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Vertical Handover between Wireless Standards

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***Abstract*—The dynamics of handover between two coexisting wireless standards and the consequent exploitation of the offered diversity by the use of multi-standard terminals has been discussed. The potential capacity benefits of mobile-initiated vertical handovers are substantial. However, it is important to choose the correct VHO criteria in order to achieve optimum load balancing and equilibrium states (global and social). Two fast-handover schemes are presented, which exhibit fast convergence to the socially optimal states by allowing a subset of the necessary VHOs among the AIs. In all cases the scheme with replicator dynamics, had the best performance at the cost of an increased vertical handover rate.**

I. Introduction

As a result of the massive deployment of coexisting wireless networks, mobile users often have several choices of colocated WLANs to connect to. This situation is exacerbated by the deployment of large scale mobile third-generation systems operated by major network operators, as well as other, smaller unregulated networks. In fact, mobile user chips already exist which support multiple standards and, additionally, there has been a significant amount of work in creating flexible radio devices that 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, due to the lack of a central controlling authority mobile users become selfish and, even though users now have more choices to connect to, they still need to compete for the finite resources of nearby access points (APs). Moreover, the repeated structure of the process makes users rely on past information available to them, in order to learn to adapt to the environment. To make things worse, since only local information about the past states of the system may be available (e.g. the average service throughput per user), it is not clear how users may use this information in an effective manner.

It is clear from the above that this process can be modelled in terms of a non-cooperative game. There have been two different directions of similar past work on this problem. To begin with, there has been a significant body of work on applications of game theory to wireless networks [2]. For example, uncoordinated random access channels have been analysed by optimising their transmission probabilities [3], or their power control [4]. Another application is in CDMA systems, [5], [6], [6], [7]. More specifically, 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 the dynamics of the vertical handover between standards.[1] We assume that users can switch air interfaces in the time-scale of seconds and call this scheme multi-mode operation (MMO), as opposed to single mode operation (SMO) where users are not capable to handover. We assume that parallel connections to both AIs are available, allowing each user to switch between AIs at rates faster than the typical session duration. However, we will assume the handover rate to be small enough in order to allow the user to feel the effect of the presence of other users connected to that interface. We do this for 2 different types of allocation of probability for each player (MMO-multi/single), as well as SMO. In addition, we employ a game-theoretic perspective in order to calculate the socially optimal states (Nash equilibria) of the system. The situation turns out to be similar to the "price of anarchy" setting of [9] since in these socially optimal states, the aggregate throughput differs from the maximum attainable level, which we show how to calculate explicitly.

A. System Model

Here we introduce the system model. We consider two standards' access-points coexisting in a given location. We assume that a given set of users exists, which have the capability to monitor both standards and are able to switch when they find it advantageous to do so. We also assume that there are MAC schedulers at every base, which over a intermediate time-scale allow each user to use the channel and transmit taking into account the number of users connected to the given base and its own channel conditions. Specifically, we assume the following throughput formula for user i connected to base r.

$$T_{ir} = \frac{c_{ir}}{N_r} \tag{1}$$

where $c_{ir} = F \log_2(1 + SNR_{ir})$ is the throughput the user connected to AP r would have if it was alone. This formula is strictly valid in the round-robin scheduling case, however the

[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.

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functional form of the user-perceived throughput on the instantaneous SNR and system load N is similar in other scheduling systems (e.g. proportional fair). Also, the association of c_{ir} with the instantaneous Shannon capacity is not always valid, since the above model for the perceived user-throughput is averaged over several time windows. In the latter case, c_{ir} should correspond to the ergodic capacity. However, we will not make this distinction here.

II. Game-theoretic Setting

We will now describe the game with which the system model of section I-A will be analysed. To that end, we begin with N heterogeneous users that will be employing one of $B = 2$ standards[2]. The heterogeneity of the users is manifested by the *coupling coefficient* c_{ir} which describes the affinity that user i bears towards standard r and is the same coefficient that appears in equation (1). Since we will only be working with two standards, we will simplify notation by referring to them as "+" and "−" with their respective coefficients denoted by $c_i^{\pm}$.

