Vertical Handover Between Wireless Service Providers

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***Abstract*—We discuss the dynamics of user handover between two coexisting wireless service providers and analyze the consequent exploitation of the offered diversity by the use of multi-standard terminals. We show that the potential capacity benefits of mobile-initiated vertical handovers (VHO) are substantial, but it is important to choose the correct VHO criteria in order to achieve optimum load balancing and equilibrium states (both globally and socially). A fast-handover scheme, based on replicator dynamics is presented, which exhibits fast convergence to the socially optimal states by allowing only a subset of the necessary VHOs among the air interfaces to take place.**

I. Introduction

Given the massive deployment of wireless networks, it is common for mobile users to have several choices of collocated WLANs to connect to. This phenomenon is made especially evident by the large scale appearance of 3G systems operated by major networks. In fact, mobile user chips which support multiple standards already exist and, additionally, there has been a significant amount of work in creating flexible radio devices capable of connecting to *any* existing standard [1]. It is therefore reasonable to expect that in the near future users will have the option to connect to different networks and to switch dynamically between them on a real-time basis, based on the offered throughput and/or price.

The dynamics of this process has several interesting aspects. Firstly, with no central authority to moderate and shepherd the users’ s selfish behavior, there is the very real danger of total lack of coordination between the users, leading to frustration and suboptimal performance. Moreover, even though users now have more choices to connect to, the (finite) resources of nearby access points (AP’s) still remain an object of competition.

It is clear from the above that this process can be modelled in terms of a non-cooperative game. Of course, this is not a novel idea in and by itself: an excellent survey of applications of game theory to networking appears in [2]. For example, uncoordinated random access channels have been analyzed by optimizing their transmission probabilities [3], or their power control [4]; another application is in CDMA systems (e.g. [5]–[7]); and, in the direction of connecting to multiple wireless nodes, [8] considered the possibility of connecting to several 802.11 APs using a single WLAN card.

In this paper we analyze instead the dynamics of vertical handover between service providers possibly employing different standards.[1] We will be assuming that users can switch air interfaces in the time-scale of hundreds of milliseconds and call this scheme multi-mode operation (MMO), as opposed to single mode operation where users are not capable to handover between air interfaces (AIs). We thus postulate that parallel connections to both AIs are available, allowing each user to switch between AIs at rates faster than the typical session duration. Due to the limited processing capabilities at the terminal, it will only be able to process and thus accept data from only one AI. Nevertheless, we will assume that it can receive a small amount of data from both AIs, in order to acquire knowledge of its possible throughput from both AIs. Also, we will consider the handover rate to be small enough so as to allow the user to feel the effect of the presence of other users connected to that interface.

Specifically, we first introduce an asymmetric congestion game to model our network, and we determine that the game admits an essentially unique Nash equilibrium in pure strategies. Of course, the existence of a pure Nash equilibrium in games of this type has been proven in [9], but the proof employed there is not well suited

[1]The results presented here were obtained within the EU-IST-2006 27960 project URANUS, with aim to design universal transceiver structures, capable of switching among different air interfaces and modes using a Generalized Multicarrier Representation (GMCR) of signal waveforms.

to our needs since it requires the users to be capable of solving an exponentially complex problem in real time. Moreover, the approach of [9] does not yield any insight in the structure of the pure equilibria in terms of the macroscopic parameters of the game (e.g. it is not at all clear how to obtain even the users' population per AI) and uniqueness issues are not discussed at all. Instead, we follow a different approach with which we completely characterize with the pure equilibria completely in terms of the game's parameters.

To facilitate the players to converge to this equilibrial state, we propose an iterative scheme following the dynamics of the so-called *logit* model [10], in which each user rates the AI's according to his connection satisfaction. We show that this approach allows the system to converge to a pure Nash equilibrium (whose existence and essential uniqueness will be already established), even in the presence of fading, wherein this equilibrium state differs greatly from one instance to the next. Remarkably, for relatively slow fading, we see that the users learn to adapt quickly enough and remain very close to this equilibrium state, despite its quickly-changing nature.

