A low-signalling scheme for distributed resource allocation in multi-cellular OFDMA systems

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Abstract—This paper considers distributed protocol design for joint sub-carrier, transmission scheduling and power management in uplink/downlink multi-cellular OFDMA wireless networks. The optimal solution to this problem is hard to achieve, both in theory and in practice. We propose a fully decentralized resource allocation scheme combining decomposition methods for convex optimization with a strategic non-cooperative game formulation of the power and sub-carrier allocation subproblem. Although the final protocols are suboptimal, they drastically reduce computation time while maintaining the overall system performance close to the optimal, exhibiting strong robustness to multiple access interference. We validate the theoretical framework and quantify the performance with numerical examples.

I. INTRODUCTION

Most of the candidate technologies for future generation wireless broadband communications will embrace multi-carrier multi-access schemes based on orthogonal frequency division multiplexing (OFDM) modulation [1], [2]. OFDM offers robustness to channel distortion and the ability to exploit channel diversity to increase the spectral efficiency through a fine-grained dynamic resource allocation. While OFDM systems divide the user data flow into several streams that are modulated and transmitted over the available sub-carriers, OFDMA assigns different sets of sub-carriers to each user based on channel state information. If full channel knowledge is available at the allocator, OFDMA can outperform the common multiple access schemes by taking advantage of multi-user diversity. Due to independent propagation channel, sub-carriers that are in deep-fade for one user may remain good for another. In this perspective, dynamic resource allocation is crucial for realizing the full potential of OFDM/OFDMA systems. However, only few papers address the complete problem due to its high complexity [3]-[6]. Distributed low-complexity solutions are still needed.

We have previously studied distributed protocol design for multi-hop wireless networks [7], and more recently centralized resource allocation in OFDMA multi-cell networks [8]. Centralized optimization problems are computationally demanding to solve and do not scale well to multi-cell OFDMA systems that use a large number of sub-carriers and provide services to many users [8]. To reduce the computation times and increase scalability in terms of the number of cells, users and sub-carriers, we propose to give up on solving the resource allocation to optimality. We focus on sub-carrier and power allocation schemes that are possibly amendable for a distributed implementation, with limited system knowledge and information exchange between nodes. One class of such solutions can be developed by studying the resource allocation as a strategic non-cooperative game where each base station is a player that competes with the others by allocating transmission powers and sub-carriers to the users within its own cell. This approach is inspired by proposals for solving similar resource allocation problems in digital subscriber lines [9], [10], and to other recent studies on distributed power allocation in Gaussian frequency-selective interference channels [11] and pre-coding strategies for wide-band non-cooperative systems [12]-[14]. Contrary to our approach, the cited works assume a continuous rate and power adaption model and define a game for non-cooperative links. In our case, we adopt fixed transmission formats and each base station serves multiple users. A specific feature of our solution is that it does not need any explicit signalling between base stations. Although we are unable to give any performance guarantees, our approach displays large computational savings and near-optimal performance in extensive simulations.

II. NETWORK MODEL

We consider a cellular system with complete reuse of the available resources. In each cell, a base station (BS) communicates with a fixed number $M$ of mobile terminals (MT). We represent the network topology by a directed graph, with base stations labelled $n = 1, \ldots, N$, and mobile terminals labelled $l = 1, \ldots, L$. Since we use separate analysis for uplink and downlink scenarios, we adopt a one-to-one correspondence between links and users. For each BS $n$, let $D(n)$ and $U(n)$ define the sets of downlinks and uplinks respectively, and let $L_D(n)$ and $L_U(n)$ indicate their cardinality. Although the results presented in the paper apply to both downlink and uplink, we will describe the downlink scenario only.

OFDMA modulation technique is adopted. The system bandwidth $W$ of a block of transmission is divided into $F$ equally sized and non-overlapping sub-carriers labelled $f = 1, \ldots, F$. Each sub-carrier can be assigned to at most one user within a cell. The allocation of a sub-carrier to users within different cells generates multiple access interference.

