Coupled Interference Based Rate Adaptation in Ad Hoc Networks

Fredrick Awuor *, Karim Djouani *IEEE Member*†, Guillaume Noel‡, Thomas Olwal *IEEE Member*§

*†‡Department of Electrical Engineering,
*†‡French South African Institute of Technology (FSATI),
*†‡Tshwane University of Technology, Private Bag X680 Pretoria 0001, South Africa
§CSIR Meraka Institute, P.O. Box 395, Pretoria 0001, South Africa
*kamfredy@gmail.com, †djouanik@tut.ac.za, ‡noelg@tut.ac.za, §tolwal@csir.co.za

Abstract—**Link adaptation provides an efficient and flexible strategy to adapt transmission rates based on channel conditions. To attain distributed optimal local and global utility, network interference need to be mitigated therein allowing the users to transmit at the minimum transmission power enough to sustain connectivity. This paper proposes coupled interference network utility maximization (NUM) strategy (i.e. CIN) for rate adaptation in WLANs that is solved using "reverse-engineering" based on Karush-Kuhn-Tucker (KKT) conditions. The users determine data rates based on their local observations (i.e. coupled interference). Both pricing and limited message passing mechanisms are employed in the NUM wherein pricing restrict users from self-interest behaviours while limited message passing assist users to announce their prices and transmit powers. It is demonstrated theoretically that CIN satisfies the conditions of the super-modular games and that its solution is optimal. Simulation results show that adapting data rates based on the link conditions can improve the performance of ad hoc networks.**

I. Introduction

Though reducing interference by employing power control increases system capacity, this has effect of yielding low signal to interference plus noise ratio (SINR) which results from the weak received signal. This consequently leads to low data rate; increase in interference range and hence increase in hidden node problem. Degrading of performance in WLAN is often due to fading, multi-path, path loss and user mobility which is commonly handled by adjusting data rates to a more error-resistant rate. Considering ideal channel condition, optimal throughput is easily achieved by transmitting at high data rates so long as the sender and the receiver are within the transmission range. Nevertheless, since transmission channels are susceptible to errors, realizing optimal throughput requires reliable transmissions that are achievable only at low data rates. Therefore, efficient link adaptation algorithm need to recognize the right time when it is advantageous to either increase or decrease the data rates for optimal performance based on the channel conditions[1].

In ad hoc networks, nodes are distributive and self-configuring and may decide to cooperate to attain global utility or to act selfishly to attaining self maximal utility without considering other users' utilities. In case of cooperation, message exchange may be employed to enhance communication among the network users such that users are able to select their utilities based on other users' choices[2]. Transmitting at high power reduces network lifetime resulting to failure in network connectivity. Moreover, high transmit powers degrade channel reuse and results to interference problem (co-channel and adjacent channel interferences[3]. The major challenge in ad hoc networks is how to mitigate interference caused by the transmitting nodes since this influences the link condition and hence the choice of data rates.

Ad hoc networks are dynamic and scalability entities that autonomously adapt to changes in topology, nodes entering the network (i.e. increasing interference) and nodes leaving the network due to poor connectivity or energy diminution. Motivated by mentioned properties, the proposed coupled interference NUM strategy optimizes the performance of ad hoc network by allowing network users to determine optimal data rates based on their local observations (i.e. coupled interference). 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 a user's transmit power choice. This compels users to transmit at the least power that can sustain the intended transmission. As a result, network users are obliged to cooperate to maximize their utilities and consequently maximizing the global network utility.

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

II. Related Work

An efficient rate-adaptation scheme need to keep track of the channel dynamics and react to channel changes by selecting an appropriate transmission rate. Common approaches to estimate channel conditions are either based on transmission history (acknowledgement (ACK) of the previous transmission), received signal strength (RSS)[4] or SINR and noise at the receiver[3]. However, SINR based schemes outperforms both RSS and ACK due to its robustness and quicker response to link dynamics therein providing accurate channel state information. ACK based rate adaptation scheme e.g. Auto Rate Fall-back (ARF), Adaptive ARF performs rate shift based on successful (or failure) of frame delivery which reflects the channel statues during the previous transmission and may not necessarily reflect the current channel statues since the channel condition is time variant [5], [6]. Hence CIN considers link adaptation based on SINR performance to derive transmit power that minimizes coupled interference in the network.

