factor ε_j , (7) can be expressed as surplus function defined in (8) where $u_i(p_i, p_{-i}) = u_i(\gamma_i(p_i; p_{-i}))$ (i.e. expressing $u_i(p_i, p_{-i})$ as a function of γ_i) [4][5].

$$S_i(p_i; p_{-i}, \varepsilon_{-i}) = u_i(\gamma_i(p_i; p_{-i})) - p_i \sum_{j \neq i} \varepsilon_j h_{ij} \quad (8)$$

Lemma 1 (KKT Conditions) [4]: For any local optimal p^* of problem (4), there exist unique lagrange multipliers $\mu_{1,u}^*, \dots, \mu_{I,u}^*$ and $\mu_{1,g}^*, \dots, \mu_{I,g}^*$ such that for all $i \in I$,

$$\frac{\partial u_i(\gamma_i(p^*))}{\partial p_i} + \sum_{k \neq i} \frac{\partial u_k(\gamma_k(p^*))}{\partial p_k} = \mu_{i,u}^* - \mu_{i,g}^* \quad (9)$$

where

$$\mu_{i,u}^*(p_i^* - p_i^{\max}) = 0, \mu_{i,g}^*(p_i^{\min} - p_i^*) = 0, \mu_{i,u}^*, \mu_{i,g}^* \geq 0 \quad (10)$$

The KKT set of problem (4) need to contain all solutions that satisfy conditions (9) and (10) for all $i \in I$ [5]. We therefore need to design a distributed algorithm that converges to KKT set.

Let

$$\varepsilon_j(p_j, p_{-j}) = -\frac{\partial u_j(\gamma_j(p_j, p_{-j}))}{\partial I_j(p_{-j})} \quad (11)$$

$I_j(p_{-j})$ is locally measured total interference at user j given by $\sum_{i \neq j} p_i h_{ij}$. Notably, the cost function $\varepsilon_j(p_j, p_{-j})$ is always non-negative and represents user j 's marginal increase in utility per unit decrease in total interference. Using (11), condition (9) can be expressed as

$$\frac{\partial u_i(\gamma_i(p^*))}{\partial p_i} \sum_{k \neq i} \varepsilon_j(p_j^*, p_{-j}^*) h_{ik} = \mu_{i,u}^* - \mu_{i,g}^* \quad (12)$$

The reward is the product of the user's transmission power p and weighted sum of other users' prices defined in (8). The notation ε_{-j} is equal to the cost c in (7) and defines the penalty inflicted on network users for generating interference to user i , hence (12) is a necessary and sufficient optimality condition for the problem in which user i chooses transmit power $p_i \in p$ to maximize the surplus function

$$S_i(p_{-i}, \varepsilon_{-i}) = \min \left(\max \left(p_{\min}, \frac{p_i}{\gamma_i(p)} \left(\frac{p_i}{\gamma_i(p)} \left(\sum_{k \neq i} \varepsilon_i h_{ik} \right) \right) \right), p_{\max} \right) \quad (13)$$

where

$$\varepsilon_i(p) = \frac{\partial u_i(\gamma_i(p))}{\partial \gamma_i(p)} \frac{(\gamma_i(p))^2}{\beta p_i h_{ij}} \quad (14)$$

In the above expression, β is the spreading factor while $\frac{\partial u_i(\omega_i)}{\partial \omega_i}$ is given by $\frac{u_i(\omega_i^t) - u_i(\omega_i^{t-1})}{\omega_i^t - \omega_i^{t-1}}$ [4].

At an instance of time t , network users announce their cost in reference to (14) and adjust their transmit power taking into account network dynamics according to (13). The chosen power is constrained to (12) and as a result, an optimal localized distributive power algorithm with costing constraints is derived where the surplus function (13) and cost function (14) are derived from (8) and (11) respectively.