So, when the game is played, each player will choose a standard by placing a *bet* $\sigma_i = \pm 1$ and will get a *payoff* u_i equal to the received throughput. To make this last statement precise, let the n-tuple $\sigma = \{\sigma_i\}_{i=1}^N$ describe the users' bets and consider the "aggregate" bet $m(\sigma) = \frac{1}{N}\sum_{i=1}^N \sigma_i$. Then, if $N_\pm$ is the number of users employing standard $\pm$, we immediately see that $N_\pm = \frac{N}{2}(1 \pm m)$, and equation (1) yields:

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

as an equivalent analytical expression for the payoff function.

Clearly, it is in every (selfish) user's best interest to try and maximize their payoff u_i; this is described by the notion of a Nash equilibrium, i.e. a bet which is such that no user can be expected to win more by changing his bet if others stick to theirs. More rigorously, a bet $\sigma^* = \{\sigma_i^*\}_{i=1}^N$ is said to be a (pure) Nash equilibrium for the game when *for all* users:

$$u_i(\sigma^*) = \max_{s_i=\pm 1}\{u_i(\ldots,\sigma_{i-1}, s_i, \sigma_{i+1},\ldots)\}. \tag{3}$$

Such equilibria always exist in the *mixed* sense of [11], whereby each user employs standard "±" with probability $p_i^{\pm}$ and one maximizes the *expected* payoff instead. To accomodate for this, we will iterate the game described above with users keeping track of their bets' performances and employing the standard (*strategy*) that performs best for them. More concretely, each player keeps a recursive score:

$$U_i^{\pm}(t+1) = U_i^{\pm}(t) + u_i^{\pm}(t) \tag{4}$$

where $u_i^{\pm}(t)$ is the payoff of equation (2) that user i would have received at time t if he had employed standard "±". Then, each user updates $p_i^{\pm}$ according to the exponential *logit* model:

$$p_i^{\pm}(t) = \frac{e^{\gamma U_i^{\pm}(t)}}{e^{\gamma U_i^+(t)} + e^{\gamma U_i^-(t)}} = \frac{1}{1+e^{\mp\gamma\Delta U_i(t)}} \tag{5}$$

where $\Delta U_i = U_i^+ - U_i^-$ and γ is the parameter that controls the users' learning rate[3].

Under this learning model, and taking the continuous time limit, one easily derives the dynamics:

$$\frac{\mathrm{d}p_i^{\pm}}{\mathrm{d}t} = \gamma p_i^{\pm}\left(u_i^{\pm}(t) - \langle u_i(t)\rangle\right) \tag{6}$$

where the averaging $\langle\cdot\rangle$ takes place over the strategies $p_i^{\pm}$ of user i; in this way, we have arrived at the standard replicator equation whose stable points are Nash equilibria. Hence, by adhering to the selfish scheme of employing the standard that yields the greatest individual payoff with a probability that depends on the disparity of the payoffs, the users eventually converge to a steady state which is socially optimal (in the sense of Nash).

This behaviour can be immediately observed in our numerical simulations of section III; however, it is important to note that social optimality does not necessarily imply a *global* gain in performance. Indeed, if we consider the aggregate payoff (aggregate received throughput) $u = \sum_{i=1}^N u_i$ as a measure of global performance, it is trivial to see that (generic) Nash equilibria lead to distinctly different values of the aggregate throughput.

Therefore, in order to obtain a measure for the performance of a socially optimal state, we need to derive the maximum value[4] of $u = \sum_i u_i$. A priori, this sounds like an easy task, but the time required for a brute-force approach increases exponentially with the number of users since one has to run through the vertices of the strategy-payoff cube $\{-1,1\}^N$. For that reason, an alternate (and more analytic) approach becomes necessary, especially in the large N setting.