In [5], an algorithm is proposed where an average value of SINR for a set of 10 frames is calculated at the receiver and conveyed back to the sender to assist determine the data rate for the subsequent transmissions. The authors in [6] proposes pre-calculation algorithm for rate selection where PHY mode table is indexed by the system status i.e. channel condition. Each entry in the table is presumed the optimal PHY mode that optimizes throughput. However, this is an offline algorithm that requires strict condition that the sender perceives exact channel condition variance for proper choice of PHY mode. In [7], rate adaptation scheme is proposed wherein nodes select the power-rate pair to maximize their utility based on the previous measured SINRs. The values of SINR employed by [5],[6] and [7] may not be reactive to link dynamics since the perceived SINR is captured from the previous transmissions and not as a function of the current transmission interference or power thus the information could be stale.

In our proposed, coupled interference is controlled by dynamically adjusting network users' transmit power choices based on the network link conditions and interference cost penalties attached to that transmit power choice. The users are therefore aware of the current link status while determining their data rates. In addition, every user maximizes utility of other users as it maximize its own due to the forced cooperation, hence, improving network performance.

III. Coupled Interference Based Rate Adaptation

A. System Model

Consider an ad hoc network with N stations where the sender i communicates to receiver j on a single hop. It is assumed that all the stations can hear transmissions from each other such that a user's transmission interferes with other users in the network. Ordinarily, the link between i and j is subject to path loss, shadowing and multi path fading dynamics[8]. Further, consider p as a set of discrete power levels $p = \{p_{\min}, p_1, p_2 ..., p_{\max}\}$ constrained by minimum and maximum transmit power allowed to transmitter i while transmission rate is a set of definite values $r = \{r_{\min}, r_1, r_2 ..., r_{\max}\}$ where $r_{\min}$ and $r_{\max}$ are the maximum and the minimum data rates respectively possible in the network. These rate and power sets are assumed identical to all users in the network. The channel gain between transmitter i and receiver j is given as G_{ij}

$$p_j = G_{ij} p_i \tag{1}$$

where $i, j \in N$, p_j is the received power at j while and p_i is transmit power for transmitter i. Notably, G_{ij} is not necessarily equal to G_{ji} since the channel condition is time variant. Half duplex model is assumed i.e. a user can either receive or transmit but not both simultaneously.

The objective is to determine a user's power choice that optimizes local utility with minimal coupled interference considering that other network users equally want to optimize their utility and therefore there exist interference cost in all the transmissions. User utility function $u_n(\gamma_n(p))$ for user $n \in N$ is strictly concave, differentiable and increasing function of the received SINR [7], [9], [18]. The NUM problem based on the coupled interference can therefore be formulated as follows:

$$\max \sum_{n \in N} u_n(\gamma_n(p)) \tag{2}$$

such that

$$r_{\min} \leq r \leq r_{\max} \forall N \tag{3}$$

$$p_{\min} \leq p \leq p_{\max} \forall N \tag{4}$$

where SINR, $\gamma_n(p)$ is given by

$$\gamma_{ij} = \frac{G_{ij} p_i}{\sum\limits_{k \neq i,j} G_{kj} p_k + \eta_o} \tag{5}$$

$\sum\limits_{k \neq i,j} G_{kj} p_k$ is the sum of interference power I_{ij} at node j due to communication of other users in the network other than i. η_o is the thermal noise, G_{ij} is the channel gain while p_i is the transmit power used by i to communicate to j.