The propagation channel is assumed to be slowly time-varying and frequency selective. The coherence bandwidth of the channel is assumed to be larger than the bandwidth of each sub-carrier. Assume $G_{lmf}$ be the effective channel gain between the transmitter of link $m$ and the receiver of link $l$
when using sub-carrier \( f \), let \( \sigma_{lf} \) be the thermal noise power at the receiver of link \( l \) and \( P_{lf} \) the power used by its own transmitter. We define the signal to noise and interference ratio (SINR) of link \( l \) on sub-carrier \( f \) as

\[
\gamma_{lf}(p_f) = \frac{G_{lf}P_{lf}(\sigma_{lf} + I_{lf})^{-1}}{1}
\]

where \( p_f = (P_{1f} \cdots P_{Lf})^T \) denotes the channel power allocation vector, and \( I_{lf} = \sum_{m \neq f} G_{lmf}P_{mf} \) is the interference experienced at the receiver of link \( l \). For convenience, we define a global power allocation vector \( p = (p_1^T \cdots p_F^T)^T \).

We adopt the Shannon capacity as a measure of the achievable data rate on a given sub-carrier. Given a certain SINR, the channel spectral efficiency in bit/s/Hz is

\[
\eta_l = \log_2(1 + \gamma_{lf}(p_f))
\]

where \( \gamma_{lf}(p_f) \geq \gamma_{lt} \). The achievable transmission rate on link \( l \) is

\[
c_l = \sum_l \log_2(1 + \gamma_{lf}(p_f))
\]

Let \( c = (c_1, \ldots, c_L) \) define link rate vector, the set of achievable link rate vectors under given media access control and physical layer schemes can be written as

\[
C = \{(c_1, \ldots, c_L) \mid \exists (p_1, \ldots, p_F) \text{ satisfying (3)}\}
\]

Despite the attractive properties of continuous rate adaptation schemes, models systems will rely on a set of transmission formats to get higher resource utilization from finer granularity. Though, if the goal is to minimize power subject to rate constraints, link rate adaptation becomes progressively less effective as the number of users per cell, and hence the multi-user diversity, increases [6]. In essence, we study the simpler case of a single transmission format, i.e. we assume that links offer a single rate \( c_{lt} = WF^{-1}\log_2(1 + \gamma_{lt}) \) when the SINR exceeds a target value \( \gamma_{lt} \), the same for all links/users. We use the following notation

\[
c_{lf} = \begin{cases} 
c_{lt}, & \text{if } \gamma_{lf}(p_f) \geq \gamma_{lt} \\
0, & \text{otherwise}
\end{cases}
\]

The total transmission rate for experienced by link \( l \) is

\[
c_l = \sum_{f=1}^{F} c_{lf}x_{lf} \quad \forall l = 1, \ldots, L
\]

where \( x_{lf} = 1 \) if sub-carrier \( f \) is used by link \( l \), and 0 otherwise. This leads to a finite number of link-rate vectors \( C^{(k)} = (c_1 \ldots c_L) \), \( k = 1, \ldots, K \).

Although \( K \) may be as large as \( (F + 1)^L \), most networks will, due to interference and other technological constraints, support substantially fewer link rate vectors. By time-sharing between a given set of link rate vectors \( \{c^{(k)} \mid k \in K\} \), we can achieve the following polyhedral rate region

\[
C^K = \left\{c = \sum_{k \in K} \alpha_k c^{(k)} \mid \alpha_k \geq 0, \sum_{k \in K} \alpha_k = 1\right\}
\]

Here, the time-sharing coefficients \( \alpha_k \) represent the fraction of schedule length in which rate vector \( c^{(k)} \) is activated. If \( C^K \) contains all feasible rate-vectors \( c^{(k)} \) is activated, we will simply drop the superscript and use the short-hand notation \( c \in C \) to denote that \( c \) is an achievable long-term average link rate.

We consider a network with saturated traffic and refer to source-destination pairs as BS-MT pairs. Associated with each pair \( l \) is an average traffic rate \( s_l \) and a utility function \( u_l(c) \) describing the utility of the pair to communicate at rate \( s_l \) (cf. [15]). We assume that \( u_l \) is increasing and strictly concave, with \( u_l \to -\infty \) as \( s_l \to 0^+ \). Letting \( c = (c_l) \) be the vector of link-capacities, the network flow model imposes the following set of constraints on the long-term average link rate vector \( s \)

\[
0 \preceq s \preceq c
\]

where \( \preceq \) means component-wise inequality.