To that end, starting from (2) it can be shown that

$$u_{max} = \max_{|m|\le 1}\frac{1}{1-m^2}\left\{\sum_{i=1}^N (h_i + |g_i - mh_i|) - 2\sum_{i=q(m)}^{N_-}|g_i - mh_i|\right\} \tag{7}$$

where $h_i = c_i^+ + c_i^-$ and $g_i = c_i^+ - c_i^- - \sum_{i=1}^N (c_i^+ - c_i^-)/N$ and $q(m) \in \{1\ldots N\}$ is the index beyond which[5] $g_{q(m)} > mh_{q(m)}$. This last expression can be explicitly evaluated for any given distribution of the coupling coefficients $c_i^{\pm}$ and, when N is large, we may easily descend to the continuous limit in order to harvest its critical points. In this way, we obtain a concise analytic expression for the maximum aggregate throughput for any number of players, even when N is large enough to render enumerative methods nonviable.

III. Numerical Experiments

To gain conrete insight about the system we simulated an area with two base stations (one for each of the 2 available

[2] The game-theoretic analysis can be easily adapted to accommodate for more than 2 standards (see [10]).

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

[4] In reality, we should be maximizing the expected payoff $\mathbf{E}(u)$; however, since it is a harmonic function on the mixed strategies $p_i^{\pm}$, it will attain its maximum value on the boundary of its domain of definition. Hence, we only need to look at pure strategies (i.e. we simply have to maximize u instead).

[5] We are here assuming (without loss of generality) that the users are indexed so that $g_i - mh_i$ is an increasing sequence.

air interfaces (AIs)) and a number of scattered users. The objective was to determine a scheme which could lead the users to choose the optimum (socially and globally) air interface at the minimum time, avoiding unnecessary handovers and ping pong effects. The criteria for optimality where related to the individual and the aggregate throughputs measured over the simulation time. We use (1 for the throughput per user and allow the SNR of each user to fade independently (assumed speed 30kmph, frequency 2GHz).

¿From the aforementioned expression 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 at the edge of coverage or 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). The following cases were simulated:

- Single Mode Operation. In that case each user was assigned in the beginning of the simulation to an air interface and was not allowed to perform a vertical handover within the packet call duration.
- MMO-M. According to this scheme (involving multiple criteria), at each instant the user would perform a vertical handover if all the conditions below were met:
  1) Condition C_1 (action probability): The user would make the VHO check with a specific probability P(VHOcheck) = p. This ensures that the users are given the option to hop often enough.
  2) Condition C_2 (instantaneous throughput): The instantaneous throughput offered by the other AI would be higher than the throughput offered by the home AI by a factor: $T_0 \geq \alpha \cdot T_h$. This ensures that only users with significant potential gains hop.
  3) Condition C_3 (satisfaction criterion): The ratio of time for which the user was served with higher throughput than the throughput offered by the other AI was lower than a threshold:

$$\mathrm{SAT} = \frac{\text{Time for which } T_h > T_0}{\text{Total Connection Time}} \leq b \qquad (8)$$

- MMO-S. This scheme included a single criterion (matching the aforementioned action game analysis), expressed by (5) where the average throughputs offered by the AI_1 and the AI_2 to the user respectively for a specific time window of duration t_D.