D. Rate Adaptation

From the SINR of the distributed coupled interference NUM strategy derived above, we determine the best constellation size for $M - QAM$ modulation supported by SINR (i.e., γ_i) in (13) and (14). Based on Shannon theory of communication ([12]), $M = 1 + \left(\frac{-\vartheta_1}{\ln(-\vartheta_2 BER)} \right) SINR$ where BER is the bit error rate while ϑ_1 and ϑ_2 are modulation type dependent constants. Let $\delta = \frac{-\vartheta_1}{\ln(\vartheta_2 BER)}$, then data rate r_i for transmit power p_i between transmitter i and receiver j is a function of $\gamma_i(p_i)$ given as $M = 1 + \delta \gamma_i(p_i)$ i.e.,

$$r = \frac{1}{T} \log_2(1 + \delta \gamma_i(p_i)) \approx r = \frac{1}{T} \log_2(\delta \gamma_i(p_i)) \quad (15)$$

where $\delta SINR \gg 1$ while $\frac{1}{T}$ is the bandwidth of the channel used for data transmission. When the signal level is much higher than the interference level or when the spreading gain is large, then r lies within (2).

E. Convergence and Optimality

By RAP, the derived solution is unique and optimal if the power vector $p = [p_{\min}, \dots, p_{\max}]$ exist for all the transmissions. In such a solution, an iterative power control algorithm $p(q+1) = I(p(q))$ is optimal if $\forall p \geq 0$, the following properties are observed [2][17].

- Positivity: $I(p) \geq 0$ and
- Monotonicity: if $p \geq p'$, then $I(p) \geq I(p')$ where $I(p)$ is the interference function.

Proposition 1: If RAP is optimal on $[p_i, \bar{p}_i] \forall i$, the interference function is defined as $I(p) = [I_1(p), I_2(p), \dots, I_n(p)]$ where $p = [p_{\min}, \dots, p_{\max}]$ and $I_i(p) = \gamma_i(p)$, then the following properties can deduced from γ_{ij} defined in (1).

The positivity is ensured since background noise $\eta_0 > 0$ and therefore $I(p) > 0$.

The monotonicity is guaranteed as well: $I(p) = \gamma_i(p_i) = \frac{SINR_i}{\psi_i}$ where $\psi_i = h_{ii} \left(\sum_{j=1, j \neq i}^K h_{ij} p_j + \eta_0 \right)$, we get $\psi_i(p) \leq \psi_i(p^*)$ for $p \leq p^*$. Since $\gamma_i(p_i)$ increases with increase in p_i on $[p_i, \bar{p}_i] \forall i$, $I(p)$ is increasing with p_i . Therefore, for a fixed price coefficient ε_{-i} , $I(p^*) \geq I(p)$.

We further analyse the optimality and uniqueness of RAP solution using super-modular game theory as follows:

Lemma 2 [1]: Let $X \subseteq \mathbb{R}$ and $T \subset \mathbb{R}^k$ for some k , a partial ordered set with the usual vector order. Let $f : X \times T \rightarrow \mathbb{R}$ be a twice continuously differential function. Then, the following statements are equivalent:

- The function f has increasing differences in (x, t) ,
- For all $t' \geq t$ and $x \in X$, we have $\frac{\partial f(x, t')}{\partial x} \geq \frac{\partial f(x, t)}{\partial x}$ and,
- For all $x \in X, t \in T$ and all $i=1, 2, \dots, k$, we have $\frac{\partial^2 f(x, t)}{\partial x \partial t_i} \geq 0$.

Theorem 1 Define $X \subseteq \mathbb{R}$ as a compact set and T as some partially ordered set. Assume that the function $f : X \times T \rightarrow \mathbb{R}$ is upper semi-continuous in x for all $t \in T$ and has increasing differences in (x, t) . Define $x(t) = \arg \max_{x \in X} f(x, t)$. Then, we have: for all $t \in T$, $x(t)$ is non-empty and has a greatest and least element, denoted by $\bar{x}(t)$ and $\underline{x}(t)$ respectively and, for all $t' \geq t$, $\bar{x}(t') \geq \bar{x}(t)$ and $\underline{x}(t') \geq \underline{x}(t)$ [1][2].

