Non-cooperative power control for energy-efficient and delay-aware wireless networks

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***Abstract*—This work aims at developing a distributed power control algorithm for energy efficiency maximization (measured in bit/Joule) in wireless networks. Unlike most previous works, a new formulation is proposed to jointly account for the energy efficiency and communication delay while ensuring quality-of-service constraints. A non-cooperative game-theoretic approach is taken, and feasibility conditions are derived for the best-response of the game. Under the assumption that these conditions are met, it is shown that the game admits a unique Nash equilibrium, which is guaranteed to be reached by implementing the game best-response dynamics. Based on these results, a convergent power control algorithm is derived, which can be implemented in a fully decentralized fashion.**

I. Introduction

Currently, the percentage of the global world CO_2 emissions due to the Information and Communication Technology (ICT) is estimated to be 5% [1]. While this may seem a small percentage, it is rapidly increasing, and the situation will escalate in the near future with the advent of 5G networks. It is anticipated that the number of connected devices will reach 50 billions by 2020 [2], and that a 1000x data rate increase is required to serve so many connected devices [3]. However, it is also clear that obtaining the required 1000x by simply scaling up the transmit power is not possible, as it would result in an unmanageable energy demand, and in greenhouse gas emissions and electromagnetic pollution above safety thresholds. Instead, the data rate must be increased by a factor 1000, at a similar power consumption as in present networks. This requires a $1000\times$ increase of the energy efficiency (EE), i.e., the efficiency with which ICT systems use energy to transmit data [4]. This is of paramount importance for operators (e.g., to save on electricity bills) and end-users (e.g., to prolong the lifetime of batteries) and thus has motivated a great interest in studying and designing power control strategies taking into account the cost of energy.

The objective of this work is to develop a distributed power control algorithm for energy efficiency maximization. Unlike centralized solutions, distributed approaches allow for a limited feedback overhead and require less computational complexity. The proposed solution is derived by modeling the mobile terminals as utility-driven rational agents that engage in a non-cooperative game [5]. Among the existing works in the context of non-cooperative energy efficiency maximization, the authors in [6] study the Nash equilibrium (NE) problem for a group of players aiming at maximizing their own EE while satisfying power constraints in single and multi-carrier systems. A quasi-variational inequality (QVI) approach is taken in [7], where power control algorithms for networks with heterogenous users are developed. In [8], [9], a similar problem is considered for relay-assisted systems. A common drawback of all of these works is that no rate requirement is taken into account. This might result into fairly low rates at the equilibrium. Imposing target rates changes the setting drastically since any user's admissible power allocation policy depends crucially on the policies of all other users. This problem has been studied in [10] wherein Nash equilibria are found to be the fixed points of a water-filling best-response operator whose water level depends on the rate constraints and circuit power. Another example in this context is given by [11] wherein the authors propose a general framework to investigate different cooperative and non-cooperative energy efficiency maximization problems looking at some candidate 5G technologies.

All the aforementioned works do not take into account communication delays. The latter are included in the analysis in [12], wherein a non-cooperative energy efficiency maximization is carried out subject to minimum delay guarantees. In [13], a new performance metric accounting at the same time for both delay and energy efficiency is given. In light of the described state of the art, this work makes the following major contributions:

- The framework proposed in [13] is extended to include quality-of-service (QoS) constraints in terms of minimum bit error rate or minimum achievable rate. Following [11], a more general users' signal-to-interference-plus-noise-ratio (SINR) expression is considered so as to encompass some of the emerging 5G technologies.
- A non-cooperative game formulation is taken, and it is proved that the energy-efficient non-cooperative power control problem has a unique NE , which can be reached by a fully distributed algorithm based on the game best response dynamics (BRD), provided that some feasibility

This research has been supported by the German Research Foundation (DFG), within the project CEMRIN - grant ZA 747/1-3, by the ERC Starting Grant 305123 MORE and by the PRA 2016 research project 5GIOTTO funded by the University of Pisa.

conditions are fulfilled.

- Numerical results are used to assess the performance of the proposed algorithm. To this end, a massive multiple-input multiple-output (MIMO) system is considered.