III. A MATHEMATICAL PROGRAMMING MODEL

We formulate the problem of joint sub-carrier and power management in uplink/downlink multi-cellular OFDMA wireless networks as one of utility maximization (cf. [15])

\[
\text{maximize } \sum_l u_l(s_l) - \omega^T p
\]

subject to \( 0 \preceq s \preceq c, \quad c \in C \)

Unlike [15], the link capacities in (7) are not fixed a priori but depend in a non-trivial way on both MAC and the allocation of radio resources, such as sub-carriers, transmit powers and time-slots to the users. The above optimization aims to maximize the utility of the network while minimizing power (and hence interference). Much like multi-criterion optimization problems, we introduce a fixed weight \( \omega \in [0, \infty) \) to trade these conflicting objective by a specified amount [16].

We have previously studied centralized solutions to this problem in [8] by combining dual decomposition with a column generation procedure. Moreover, in [7] we proposed distributed end-to-end bandwidth allocation in STDMA wireless networks based on a cross decomposition method. Due to space constraint, we will briefly review the optimization framework presented in [7] since it is an important component of our decentralized solution approach to the joint sub-carrier and power management problem (7).

The cross decomposition solution relies on re-writing (7) as

\[
\text{maximize } \nu(c) \quad \text{subject to } \quad c \in C
\]

where

\[
\nu(c) = \max \sum_l u_l(s_l) - \omega^T p \mid s \preceq c, \quad s \geq 0
\]

For a fixed link capacity vector \( c \), corresponding to a given schedule and power allocation \( p \), the function \( \nu(c) \) is readily evaluated, and its properties can be studied using duality theory. Introducing Lagrange multipliers \( \lambda \) for the capacity constraints \( s \preceq c \) we can form the Lagrangian

\[
L(s, \lambda) = \sum_l (u_l(s_l) - \lambda_l s_l) + \lambda^T c - \omega^T p
\]

where \( \lambda_l \) can be interpreted as the congestion price for link \( l \). Since the Lagrangian is separable in the long-term average
link rate $s_l$ for a fixed $c$, the dual function
\[
g(\lambda) = \sup_{s \in \mathbb{R}^+_{\geq 0}} L(s, \lambda)
\]
can be evaluated by letting sources optimize their average rates individually based on the total congestion price, i.e., by letting
\[
s_l = \arg \max_{z \geq 0} u(z) - \lambda_l z
\]
and the dual problem to (7), i.e. maximizing $g(\lambda)$ subject to $\lambda \geq 0$ can be solved by the projected gradient iteration
\[
\lambda_l^{(k+1)} = \left[ \lambda_l^{(k)} + \omega_l^{(k)} \left( s_l^{(k)} - c_l \right) \right]^+
\]
where $\{\omega_l^{(k)}\}^+$ is a step length sequence and $[\cdot]^+$ denotes projection onto the positive orthant. The vector of optimal Lagrange multipliers to the capacity constraints found via (9) represents a subgradient of $\nu$ at $c$. Thus, in order to update the link rate vector $c$, it is natural to augment the schedule with the scheduling subproblem
\[
\begin{align*}
\text{maximize} & \quad \lambda^T c - \omega^T p \\
\text{subject to} & \quad c \in \mathcal{C}
\end{align*}
\]
where $\mathcal{C}$ represents the average link-rate vector offered by the schedule (consisting of $k$ time-slots of equal length). BS:es are initially scheduled in a TDMA-like fashion, with an equal number of sub-carriers allocated to users within the cell. We refer to [7] for a thorough analysis of this methodology and its properties.

V. SOLVING THE SCHEDULING SUBPROBLEM

To make the resource management problem (7) fully distributed, the scheduling subproblem (10) must rely on sub-carrier and power allocation schemes implementable in a distributed fashion, with limited system knowledge and information exchange between BS:es. One class of such solutions can be developed by studying (10) as a strategic non-cooperative game where each BS is a player that competes with the others by allocating transmission powers and sub-carriers to the users within its own cell. In this framework, a solution to (10) can be read as an equilibrium at which each player, given the allocation the other players, does not gain any revenue by unilaterally changing its own allocation.