Finally, we calculate the globally optimal state, wherein the aggregate throughput is maximized. For the realistic well-behaved distributions of users considered here we find that the optimal states lie at the edges of the bid space, i.e. when (almost) all users pile up to one or the other service provider. This result highlights the unstable nature of the optimal state, from which (almost) every user will want to defect. Based on the above, we calculate the game's *efficiency level* which is the inverse of the well-known *price of anarchy* introduced in [11]; in short, we calculate the ratio of the aggregate throughput in the evolutionarily stable user distribution to the one achieved at the optimal state. In this way, we obtain a sense of how efficient the "stable" distribution of Nash really is, a sense which we illustrate with the help of numberical simulations.

II. System Model

Our system model will consist of two overlapping access points belonging to two distinct standards. The users, wishing to connect to one of the service providers, have the capability to monitor both of them and are able to switch when they deem it advantageous to do so. We also assume that there are MAC schedulers at every base that, over an intermediate time-scale, allow each user to use the channel and transmit by taking into account the number of users connected to the given base and its own channel conditions. Specifically, if user i connects to base $r = \pm$, we will model his throughput by:

$$T_i^{\pm} = \frac{c_i^{\pm}}{N_{\pm}} \tag{1}$$

where $N_{\pm}$ is the number of users that connected to $\pm$ and $c_i^{\pm} = \log_2(1+SNR_i^{\pm})$ is the throughput the user connected to AP $r =$"$\pm$" would experience in the absence of other users.

Despite the fact that this seems like a very naïve model for the throughput, it has been shown to be of the correct form for TCP and UDP protocols in IEEE802.11 systems [12], if we limit ourselves to a single class of users. Furthermore, in the case of third-generation best effort systems, the realistic total cell-service throughput is approximately constant beyond a certain number of connected users (see e.g. [13], [14]). Also, this formula is strictly valid in the round-robin scheduling case, but the functional form of the user-perceived throughput on the instantaneous SNR and system load N is similar in other scheduling systems (e.g. proportional fairness). Moreover, the association of $c_i^{\pm}$ with the instantaneous Shannon capacity is not always valid, since the above model for the perceived user-throughput is averaged over several time windows. Hence, in this case, $c_i^{\pm}$ should be replaced by the time-averaged goodput, but we will not make this distinction here.

III. The Optimal State

We will now describe how to obtain the optimal state, in which the aggregate throughput over both access points is maximized, through cooperation between the APs. To that end, we begin with N heterogeneous users that will be employing one of two APs, their heterogeneity being manifested by the *single user capacity* $c_i^{\pm}$. A priori, this sounds like an exponentially hard problem, but we describe below a simple method that allows us to easily calculate the aggregate payoff at the optimal state.

In effect, when certain user i connects to a given AP, he assigns a value to the random variable $\sigma_i = \pm 1$ that describes his bet; then, as above, the number of users employing the AP $\pm$ will be $N_{\pm} = \frac{1}{2}\sum_i (1 \pm \sigma_i)$. It is therefore convenient to define the quantity $m = \frac{N_+ - N_-}{N} = \frac{1}{N}\sum_i^N \sigma_i$. Then, (1) becomes:

$$T_i = \frac{1}{N}\left(\frac{c_i^+(1+\sigma_i)}{1+m} + \frac{c_i^-(1-\sigma_i)}{1-m}\right) \tag{2}$$

In this way, we see that T_i only depends on the user's particular choice $\sigma_i = \pm 1$ and on the aggregate quantity m; in other words, what we have is an *asymmetric* *congestion game* with the player-specific payoffs being determined by (2).

We now want to maximize the sum $T_{tot} = \sum_i T_i(\sigma)$. To do this we will first find the (relative) optimal state for a *fixed* m and then we will find the m that yields the greatest aggregate throughput. This is quite straightforward: we first need to order the users i in such a way that the quantity $c_i^+/N_+ - c_i^-/N_-$ is (for fixed N_-), a non-decreasing function of i; then, we allocate the lowest N_- users to "−" and the rest of the users to "+". This will be the optimal distribution for fixed m so, we are only left to optimize the resulting aggregate payoff w.r.t. m.

Omitting the algebra for the sake of clarity, we thus obtain:

$$T_{max} = \max_{|m|\leq 1} \frac{\sum_{i=1}^{N}(h_i - mg_i) + \sum_{i=1}^{N_-}(mg_i - h_i) + \sum_{i=N_-+1}^{N}(h_i - mg_i)}{1 - m^2} \quad (3)$$

where $h_i = c_i^+ + c_i^-$ and $g_i = c_i^+ - c_i^- - \sum_{i=1}^{N}(c_i^+ - c_i^-)/N$. This last expression can be explicitly evaluated for any given distribution of $c_i^\pm$ and, in this way, we can get a concise analytic expression for the maximum aggregate throughput for any number of players.