II. System model

Consider the uplink of a wireless interference network, with K transmitters and M receivers and let the SINR of user equipment (UE) k take the following general form:

$$\gamma_k = \frac{p_k \alpha_k}{\sigma_k^2 + \phi_k p_k + \sum_{j \neq k} p_j \beta_{k,j}} \,. \quad (1)$$

In (1), p_k is the transmit power of UE k, α_k is the k-th link's channel power gain, σ_k^2 is the noise power at the receiver associated to UE k, $\{\beta_{j,k}\}$ are multi-user interference coefficients depending on the other links' channel coefficients as well as on global system parameters, and ϕ_k is a self-interference coefficient which depends on the k-th user's channel and possibly on global system parameters. The presence of non-zero coefficients $\{\phi_k\}$ makes (1) more general than the traditional SINR expression encountered in wireless networks, which can be obtained by simply setting $\phi_k = 0$. The SINR (1) arises in several relevant instances of wireless communication systems such as hardware-impaired networks, receivers with imperfect channel state information (CSI) estimation, relay-assisted communications, and systems affected by inter-symbol interference [8], [11], [14]. In particular, [11] shows how (1) arises when adopting candidate 5G technologies like cooperative communications and massive MIMO. Indeed, it should be stressed that (1) is not limited to single-antenna systems, but also models vector channels with matched filtering or zero forcing detectors. Additionally, in multi-carrier networks, (1) models the SINR achieved on each transmit subcarrier individually and forms the basis for system analysis and design [11].

In the considered system model, two relevant performance metrics are the transmission delay and the energy consumption of the communication link. As for the transmission delay, following the approach proposed in [13], we consider a system in which packets arrive at the transmit queue of UE k independently from one another and from transmission success and failure events. Under these assumptions, we denote by $S_k(\gamma_k)$ the probability of correct packet reception and let R be the communication rate in bit/s. Therefore, the average time required for the reliable transmission of a data packet is expressed as:

$$c_{d,k} = \frac{1}{R(S_k(\gamma_k) - \lambda_k)} \quad (2)$$

wherein λ_k is a delay parameter accounting for the additional delay due to queuing and buffering at the UE side. Otherwise stated, the communication delay depends on both the time necessary for the correct packet reception, and on the waiting time to receive the packet from the upper layer. Observe that (2) represents a valid delay only if $S_k(\gamma_k) - \lambda_k > 0$.

The trade-off between reducing energy consumption and obtaining fast and reliable communication can be mathematically captured by considering the cost-benefit ratio of the communication link, in terms of consumed energy and corresponding amount of data reliably decoded at the receiver. This leads to the following definition:

$$c_{e,k} = \frac{\mu_k p_k + P_{c,k}}{R S_k(\gamma_k)} \quad (3)$$

wherein $\mu_k = 1/\eta_k$ with η_k being the efficiency of the transmit amplifier of UE k and $P_{c,k}$ is the static hardware power dissipated in all other circuit blocks required to operate the k-th communication link. Thus, (3) is measured in Joule per bit, and represents the amount of the energy to be spent to transmit a given amount of data, or, otherwise stated, as the energy cost per reliably transmitted bit.[1]

The explicit expression of S_k depends on the system under investigation and it can be a very involved function. A widely used approximation is given by [8], [13]:

$$S_k(\gamma_k) = 1 - e^{-\delta_k \gamma_k} \quad (4)$$

where $\delta_k > 0$ is a design parameter that can be chosen to refine the approximation according to the different system under investigation. However, the following analysis is not limited to the expression in (4) but it applies to any function that has the following general properties:

1) $S_k(\gamma_k) \geq 0$, for all $\gamma_k \geq 0$, with $S_k(0) = 0$, i.e. a non-negative amount of data is transmitted for any $\gamma_k \geq 0$, but no data is sent if no transmit power is used, and in this case the energy cost (3) tends to infinity;
2) $\frac{1}{\gamma_k} S_k(\gamma_k) \to 0$ for $\gamma_k \to +\infty$, i.e. by using an infinite amount of power, the energy cost diverges;
3) $S_k(\gamma_k)$ is increasing for all $\gamma_k \geq 0$, i.e. more data can be sent by spending more power;
4) $S_k(\gamma_k)$ is concave for all $\gamma_k \geq 0$.

It is easy to check that (4) fulfills Properties 1 – 4. The same happens if $R S_k(\gamma_k)$ is replaced by the achievable rate $W \log_2(1 + \gamma_k)$. Note that in this case the measure units of both (2) and (3) do not change, since the achievable rate can be regarded as an upper-bound to the amount of bits which can be reliably transmitted per unit of time. Indeed, the achievable rate is also a very popular choice to model the energy efficiency of a system [**?**], [6], [16].