B. Coupled Interference Minimization

Every network user has a coupled utility function - due to existence of mutual interference - that depends on both the user's local decision and other users' decisions in the network. We can therefore derive NUM problem that all users must maximize to attain both local and global optimality from (2) as follows:

$$\max_{\{p : p_i \in P \forall n\}} \sum_{n=1}^{N} u_n \left(\gamma_n \left(p \right) \right) \tag{6}$$

such that (3) *and* (4)

The problem in (6) is a coupled objective function which requires "consistency pricing" [17] or dual decomposition[10] approaches to solve. However, these approaches employs significant message passing before the users can derive optimal decision. Moreover, they require strict convexity in the NUM problem whereas $U_k(.)$ in (6) is concave in γ_n. We therefore adopt reverse-engineering based on KKT conditions proposed in [9], [11] where the network objective function is localized and limited message passing used to keep user's aware of their neighbour's utility choices.

Define p_i as the power profile of user i in the network and p_{-i} as the power profile for user i's opponents i.e. $p_{-i} = (p_1, ..., p_{i-1}, p_{i+1}, ..., p_n)$ such that $p \in \{p_i; p_{-i}\}$. The utility maximization for such a network can be modelled as a power control game $G = [N, \{p_i\}, \{u_i\}]$ where all the players, $N = n$ selects transmit power p_i that maximize their utility u_i given that $u_i(i)$ represents user i's pay-off (or reward). Then user

i's optimal response is p_i that maximizes its utility u_i given by $u_i(\gamma_i(p_i, p_{-i}))$ formulated as (7) (ref.[12], [13]).

$$\beta_n(p_{-i}) = \underset{p_i \in p}{\arg\max}\, u_i(\gamma_i(p_i, p_{-i})) \tag{7}$$

Assuming fixed p_{-i}, reward $u_i(\gamma_i(p_i, p_{-i}))$ in (7) is strictly increasing with p_i.

In view of a Non Cooperative Game (NCG) where players selfishly select optimal power levels to maximize their rewards at the expense of others players, a fixed point $p = p^*$ defined by (8) is the nash equilibrium (NE)[18].

$$u_i\left(\gamma_i\left(p_i^*; p_{-i}^*\right)\right) \geq u_i\left(\gamma_i\left(p_i^{'}; p_{-i}^{'}\right)\right) \tag{8}$$

where $p' \in p$ is any power chosen by any user 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} [7], [9].

Since the NE in (8) may not necessarily be the social optimal operating point, introducing pricing in a user's choice can assist to achieve both local and global optimality given that pricing has effect of discouraging user's selfish behaviours but promoting user's cooperation. Therefore if $f_i(\gamma_i)$ in (9) is the reward/pay-off for choosing transmit power p_i, every network user will strive to minimize its cost c in (9) attached to transmitting with p_i.

$$u_i(p_i, p_{-i}) = f_i(\gamma_i) - cp_i \tag{9}$$

Considering (9) as cost function obtruded to user i for generating interference to other network users, user i have to minimize the cost it pays to other network users for it to maximizes its utility. Rewriting $u_i(p_i, p_{-i})$ as a function of γ_i, results to $u_i(p_i, p_{-i}) = u_i(\gamma_i(p_i; p_{-i}))$, and since the cost c depends on G_{ij} and network factor ε_j, we can rewrite cost function (9) as a surplus function below:

$$S_i(p_i; p_{-i}, \varepsilon_{-i}) = u_i(\gamma_i(p_i; p_{-i})) - p_i \sum_{j \neq i} \varepsilon_j G_{ij} \tag{10}$$

Lemma 1 (KKT conditions) [9]: For any local optimal p^* of problem (6), there exist unique lagrange multipliers $\mu_{1,u}^*, ..., \mu_{I,u}^*$ and $\mu_{1,g}^*, ..., \mu_{I,g}^*$ such that for all $n \in N$,

$$\frac{\partial u_i\left(\gamma_i\left(p^*\right)\right)}{\partial p_i} + \sum_{k \neq i} \frac{\partial u_k\left(\gamma_k\left(p^*\right)\right)}{\partial p_k} = \mu_{i,u}^* - \mu_{g,u}^* \tag{11}$$

where

$$\mu_{i,u}^*\left(p_i^* - p_i^{\max}\right) = 0, \mu_{i,g}^*\left(p_i^{\max} - p_i^*\right) = 0, \mu_{i,u}^*, \mu_{g,u}^* \geq 0 \tag{12}$$