IV. Equilibrial States

We will now describe the game, which we will use to study the system model of section II. In normal form, it will consist of N users with the common set of actions $\mathfrak{F} = \{\pm 1\}$ (facilities) and payoffs determined by (2); we have already seen that this is a congestion game with player-specific payoff functions, as in [9].

Clearly, the motivation of every (selfish) user is to try and maximize their individual payoff T_i but, of course, users all compete with one another for the limited resources of the APs. The stable resolution of this conflict is described by the notion of a Nash equilibrium, i.e. a state $\boldsymbol{\sigma}^*$ such that no user can gain anything by deviating unilaterally. More rigorously, a bet $\sigma^* = \{\boldsymbol{\sigma}_i^*\}_{i=1}^N$ is said to be a (pure) Nash equilibrium for the game when *for all* users:

$$T_i(\sigma^*) = \max_{s_i=\pm 1} \{T_i(\ldots, \sigma_{i-1}, s_i, \sigma_{i+1}, \ldots)\}. \quad (4)$$

Such equilibria always exist in the *mixed* sense of [15], whereby each user employs access point "±" with probability $p_i^\pm$ and one maximizes the *expected* payoff instead. In the *pure* case, it has been shown in [9] any congestion game with player-specific payoff functions possesses a Nash equilibrium in *pure* strategies. The approach used in [9] is to add players inductively and construct a finite *best-reply path*[2] whose endpoint is a pure Nash equilibrium. However, in order for players to carry out this construction, they will have to solve the exponentially hard problem of deciding *who* will actually be allowed to switch to a better strategy at every iteration of the game, a calculation which is impossible to conduct in real time. Moreover, this algorithmic construction does not allow the characterization of the pure Nash equilibria in terms of measurable macroscopic quantities of the system (such as the number of players per AI).

To obtain such a characterisation, we first define the users' "+"-*bias* to be the ratio $\psi_i = \log \frac{c_i^+}{c_i^-}$; then, without loss of generality, we may assume that the players are indexed in order of decreasing bias, i.e. $\psi(i) \geq \psi(j)$ for $i < j$. So, if $x \in \mathbb{N}$ is the number of players that choose "+" $(0 < x < N)$[3], we easily see that a bet $\boldsymbol{\sigma}$ will be at Nash equilibrium if and only if the x players that connected to "+" have $\psi(i) \geq \phi(x)$ while the other $N - x$ players have $\psi(i) \leq \phi(x+1)$, where $\phi(x) = \log \frac{x}{N-x+1}$.

Let us assume now that $\boldsymbol{\sigma}^*$ is a pure equilibrium state with ξ users connected to "+"; obviously, the smartest choice would be to have the users with the highest "+"-bias connect to "+" and the rest to "−". Thus, since ψ is decreasing, the equilibrium condition reduces to finding a ξ s.t. that $\psi(\xi) \geq \phi(\xi)$ and, also, $\psi(\xi+1) \leq \phi(\xi+1)$. Then, if we let $\xi = \sup\{x = 1 \ldots N-1 : \psi(x) > \phi(x)\}$ the above conditions will be both satisfied since ξ will be the greatest integer with the property $\psi(\xi) > \phi(\xi)$. This shows that *there exists an equilibrium point in pure strategies*.

Furthermore, it is easy to see that the only other possible equilibrium points are obtained either by changing the allocation of users ξ and $\xi + 1$, or possibly by allocating $\xi + 1$ users to "+" when $\phi(\xi+1) = \psi(\xi+1)$ (otherwise, the inequality $\phi(\xi+1) \leq \psi(\xi+1)$ is strict and $\xi + 1$ cannot be an equilibrium). However, for a large number N of users, and given that the $c_i^\pm$ coefficients are randomly distributed, the above conditions represent events of measure 0 and we thus also see that, as $N \to \infty$ *the game admits a Nash equilibrium in pure strategies which is almost surely unique*.

[2]In short, this is a sequence of iterations of the game: at each iteration one (and only one) player switches to his best-response strategy.

[3]We will not consider the trivial cases where an equilibrium is obtained in the borders of the bid space, i.e. the degenerate cases whereby all users choose the *same* AI and still have no incentive to deviate.