Observe that, while Properties 1 – 3 stem from natural physical considerations (as explained above), Property 4 is not necessarily fulfilled by all physically meaningful functions $S_k(\cdot)$. Indeed, another popular approximation of the probability of correct packet reception is:

$$S_k(\gamma_k) = (1 - e^{-\gamma_k})^Q \quad (5)$$

with Q being the number of bits in the packet. The two approximations in (4) and (5) are closely related, and indeed

[1]The quantity in (3) can be seen to be the inverse of the so-called energy efficiency of link k, which is a more widely used, yet equivalent, metric to measure the efficiency with which energy is used to transmit data [15].

both use the exponential function to approximate the true probability of correct packet reception. However, (5) is not a concave function in γ_k and therefore cannot be included in the framework developed in this work.

The joint optimization of the energy and delay costs of a communication link can be cast as a multi-objective optimization problem [17] in which the two objective functions to minimize are given by (2) and (3). Applying the well-known *scalarization* technique, an overall cost function for the generic link k can be formulated by taking a linear combination of the delay and energy costs. In doing this, we obtain:

$$c_k = \rho_k c_{d,k} + c_{e,k} = \frac{1}{R}\left(\frac{\rho_k}{S_k(\gamma_k) - \lambda_k} + \frac{\mu_k p_k + P_{c,k}}{S_k(\gamma_k)}\right) \quad (6)$$

where ρ_k is a positive coefficient[2] weighting the relative importance of the delay cost $c_{d,k}$ with respect to the energy cost $c_{e,k}$.

By taking a distributed approach to the power control problem, each UE k aims at optimizing its own system performance by locally minimizing the corresponding cost function (6). To this end, we model the UEs as independent decision-makers which engage in the following non-cooperative game (in normal form) [18]:

$$\mathcal{G} = \left\{\mathcal{K}, \{\mathcal{A}_k\}_{k=1}^{K}, \{c_k\}_{k=1}^{K}(p_k, \mathbf{p}_{-k})\right\} \quad (7)$$

wherein $\mathcal{K} = \{1, \ldots, K\}$ is the players' set, $\mathbf{p}_{-k} = [p_1, \ldots, p_{k-1}, p_{k+1}, \ldots, p_K]$, and $\mathcal{A}_k$ is the k-th player's action set. The latter defines the feasible set in which player k can choose its transmit power p_k. We assume that the feasible powers are limited by a maximum transmit power $P_{\max,k}$ and a minimum QoS constraint θ_k. Then, we have that:

$$\mathcal{A}_k = \{p_k \in \mathbb{R}^+ : p_k \leq P_{\max,k} \ , \ S_k(\gamma_k) \geq \theta_k\}. \quad (8)$$

Given the above notation, the best response (BR) of player k to a given power vector $\mathbf{p}_{-k}$ can be determined as the solution of the following problem:

$$\min_{p_k} \quad c_k(p_k, \mathbf{p}_{-k}) \quad (9a)$$

$$\text{s.t.} \quad p_k \in \mathcal{A}_k. \quad (9b)$$

The coupled problems (9) for $k = 1, \ldots, K$ define the BRD of $\mathcal{G}$, and a fixed point, if any, of the BRD is a NE of $\mathcal{G}$ [18]. The main challenges posed by the game (7) can be summarized as follows:

- Unlike what happens in regular non-cooperative games, in which only the players' cost functions are coupled in the players' strategies, both the cost functions and the action sets of $\mathcal{G}$ are coupled. Indeed, $\mathcal{A}_k$ depends on the SINR γ_k and therefore on the other players' transmit powers. A non-cooperative game in normal form in which both the cost functions and the action sets are coupled is referred to as a *generalized* non-cooperative game [19], [20], and its analysis is typically more involved than for regular non-cooperative games;
- Unlike most previous works, the cost functions c_k are not given by the ratio of a convex over a concave function (or vice versa for utility maximization problems). This property was used in previous works to immediately conclude that the cost functions were quasi-convex (or quasi-concave for utility maximization problems), which is one of the required conditions for the existence of an NE. In our case, expressing (6) as a single fraction does not lead to a cost function with a convex numerator and a concave denominator. This further complicates the analysis of (7).
- A third challenge lies in the SINR expression (1), which is more involved than the traditional SINR expression in cellular networks due to the presence of non-zero coefficients $\{\phi_k\}_k$. This turns the k-th user's SINR γ_k into a fractional function of the k-th user's power. This is in sharp contrast to the canonical SINR expression, which is linear in the useful power p_k.