The users were assumed to have perfect knowledge of the parameters (load and downlink SNR) of both AIs at each instant. The metrics that were used to measure the performance of the three aforementioned cases were the following:

- Individual Perceived Throughput (mean-cumulative distribution function).
- Convergence Time to a (Nash) equilibrium state for the load of each AI and the aggregate throughput.
- Vertical Handover Rate

The objective of the aforementioned algorithms was to regulate the VHO actions of the users. In order to reach the Nash equilibrium, it is necessary to allow the users to switch to their preferred AI but not all at once, since in that case the AI load will be oscillating between a maximum and a minimum value (ping-pong effect). Fig. 1 shows the variation of the load in one of the two air interfaces (for both AIs these curves are symmetric). This variation illustrates the initial ping-pong effect of the proposed VHO algorithms and, their convergence speed to the steady state and their variability (caused by some more infrequent VHOs) within the steady state. It can be seen that compared to the SMO case (where no VHOs are performed), in the MMO-M case some VHOs are performed in the beginning and then a steady state is reached in which all users most of the time refrain from hopping among AIs (average handover rate 0.0022). In the case of MMO-M more handovers are performed (average handover rate 0.054), leading to a slight constant ripple in the load curves.

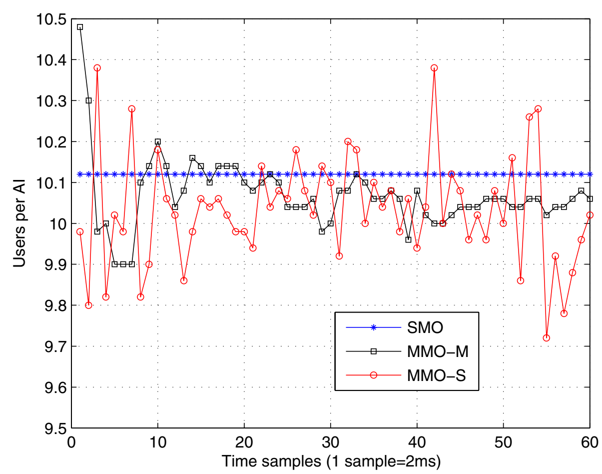

Fig. 1. Load variation in one AI vs time. The total load is fixed to N = 20, Unless specified, for all simulations here the used parameter values for conditions C_1, C_2 and C_3 are p = 0.7, α = 1.5 and b = 0.8, respectively, while the MMO_S parameters have values $\gamma = 5 \cdot 10^{-5}$ and $t_D = 10ms$.

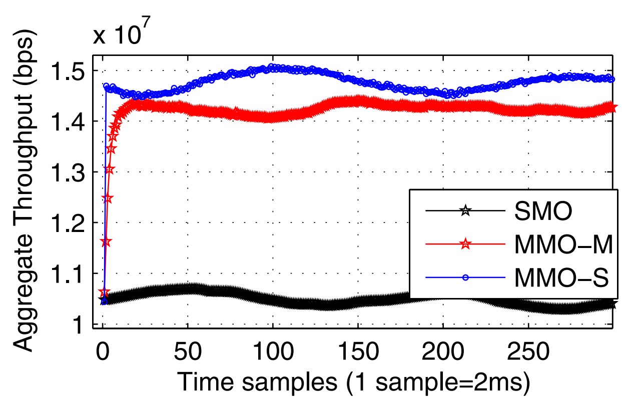

Fig. 2. Variation of the aggregate throughput vs Time

Figure 2 illustrates the variation of the aggregate throughput versus time. It can be seen that the SMO case exhibits the lowest aggregate throughput, since the users are not allowed to change their serving AI in order to improve their received QoS and throughput. Both MMO schemes have much better performance and converge quite fast to an equilibrium state, with the MMO-S achieving the top performance due to the increased freedom of the users to perform the required VHOs.

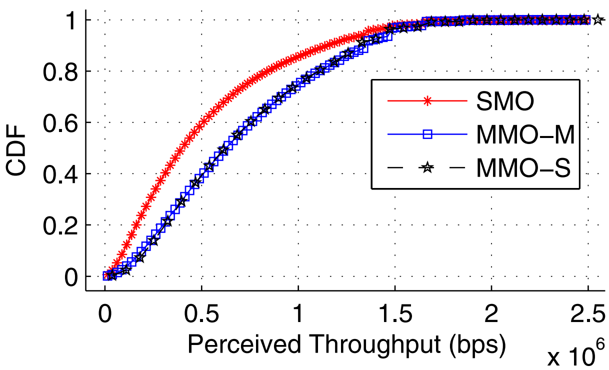

Fig. 3. CDF of the user-perceived throughput. The mean throughput for the three cases SMO, MMO-M and MMO-S is $0.52Mbps$, $0.71Mbps$ and $0.74Mbps$, respectively.