Inspired by proposals for solving similar resource allocation problems in digital subscriber lines [9]-[14], we first present a non-cooperative game formulation of (10) for a continuous rate and power adaption model. Although existence and uniqueness of the equilibrium of the game can be proved, a global optimal solution cannot be retrieved making it difficult to evaluate the goodness of the equilibria. Then, we propose distributed schemes based on a non-cooperative game formulation of (10) for fixed rate adaption. In the latter case, we can formulate (10) as mixed integer linear programming (MILP) and solve it to optimality [8], allowing to compare the distributed schemes with the global optimum.

A. Continuous rate and power adaption

For a continuous rate and power adaption model, problem (10) can be rewritten as
\[
\begin{align*}
\text{maximize} & \quad \sum_l \sum_f \lambda_l \log_2 \left( 1 + \frac{G_{lf}}{\sigma_f + I_{lf}} \right) - \omega P_f \\
\text{subject to} & \quad \text{No intra-cell freq. reuse, } P_f \geq 0, \forall l, f
\end{align*}
\]
where $\{\omega(k)\}^+$ is the average link-rate vector offered by the schedule. For a thorough analysis of this methodology and its properties.
Proof: For any given base station $n$, problem (14) can be further separated per sub-carrier. Besides, since there is no intra-cell frequency reuse, each subcarrier will be assigned to at most one link. Specifically, player $n$ assigns subcarrier $f$ to the link $l^*$ with the maximum revenue, i.e.

$$l^* = \arg \max_{j \in D(n)} \lambda_j c_{jf}(p_n, p_{-n}) - \omega P_{bf}$$

For any fixed $p_{-n}$, the operator $F_{nf} (\cdot)$ follows from the Kuhn-Tucker conditions for problem (14) restricted to sub-carrier $f$. However, if no link $j \in D(n)$ gives revenue $\Phi_{nf}(p_n^*, p_{-n}) \geq 0$, then player $n$ allocates zero power to sub-carrier $f$. ■

Definition 4.2: A feasible strategy profile $p^* = \{ p_n^* \} \in \mathcal{N}$ is a generalized Nash equilibria of the game $G$ if

$$\Phi_n(p_1^*, \ldots, p_{n-1}^*, p_n^*, p_{n+1}^*, \ldots, p_N^*) \geq \Phi_n(p_1^*, \ldots, p_{n-1}^*, p_n^*, p_{n+1}^*, \ldots, p_N^*) \quad \forall n \in \mathcal{N}, p_n \in \mathcal{P}_n$$

Finally, according to Proposition 4.1 any generalized Nash equilibria for the game $G$ must satisfy the following Corollary.

Corollary 4.3: A feasible strategy profile $p^* = \{ p_n^* \} \in \mathcal{N}$ is a generalized Nash equilibria of the game $G$ if and only if

$$p_n^* = F_n(p_1^*, \ldots, p_{n-1}^*, p_n^*, p_{n+1}^*, \ldots, p_N^*) \quad \forall n \in \mathcal{N}$$

with the operator $F_n(\cdot)$ defined as in Proposition 4.1.

Necessary and sufficient conditions that guarantee existence and uniqueness of the Nash equilibria have been studied in [9]-[13]. However, as the Nash equilibria need not to be Pareto-efficient [17], and the maximization (11) is a non-convex optimization problem, there is no a priori guarantee of the goodness of the equilibria nor a way to numerically compare the distributed solution with the global optimum. Therefore, we will concentrate on fixed rate adaptation scheme, for which a global optimum solution can be found via mathematical programming, and, to the best authors’ knowledge, a game theoretical formulation has not been studied.

B. Fixed rate continuous power adaption

Centralized (MILP) formulations of the subproblem (10) can be retrieved for fixed rate adaption with single or multi transmission formats [8]. The computation times required for solving (10) to optimality grow very quickly with the number of links, sub-carriers and rate formats, and it is hard to get computational results in reasonable time even with state-of-the art mathematical programming software [8]. To reduce the computational times and increase scalability in terms of number of cells, users and sub-carriers, we propose to give up on solving the subproblems to optimality. We reformulate the game (12) for a single transmission format and design distributed solution approaches for solving the game.