The KKT set of problem (6) need to contains all solutions that satisfy conditions (11) and (12) for all $n \in N$ [11]. We therefore need to design a distributed algorithm that converges to KKT set. Substituting (11) in (6), the KKT condition for user i can be expressed as

$$\frac{\partial u_i\left(\gamma_i\left(p^*\right)\right)}{\partial p_i} \sum_{k \neq i} \varepsilon_j\left(p_j^*, p_{-j}^*\right) G_{i,j} = \mu_{i,u}^* - \mu_{g,u}^* \tag{13}$$

where

$$\varepsilon_j(p_j, p_{-j}) = -\frac{\partial u_j\left(\gamma_j\left(p_j, p_{-j}\right)\right)}{\partial I_j(p_{-j})} \tag{14}$$

$I_y(p_{-y})$ is locally measured total interference at user j given by $\sum_{i \neq j} p_i G_{ij}$. Notably, the cost function $\varepsilon_j(p_j, p_{-j})$ is always non-negative and represents user js marginal increase in utility per unit decrease in total interference. The reward is the product of users transmission power p and weighted sum of other users' prices defined in (10). ε_{-j} is equal to c in (9) and defines the penalty inflicted on network users for generating interference to user i, hence (13) is an acceptable optimal condition for the problem in which each user i chooses transmit power $p_i \in p$ to maximize its surplus function (10)[11] compared to NE in (8).

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 (10). The chosen power is constrained to (13) and as a result, an optimal localized distributive power algorithm with costing constrains is derived. The surplus in (10) and cost function (14) can be formulated as function of the desired power p_i and SINR as in (15) and (16) respectively.

$$S_i(p_{-i}, \varepsilon_{-i}) =$$
$$\min\left(\max\left(p_{\min}, \frac{p_i}{\gamma_i(p)}\left(\frac{p_i}{\gamma_i(p)}\left(\sum_{k \neq i} \varepsilon_i G_{ik}\right)\right)\right), p_{\max}\right) \tag{15}$$

$$\varepsilon_i(p) = \frac{\partial u_i(\gamma_i(p))}{\partial \gamma_i(p)} \frac{(\gamma_i(p))^2}{\beta p_i G_{ij}} \tag{16}$$

where β is the spreading factor while $\frac{\partial u_i(\omega_i)}{\partial \omega_i}$ is given by $\frac{u_i(\omega_i^t) - u_i(\omega_i^{t-1})}{\omega_i^t - \omega_i^{t-1}}$ [18].

C. Link Adaptation

From the SINRs of the distributive pricing power control algorithm above, best constellation size for $M - QAM$ modulation that is supported by SINR (i.e.γ_i) in (15) and (16) is determined. From Shannon theory of communication ([14]) we can deduce the following: $M = 1 + \left(\frac{-\vartheta_1}{ln - \vartheta_2 BER)}\right) SINR$ 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 the sender i and receiver j is a function of $\gamma_i(p)$ given as $M = 1 + \delta\gamma_i(p)$ and hence

$$r_i = \frac{1}{T}\log_2\left(1 + \delta\gamma_i(p)\right) \approx r_i = \frac{1}{T}\log_2\left(\delta\gamma_i(p)\right) \tag{17}$$

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_i lies within (3).