V. Evolution and Steady States

Now, in order to actually reach this Nash equilibrium, we will iterate the game described above by having users keep track of their choices' performances and then employing the standard that performs best for them. More concretely, each player keeps a recursive score:

$$U_i^{\pm}(t+1) = U_i^{\pm}(t) + T_i^{\pm}(t) \tag{5}$$

where $T_i^{\pm}(t)$ is the payoff of equation (2) that user i would have received at time t if he had employed standard "±". Then, each user updates the probability $p_i^{\pm}$ with which he employs AI ± based on the exponential learning model:

$$p_i^{\pm}(t) = \frac{e^{\gamma U_i^{\pm}(t)}}{e^{\gamma U_i^{+}(t)} + e^{\gamma U_i^{-}(t)}} = \frac{1}{1 + e^{\mp\gamma \Delta U_i(t)}} \tag{6}$$

where $\Delta U_i = U_i^+ - U_i^-$ and γ is a parameter that controls the users' learning rate.[4]

Under this learning model, we will see that players rapidly converge to an evolutionarily stable state which is a Nash equilibrium in pure strategies. To see this analytically, note that differentiation of (6) w.r.t. t readily yields:

$$\frac{\mathrm{d}p_i^{\pm}}{\mathrm{d}t} = \gamma p_i^{\pm}\left(\frac{\mathrm{d}U_i^{\pm}}{\mathrm{d}t} - \sum_{\pm} p_i^{\pm}\frac{\mathrm{d}U_i^{\pm}}{\mathrm{d}t}\right) \tag{7}$$

Then, coupled with (5) and some mild ergodicity assumptions, we may easily see that the above equation can actually be rewritten as:

$$\frac{\mathrm{d}p_i^{\pm}}{\mathrm{d}t} = \gamma p_i^{\pm}\left[T_i^{\pm}(p) - T_i(p)\right] \tag{8}$$

where $T_i^{\pm}(p)$ is the expected throughput of user i when connected to the AI ± while the other users employ AI ± with probabilities determined by $p_j^{\pm}$ ($j \neq i$), and $T_i = p_i^+ T_i^+ + p_i^- T_i^-$. In this way, we see that the exponential learning model (6) essentially leads to the *standard multi-population replicator dynamics* (see e.g. [16], [17]).

These dynamics are extremely powerful since, as is shown in [16], their asymptotically steady states are precisely the (strict) Nash equilibria of the underlying game; however, it is also proven in [17] that only pure profiles can be asymptotically steady states of (8). Hence, having established the existence of pure Nash equilibria, we conclude that, *under exponential learning, the users will almost surely converge to a Nash equilibrium in pure strategies*.

[4]Already, note that this is a generalisation of the "best-response" scheme that can be recovered as $\gamma \to \infty$.

VI. Numerical Experiments

Nevertheless, it is important to note that social stability does not necessarily imply optimality in aggregate performance, a behaviour that can readily be observed in numerical simulations. So, to gain concrete insight about the system, we simulated an area with two base stations (one for each of the 2 available air interfaces (AIs)) and a number of users. For simplicity they were assumed to have the same average SNR to both AIs. The objective was to validate by simulation the analytical results that were discussed in the previous sections. To that aim, the following scheme was simulated: Each user within the system was allocated to one of the two available air interfaces in the beginning of the simulation. (1) was used for the throughput of each user, allowing the SNR of each user to fade independently (assumed speed 3km/hr and 15kmph, with frequency 2GHz). During the simulation each user could perform a vertical handover with a probability given by (6). The parameter γ was set to 5000 and the throughput difference values were averaged using a sliding window of length equal to 10 samples (1 sample=2ms). The users were assumed at every instant to have full information about the offered throughput of both air interfaces.

From (1) it can be observed that the throughput per user is sensitive to both the received SNR and the number of users per AI (load), therefore users in a heavily loaded cell are bound to experience much lower throughput levels. Each user is assumed to download content from the base station consisting of sub-blocks at specific time slots (infinite buffer lengths were assumed for each user queue).