From lemma 2 and theorem 1, every user's utility function $u_i(p_i, p_{-i})$ has increasing differences in (p_i, p_{-i}) given that $\frac{-\gamma_i f_i''(\gamma_i)}{f_i'(\gamma_i)} \geq 1, \forall \gamma_i \geq 0$ hence the convergence.

Definition 1 [1]: Super modular games have the following properties:

- Pure strategy NE exists,
- The largest and smallest strategies are compatible with iterated strict dominance nationalization, correlated equilibrium, and NE are the same and,
- If a super modular game has a unique NE, it is dominance solvable (and lots of learning and adjustment rules converge to it, e.g., optimal (best) response dynamics).

Assume $(I, (p), (u_i))$ is a super modular game. Then $\beta_i(p_{-i})$ in (5) has a greatest and least element, denoted by

$\bar{\beta}_i(p_{-i})$ and $\beta_i(p_{-i})$, and if $p'_{-i} \geq p_{-i}$ then $\bar{\beta}_i(p'_{-i}) \geq \bar{\beta}_i(p_{-i})$ and $\underline{\beta}_i(p'_{-i}) \geq \underline{\beta}_i(p_{-i})$ [1][15]

This implies that each player's best response is increasing in the actions of other players. The set of strategies that survive iterated strict dominance (i.e., iterated elimination of strictly dominated strategies) has greatest and least elements \bar{p} and \underline{p} , which are both pure strategy in NE. Since (5) satisfies all the conditions of a super modular game, the solution derived from (5) is optimal. Comprehensive definition and formulation of super-modular game theory can be found in [1][2][5].

F. RAP Algorithm

- 1) **At time $t = 0$, do**
 - a) **For user $i : N$**
 - i) Initialize power $p(t)$ and cost $\varepsilon_{-j}(t)$ such that $p(t), \varepsilon_{-j}(t) > 0$
 - ii) Determine data rate $r(t)$ according to (15)
 - b) **End for**
- 2) **For $t = 1 : end_of_communication$, do**
 - a) **For user $i : N$**
 - i) Update and advertise cost $\varepsilon_{-j}(t)$ according to (14)
 - ii) Update power $p(t)$ according to (13)
 - iii) Determine data rate $r(t)$ according to (15)
 - b) **End for**

IV. SIMULATION TEST AND RESULTS

Simulation is performed in MATLAB considering simulation parameters in table I where only transmitter Tx and receiver Rx are assumed to transmit while other network users are actively interfering. It is further summed that all transmissions are successful.

TABLE I
SIMULATION PARAMETERS

Parameter	Values
Thermal noise	-96dB
Simulation area	20m by 20m
Radio propagation model	Free space
Number of nodes	32
Number of transmissions	50
P_{max}	10dBm
P_{min}	5dBm
Spreading factor, β	5
Initial cost	0.1
Utility function, $u_i(\gamma_i)$	$\log(\gamma_i)$
Channel bandwidth	20MHz
Speed of mobility	10km/s
Interval of mobility	After 2 transmission

Two scenarios as considered: scenario 1 reflects a stationary network where all the users are static while scenario 2 considers random movement. $Tx - Rx$ pair moves in the same direction while the other network users move on a predefined trajectory whereby the distance of separation between $Tx - Rx$ and other network users always increases with increase in transmission. We compare the performance of RAP to both

IEEE 802.11 and adaptive auto response power and rate control algorithm (LP) proposed by [7].

It is observed that RAP achieves high data rates at minimal transmission power (thus minimal interference) in all the runs compared to both 802.11 and LP. The pricing mechanism in effect drives the power selection choice in RAP to the most cost effective option. At the beginning, high transmit power is employed owing to limited channel condition information available to Tx . As the other users advertises their network costs, Tx is able to determine the most feasible transmit power for the subsequent transmissions till most optimal transmission power is attained. This is the NE. The improvement on RAP compared to LP and 802.11 is that RAP transmits at optimal power just enough to sustain connectivity and correct decoding of the packets at Rx .