D. CIN Algorithm

1) Let time $t = 0$
2) For user $i : k$
    a) Initialize power $p(x)$ and cost $\varepsilon_{-j}(x)$, $p(x), \varepsilon_{-j}(x) > 0$
    b) Determine data rate $r(x)$ according to (17)
3) End if
4) For $t = 1 : end\_of\_communication$
    a) For user $i : k$
        i) Update and advertise cost ε_{-j} according to (16)
        ii) Update power $p(x)$ according to (15)
        iii) Determine data rate $r(x)$ according to (17)
    b) End if
5) End if

E. Convergence and Optimality of CIN

By CIN, a the derived solution is unique and optimal if the power vector $p = [p_{\min}, ..., p_{\max}]$ 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 [7].

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

Preposition 1: If CIN is optimal on $\left[\underline{p_i}, \overline{p_i}\right] \forall i$, the interference function is defined as $I(p) = [I_1(p), I_2(p), ..., I_n(p),]$ where $p = [p_{\min}, ..., p_{\max}]$ and $I_i(p) = \gamma_i(p)$, then the following properties can deduced from (5). There exist positivity since background noise $\eta_0 > 0$ and therefore $I(p) > 0$. There exist monotonicity as shown: $I(p) = \gamma_i(p_i) = \frac{SINR_i}{\psi_i}$ where $\psi_i = G_{ii}\left(\sum_{j=1, j\neq i}^{K} G_{ij}p_j + \eta_0\right)$, 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 $\left[\underline{p_i}, \overline{p_i}\right] \forall i, I(p)$ is increasing with p_i. Therefore, for a fixed price coefficient ε_{-i}, $I(p^*) \geq I(p)$. The optimality and uniqueness of CIN solution is further analysed using super-modular game theory in the appendix.

IV. Simulation Test and Results

Simulation is performed in MATLAB with 32 nodes randomly placed in a $20m \times 20m$ field free of obstacles. It's assumed that only Tx and Rx are transmitting while the other network users are actively interfering. Performance metrics are evaluated for 50 independent runs (transmissions). For all the simulations, we assume single hop with the following simulation parameters: path loss model exponent = 1, AWGN = -96dB, P_{max} = 10dB, P_{min} = 1dB, initial cost = 0.1 and utility function, $u_i(\gamma_i)$ is given by $\log(\gamma_i)$. It is further summed that all transmissions are successful. Channel bandwidth of *20MHz* and spreading factor, $\beta = 5$ is also assumed. 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. The interval of mobility is after 2 transmissions at a velocity of $20kmph$.

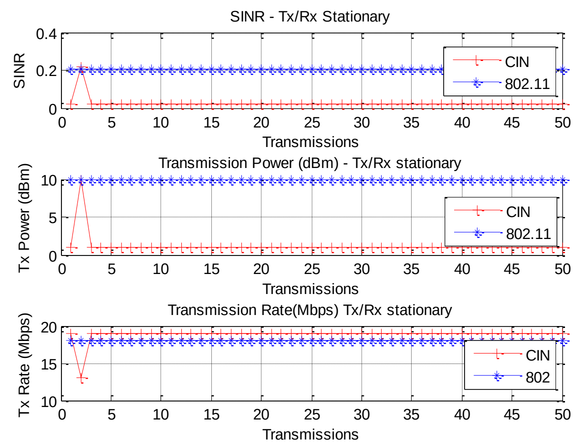

Fig. 1. Stationary Users

In all the runs, it's observed that CIN attains the higher data rates at minimal transmission power compared to the legend 802.11. The costing mechanism drives the power selection response in CIN to the most cost effective option. At the beginning, transmission power hikes due to limited information available to Tx on the channel conditions. As the other users advertises their network costs, Tx determines the most appropriate power level for the subsequent transmissions till most optimal transmission power is attained. This is the NE. 802.11 transmit at higher power levels and hence attains higher SINR than CIN. However, CIN still attains the higher data rate which is the global data rate for the network. The improvement on CIN compared to 802.11 is that CIN operates at optimal power just enough for the transmission packets to be decoded at the Rx.