Let $G'$ be the game whose set of admissible power allocation strategies $p_n \in \mathcal{P}_n(p_{-n})$ of player $n$, across sub-carriers, is

$$\mathcal{P}_n(p_{-n}) \triangleq \{ p_n \in \mathbb{P}_n^{FLD_n} \mid \gamma_{lbf}(p_n, p_{-n}) \geq \gamma_{lbf}, l \in D(n) \}$$

Due to the SIR constraints, the set of feasible strategies $\mathcal{P}_n(p_{-n})$ of the $n$-th player depends on the power allocation $p_{-n}$ of the other players. The optimal strategy for the $n$-th player, given the power allocation of the others, solves problem (14) using new frequency payoff functions $\Phi_{nf}(p_n, p_{-n})$ defined as in (13) but with $c_{jbf}^l$ defined as in (5). Similarly to the continuous rate adaption model we have:

Proposition 4.4: For any fixed and non-negative $p_{-n}$, the optimal solution $p_n^* = \{ p_n^* \} \in \mathcal{P}_n(p_{-n})$ to the optimization problem (14) with $\Phi_{nf}(p_n, p_{-n})$ exists and takes the form

$$p_n^* = F_n'(p_1, \ldots, p_{n-1}, p_{n+1}, \ldots, p_N) = F_n'(p_{-n})$$

where for each sub-carrier $f$ the operator $F_n'(\cdot)$ is defined as

$$F_n'(p_{-n}) \triangleq \begin{cases} \gamma_{lbf} I_{lf} - (\gamma_{lbf} + I_{lf}) G_{lf}^{-1} \sigma_{lf} + \gamma_{lbf} I_{lf}, & \text{if } \Phi_{n_f}(p_n^*, p_{-n}) \geq 0 \\ 0, & \text{otherwise} \end{cases}$$

where

$$l^* = \arg \max_{j \in D(n)} \lambda_j c_{jbf}^l - \omega P_{bf}$$

Proof: For any given $p_{-n}$, the condition $p_n \in \mathcal{P}_n(p_{-n})$ in the new problem (14) translates into

$$P_{lf} \geq \gamma_{lbf} (\sigma_{lf} + I_{lf}) G_{lf}^{-1} \quad \forall f \in D(n)$$

with transmission power $P_{lf}$ that satisfies (18) exactly. However, if there are no links $j \in D(n)$ such that $\Phi_{nf}(p_n^*, p_{-n}) \geq 0$, then player $n$ allocates zero power to sub-carrier $f$. ■

Similarly to the continuous rate adaption case, the solution to the game $G'$ is a generalized Nash equilibria:

Corollary 4.5: A feasible strategy profile $p^* = \{ p_n^* \} \in \mathcal{N}$ is a generalized Nash equilibria of the game $G'$ if and only if

$$p_n^* = F_n'(p_1, \ldots, p_{n-1}, p_{n+1}, \ldots, p_N) \quad \forall n \in \mathcal{N}$$

with the operator $F_n'(\cdot)$ defined as in Proposition 4.4.

C. Update order and finite termination

The order in which players update their strategy can affect the solution dynamics. This update can be performed in many ways, but here we propose and compare sequential and simultaneous updates of the fixed rate game respectively. In addition, since at this stage we cannot provide any condition for the convergence of the game to an equilibrium, we rely on a finite termination of the algorithm after a fixed number of iteration Max_Itr. Clearly, if an equilibrium has not been found after Max_Itr iterations, the solution will be suboptimal.

V. THE COMPLETE SOLUTION

The contribution of this paper is a fully decentralized protocol design for resource management in multi-cell ODFMA systems that combines cross decomposition techniques with a strategic non-cooperative game formulation of the power and sub-carrier allocation subproblem. Starting from any initial schedule, at iteration $k$ each base station evaluates $\nu(k)$
by solving (7) for \( c = \pi^{(k)} \). To this end, BS:es update the
dual variables corresponding to links \( l \in D(n) \) using the
gradient method (9), while the optimal long-term average link
rates follow (8). Hence, the inner maximization (10) is locally
solved at the BS:es by using the new \( \lambda \) in the game \( \mathcal{G}' \).
Finally, BS:es locally augment their own schedule with the
new transmission group and compute the associated \( \pi^{(k+1)} \)
and the algorithm is repeated until convergence.

The strengths of this methodology are clearly its distributed
nature and low complexity. We would like to stress that in this
procedure there is no local nor global information exchange
between base stations, which only need to measure the interfer-
ence plus noise levels and to greedily allocate powers and sub-
carriers to users within their own cell to maximize their own
utility. Contrary to similar game theoretical formulations for
resource allocation problems, we adopt a fixed rate adaption
model and define a non-cooperative strategic game where each
base station handles multiple links.