Figs. (1a) and (1b) illustrate the variation of the aggregate throughput with time for 50 mobile users having speeds of 3km/hr and 15km/hr, respectively. The aggregate throughput was calculated in three different ways. The top curve corresponds to the optimal aggregate throughput as calculated using (3). The intermediate curve is the aggregate throughput attained at the instantaneously evaluated Nash equilibrium, while the third curve is the one generated through simulations using the dynamics described by (6). Interestingly, for low speeds (Fig. (1a)) the dynamics manage to closely follow the Nash equilibrium. For faster fading (Fig. (1b)) the dynamics can approach the Nash equilibrium values relatively well. The initial ping-pong-like deviation is due to the initial conditions, which eventually fades away. Both estimation and simulation curves are below the optimal values (as expected) and their ratio is depicted on Figs. (1e) and (1f), denoted there as efficiency: this is the game's efficiency level

$$\alpha = \frac{\sum_{i=1}^{N} T_i(\boldsymbol{\sigma}^*)}{\sum_{i=1}^{N} T_i(\boldsymbol{\sigma}_0)} \tag{9}$$

where $\boldsymbol{\sigma}^*$ is the game's (essentially unique) pure equilibrium[5] and $\boldsymbol{\sigma}_0$ is the optimal state; i.e. the efficiency level is the inverse ratio of what is usually called the "price of anarchy" [11]. Figs. (1c) and (1d) illustrate the load variation with time of one air interface (the other air interface has a symmetric load curve), for speeds 3km/hr and 15km/hr respectively. The handover rate hovers close to 3% for v = 3km/hr and 15% for v = 15km/hr, respectively. It can be seen that there is an initial period of frequent handovers which leads to an oscillation of the AI load, but in few time samples the system reaches the equilibrium state of an average load equal to 25 users.

VII. Conclusions

Our main purpose has been to discuss the dynamics of terminal handover between two co-existing service providers and to discuss the consequent exploitation of the offered diversity by the use of multi-standard terminals. Indeed, it turns out that the potential benefits of mobile-initiated vertical handovers are substantial since one observes an increase of both the user-perceived as well as the aggregate system capacity. The key instrument to control these vertical handovers is to base them on replicator dynamics which exhibit fast convergence to evolutionarily stable equilibrial states, while maintaining a relatively small handover rate. We see that even though users do not communicate with one another and act upon a completely selfish agenda, they quickly learn to perform with an unexpected efficiency. In fact, their performance closely rivals the (exponentially hard to calculate) optimal distribution which maximizes the aggregate throughput and which would be difficult to implement even within the premises of a centrally controlled network. It will be of interest in future studies to check the sensitivity of these schemes when imperfect system information is provided and the users would only be able to *estimate* the throughput offered by the other AI.

[5]Even for small N when multiple pure equilibria possible, it can be shown that they have the same aggregate payoff up to order $O(1/N)$; alternatively, one might simply consider the inf of (9) over all pure equilibria.

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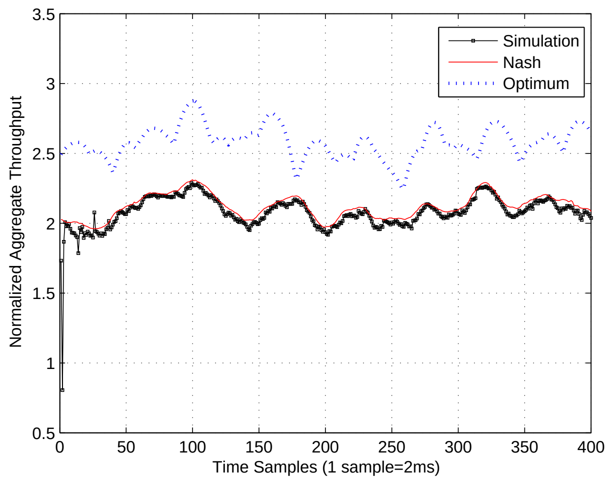
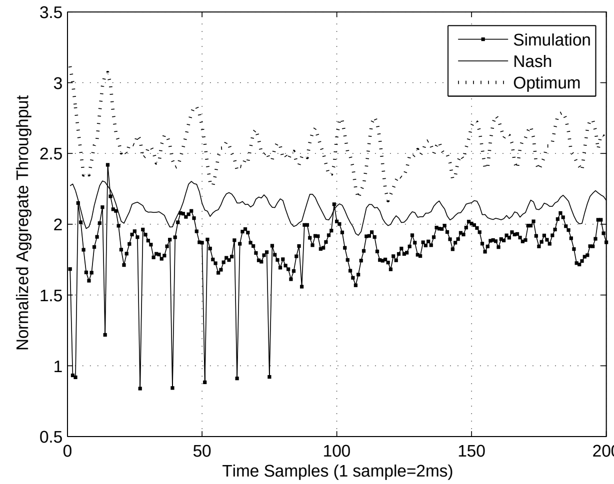
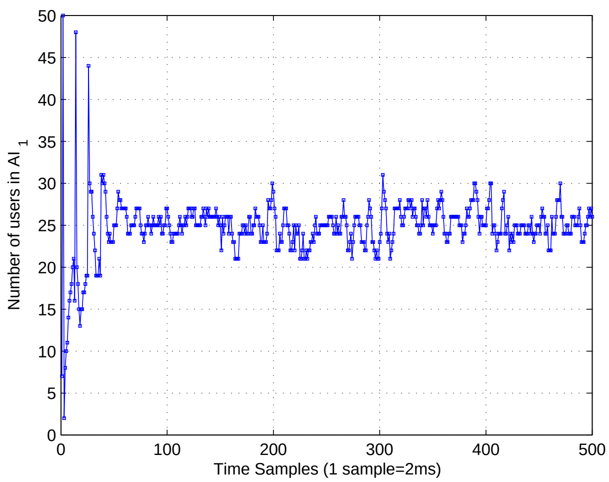