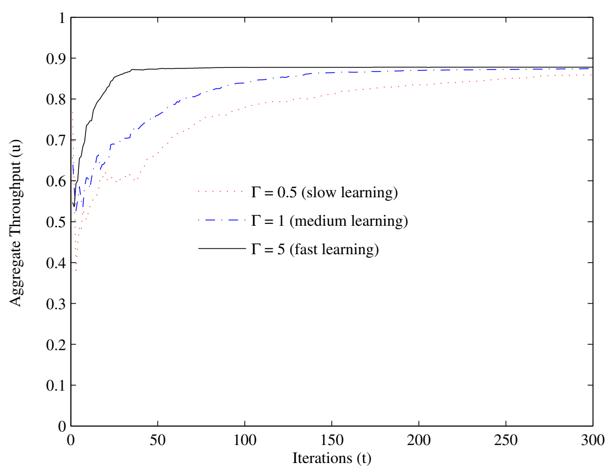

Fig. 4. Comparing the aggregate payoff in the socially optimal steady state to the minimum and maximum attainable values (0 and 1 respectively). We also illustrate the effect of the learning rate Γ.

Figure 3 illustrates the CDF of the users during the simulations. It is evident that the throughput performance of the SMO case is lower than the two MMO cases, that exhibit very similar results. Again, MMO-S has slightly better throughput results than the MMO-M case

Finally, in order to compare the performance of the system at its socially optimal state (Nash equilibrium) to the global maximum, we performed a simulation of the game described in section II for $N = 30$ users following the logit model of equation 6 (MMO-S scenario). The users' SNRs and payoffs are calculated as above[6], and the maximum(minimum) throughput that they may receive is calculated exactly by running through the 2^N vertices of the payoff cube. In Figure 4 , we plot the (time-averaged) aggregate payoff (throughput) received by the users, normalised so that the maximum throughput is at 1 (fully efficient system) and the minimum throughput is at 0 (0% efficiency). We also use different learning rates to exhibit how the state of convergence is affected.

In Fig. 4 we observe that the game quickly converges to a social optimum whence users have no incentive to deviate (this is especially evident in the case of faster learning rates). As expected, this state does not depend on the learning rate (which only controls the speed of convergence) and, therefore, even the hardest "best-response" schemes will yield good results. More to the point, we see that the level of aggregate throughput attained is very close to its absolute maximum; to be precise, the game of Figure 4 converges to an efficiency level of 87.3%, a metric that can be considered as a suitable adaptation of the price of anarchy to our setting. 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.

IV. Conclusions

The dynamics of a multi-standard environment and the the consequent exploitation of the offered diversity by the use of multi-standard (such as URANUS) terminals has been discussed. The potential benefits of mobile-initiated vertical handovers are substantial for both coverage and capacity. However, it is important to choose the correct VHO criteria in order to achieve optimum load balancing and equilibrium states (global and social). Both MMO schemes that were presented exhibited fast convergence to the optimal states by allowing a subset of the necessary VHOs among the AIs. In all cases the scheme with the single VHO criterion (MMO-S) that resembled the analyzed game, had the best performance at the cost of an increased vertical handover rate. We see that, eventhough 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 maximises 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 will only be able to estimate the throughput offered by the other AI. Additionally, it will be of interest to take into account the cost of vertical handover (in terms of additional delay or reduced throughput efficiency), to get a more concrete view of the related VHO tradeoffs.

[6]For simplicity, we have not included fading in this case.

Acknowledgements

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