VI. NUMERICAL EXAMPLES

We can now evaluate the performance of the proposed
resource management technique for fixed rate adaption model.
To achieve proportional fairness we will assume logarithmic
utility functions throughout. We will isolate and quantify the
performance of the optimal and decentralized solution
approaches in terms of total aggregate utility and computation
time. Finally, rather than augmenting the schedule indefinitely
a more practical approach would be to maintain and update a
schedule with finite length, say \( H \) time slots, and to sequen-
tially replace the oldest ones in a rolling horizon fashion. We
refer to this approach as rolling horizon optimization.

All networks are generated following the same procedure.
The system bandwidth \( W = 2 \text{MHz} \) is split into \( F = 12 \)
sub-carriers\(^1\) and sampling time is \( T_s = 200 \text{ns} \). The channel
attenuation is due to path loss only, proportional to the distance
between BS and MT, with path loss exponent \( \nu = 4 \). We adopt
a frequency selective Rayleigh fading channel model with and
exponential power delay profile (see e.g. [6]). The power of
the \( i \)-th path is given as \( \sigma_i^2 = \sigma_n^2 \exp(-\frac{d_i}{\sigma_n}) \), where \( \sigma_n^2 \)
is a normalization factor, \( \sigma_n = \sigma_r/T_s \) is the normalized delay
spread and \( N_i = \lfloor 3\sigma_n \rfloor \) is the number of paths taken into
account. Finally, we use a single spectral efficiency \( \eta = 2 \)
bit/s/Hz corresponding to \( \gamma_{\text{trt}} = 3 \).

A. Results for a sample network

We begin showing in detail the results for a network with
7 hexagonal cell with radius \( R = 500 \text{m} \) and \( M = 7 \) mobile
terminals randomly placed within each cell. We evaluate the
performance of our distributed protocol with sequential and
simultaneous base stations update, and compare it with the
optimal theoretical value. Figure 1 shows the network utility
of the cross decomposition method, with and without rolling

\(^1\)Although the proposed distributed approach allows to deal with large
problem instances, we limit our experiments to \( F = 12 \) sub-carriers and
a maximum of \( M = 7 \) users per cell due to the high computational effort
required by the centralized (MILP) solution of problem (10).

horizon, for Max_Itr = 5N and horizon \( H = 20 \) time
slots. Slightly better results have been observed with longer
horizon [8]. Figures 2(a) and 2(b) show the effect on the
performance due to the finite termination of the fixed rate
resource allocation game for values of Max_Itr ranging from
\( N \) to 10N. Both schemes achieve near-optimal performance
and large computational savings for Max_Itr \( \geq 3N \).

B. Results for larger set of networks

We used the previous results as a benchmark to tune Max_Itr
and \( H \) to reasonable values. We further provide extensive
numerical simulations to demonstrate how the proposed algo-
rithms scales as the number of users in the network increases.
We choose to use Max_Itr of 5N and 10N and the horizon
\( H = 20 \) time slots. Keeping fixed the number of cells and
frequencies, we augment the number of users per cell from one
to seven. For each case, we generate a set of hundred networks
and evaluate the average error in network utility and the
relative computation time with respect to the optimal solutions.
Figures 3(a) and 3(b), show an average utility error below 2% for
all schemes and substantial computational savings when
users serve more than one user.

VII. CONCLUSIONS

We have proposed a distributed protocol design for joint
sub-carrier and power management in uplink/downlink multi-
cellular OFDMA wireless networks. We have posed the
problem as one of utility maximization subject to link-rate con-
straints, power control and transmission scheduling in terms
of allocation of transmission frames and sub-carriers to users.
The design combines cross decomposition techniques with a
strategic non-cooperative game formulation of the power
and sub-carrier allocation subproblem. The resulting solution
approach is totally distributed. Each base station allocates
resources to users within its own cell trying to maximize its
own utility. No information exchange, neither local nor global,
is needed between base stations. Although in this preliminary
study we have been unable to give any performance guarantees
for our combined approach, extensive numerical simulations have shown that the resulting distributed schemes achieve near-optimal performance and substantial computational savings. We are currently investigating conditions for existence and uniqueness of the equilibria in the game for fixed rate adaption.

REFERENCES