Similar to figure 1, 802.11 records better SINR performance than CIN in figure 2. 802.11 employs maximum allowable power throughout the transmission process without taking into account channel conditions. In CIN, power is adjusted depending on the network conditions and the users are restricted from using higher transmit powers 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 delivery of data frames is always chosen and hence the low SINR in CIN. The single power choice made by 802.11 makes it to have a constant maximum SINR throughout the transmission process. The power level that CIN settles on is apparently the most optimal power that maximizes both local and global utility based on the network conditions. 802.11 have no effect of reducing interference in the network thus users are

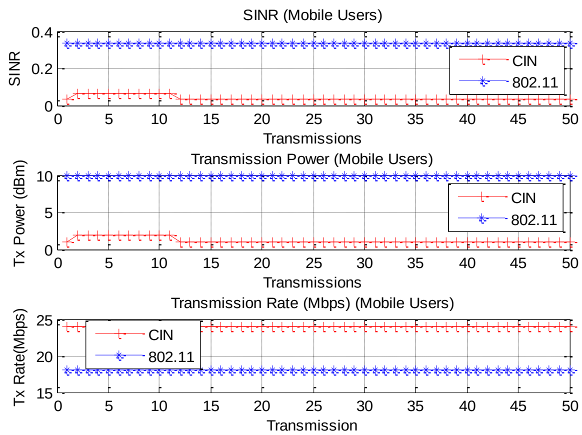

Fig. 2. Mobile Users

at will to use power levels that maximize their utility without considering others.

After few iterations, CIN converges to NE transmit power where interference cost function is always minimized while reward function (data rate) is maximized hence improving network performance.

V. Conclusion

This paper proposes a distributive algorithm that adapts data rates based on coupled user interference in the network. Users are obligated to transmit at minimum cost (interference) by employing minimum power that can sustain successful transmission between the transmitter and receiver to maximize its utility. The NUM problem is formulated as coupled interference minimization strategy subject to channel condition dynamics. Reverse-engineering based on KKT conditions is used to solve the NUM problem with limited message passing to update user's of their neighbour's utility choices. The simulation results shows that penalizing selfish behaviours of users in the network can improve network performance since every user aims to transmit at NE.

VI. Appendix

Lemma 2 [15]: Let $X \subseteq \mathbb{R}$ and $T \subset \mathbb{R}^k$ for some k, a partial ordered set with the usual vector order. Let $f : X \times T \to \mathbb{R}$ 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,...,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 $f : X \times T \to \mathbb{R}$ is upper semi-continuous in x for all $t \in T$ and has increasing differences in (x, t). Define $x(t) = \arg\max_{x \in \mathrm{X}} f(x, t)$. Then, we have: for all $t \in T$, $x(t)$ is non-empty and has a greatest and least element, denoted by $\overline{x}(t)$ and $\underline{x}(t)$ respectively and, for all $t' \geq t$, $\overline{x}(t') \geq \overline{x}(t)$ and $\underline{x}(t') \geq \underline{x}(t)$.

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 [15]: Super modular games have the following properties:

- Pure strategy NE exist.
- The largest and smallest strategies are compatible with iterated strict dominance nationalization, correlated equilibrium, and NE are the same.
- 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 $B_i(p_{-i})$ in (7) has a greatest and least element, denoted by $\overline{B_i}(p_{-i})$ and $\underline{B_i}(p_{-i})$, and if $p'_{-i} \geq p_{-i}$ then $\overline{B_i}(p'_{-i}) \geq \overline{B_i}(p_{-i})$ and $\underline{B_{-i}}(p'_{-i}) \geq \underline{B_{-i}}(p_{-i})$ [15], [16]

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 $\overline{p}$ and $\underline{p}$, which are both pure strategy in Nash Equilibrium. Since (7) satisfies all the conditions of a super modular game, the solution derived from (7) is optimal.

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Fredrick Awuor received his BSc. in Computer Science in 2008 from Moi University, Kenya. He is currently pursuing Masters degree at FSATI/Tshwane University of Technology, South Africa. His research interests are in the area of resource allocation and link adaptation in wireless networks.