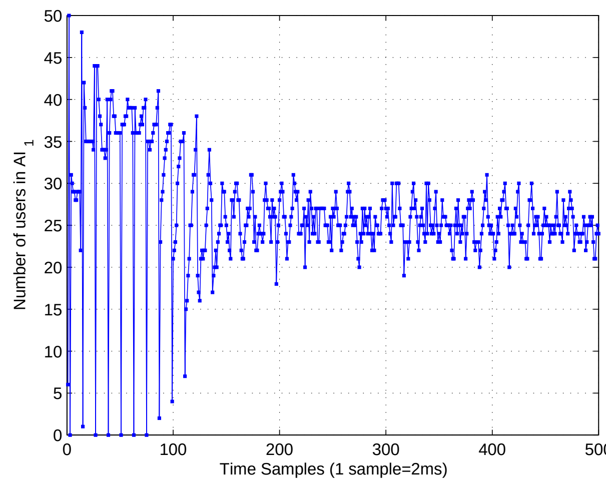
(a) Aggregate throughput $v = 3km/hr$



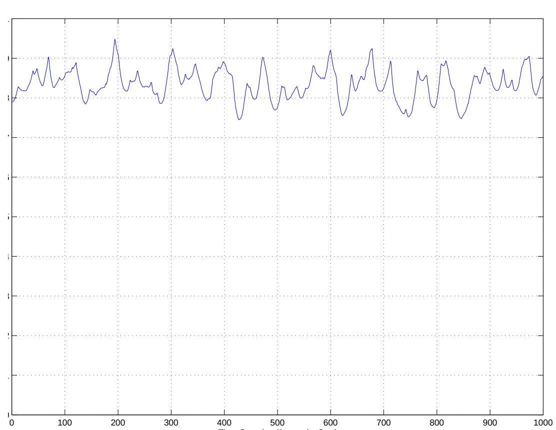
(b) Aggregate throughput $v = 15km/hr$



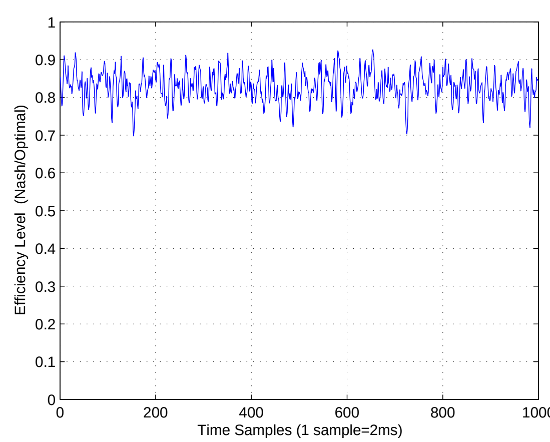
(c) AP1 Load $v = 3km/hr$



(d) AP1 Load $v = 15km/hr$



(e) Game Efficiency $v = 3km/hr$



(f) Game Efficiency $v = 15mk/hr$

Fig. 1. Plots of total throughput, load of access point 1 and game efficiency for two fading speeds, $v = 3km/hr$ and $v = 15km/hr$