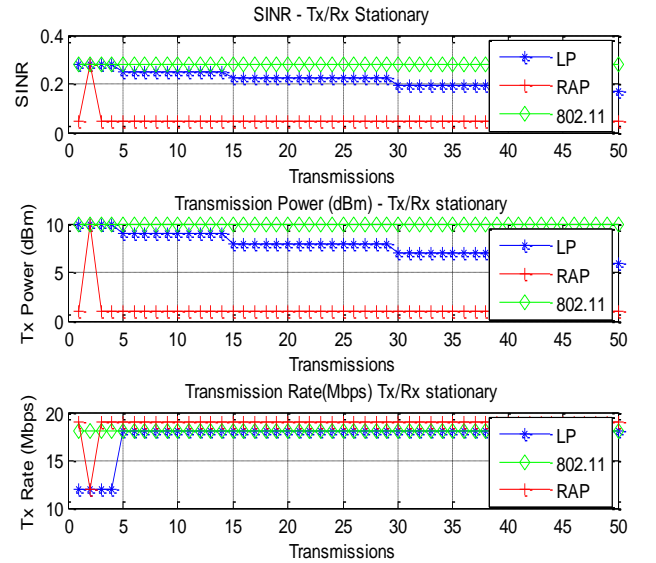


Fig. 1. Stationary Users

Similar to figure 1, 802.11 records better SINR performance than RAP in figure 2 since 802.11 scheme employs maximum allowable power throughout the transmission with no much attention to link dynamics. However, in RAP, transmit power is adjusted depending on the network channel status. Moreover, users are restricted from using high transmit powers (unless deemed necessary) as this would result to high interference cost and thus lowers the user's utility. As a result, minimal power level that can sustain the connectivity and ensures correct delivery of data frames is always chosen. Further, 802.11 has constant SINR throughout the transmission process due to its fixed single power choice. The power level that RAP settles on is apparently the most optimal power that

maximizes both local and global utility based on the network conditions. 802.11 has no effect of reducing interference in the network thus users are at will to use feasible transmit power to maximize their utility without consideration to other users' utilities. After few iterations, RAP converges to NE

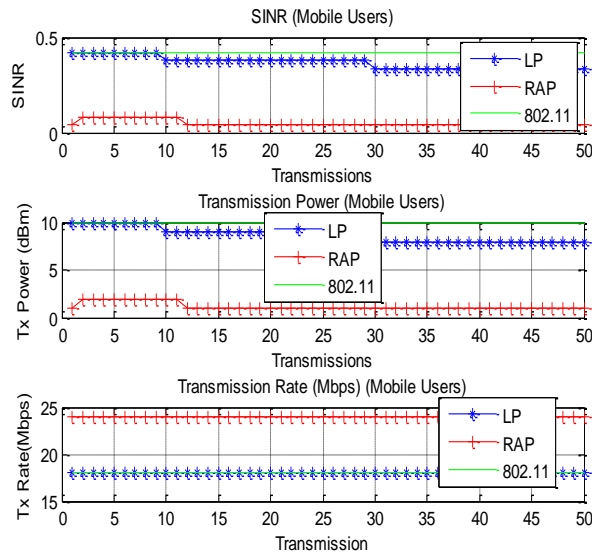


Fig. 2. Mobile Users

transmit power where interference cost function is always minimized while reward function (data rate) is maximized hence improving network performance.

V. CONCLUSION

In this paper, rate adaptation algorithm based on pricing (cost/penalty) in ad hoc networks is proposed. Transmission power choices of users in the network are dynamically adjusted to control the influence of coupled interference. Such dynamic adjustments exploit the locally available network link conditions and interference cost penalties attached to that transmit power choice. Therefore the users are conversant with the link conditions as they determine data rates. This results to a super-modular game equivalence where users maximize utility of other users as they maximize their own due to the inevitable cooperation, hence, improving a collective network performance (utility). Future work may consider cross layering optimization whereby packet routing is incorporated in the model. Further, proposed model may need to consider different properties of network nodes (e.g. energy consumption e.t.c).

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