In the next section, sufficient conditions will be derived which guarantee the existence of a unique NE for the game (7), and the convergence of its BRD.

III. Distributed power control

Plugging (6) into (9), the BRD of (7) is obtained solving $\forall k$:

$$\min_{p_k} \quad \frac{\tilde{\rho}_k}{S_k(\gamma_k) - \lambda_k} + \frac{p_k + \tilde{P}_{c,k}}{S_k(\gamma_k)} \quad (10a)$$

$$\text{s.t.} \quad p_k \in \mathcal{A}_k \quad (10b)$$

where we have defined $\tilde{\rho}_k = \rho_k/\mu_k$ and $\tilde{P}_{c,k} = P_{c,k}/\mu_k$, and we have neglected the constant factor R. Also, we assume $\theta_k > \lambda_k$, recalling that the SINR range of interest is $\gamma_k > S^{-1}(\lambda_k)$.

In order to develop a distributed power control algorithm, it is necessary to characterize the properties of the generalized non-cooperative game (7). Specifically, we are interested in answering the following questions:

- Are the best-response problems in (10) always feasible?
- Does the generalized non-cooperative game (7) admit an NE? If yes, is there a unique NE?
- Is the BRD (10) guaranteed to converge from any initialization point?

Specific answers to the above questions are provided by the following propositions, whose proofs are omitted for space limitations (more details will be provided in the extended version).

***Proposition** 1: A sufficient condition for the best-response problem* (9) *to be feasible for any* $\mathbf{p}_{-k}$ *is*

$$S_k\left(\frac{\alpha_k}{\phi_k}\right) > \theta_k \quad (11)$$

$$P_{\max,k} \geq \frac{S_k^{-1}(\theta_k)\left(\sigma_k^2 + \sum_{j\neq k}\beta_{k,j}P_{\max,j}\right)}{\alpha_k - S_k^{-1}(\theta_k)\phi_k} \ . \quad (12)$$

[2]Note that ρ_k is a dimensional constant measured in J/s, in order to ensure that $\rho_k c_{d,k}$ has the same dimensions as $c_{e,k}$.

***Proposition** 2: If* (9) *is feasible, then its solution is given by*

$$p_k^* = \min\{P_{\max}, \max\{P_{\min,k}, \bar{p}_k\}\} \tag{13}$$

in which $\bar{p}_k$ *is the unique stationary point of the objective* (9a) *whereas*

$$P_{\min,k} = \frac{S_k^{-1}(\theta_k)\omega_k}{\alpha_k - S_k^{-1}(\theta_k)\phi_k} \tag{14}$$

with

$$\omega_k = \sigma_k^2 + \sum_{j \neq k} p_j \beta_{k,j}. \tag{15}$$

Moreover, if (9) *is feasible* $\forall k$, *then the non-cooperative generalized game* (7) *admits an* NE.

***Proposition** 3: Assume* (9) *is feasible* $\forall k$, *and that* S_k *is such that* $\forall k$

$$S_k(\gamma_k)S_k^{'}(\gamma_k) - \gamma_k(S_k^{'}(\gamma_k))^2 + \gamma_k S_k(\gamma_k)S_k^{''}(\gamma_k) \leq 0\ . \tag{16}$$

Then, the game (7) *admits a unique NE, and the BRD is guaranteed to converge to the unique NE.*

On the basis of above results, a distributed power control algorithm can be obtained by implementing the BRD (10) until convergence.

At a first sight, it would seem that implementing the BRD (13) in a distributed fashion is not possible, since a player k needs to know the other players' channels and transmit powers to compute its best-response. More in detail, each player k needs to know the parameter ω_k, which depends on the interference coefficients $\{\beta_{k,j}\}_j$ and on the interfering powers $\{p_j\}_j$, which are not locally available to player k. However, this issue can be overcome as explained next. Solving for ω_k in (1), we obtain the following equivalent expression for ω_k:

$$\omega_k = \frac{\alpha_k p_k}{\gamma_k} - \phi_k p_k\ . \tag{17}$$

The advantage of this reformulation is that γ_k is locally available for link k. Indeed, γ_k can be measured at the receiver associated to UE k, and fed back by a return downlink channel, which is typically available in wireless communication systems. We stress that such an approach does not require any overhead communication between a given receiver and the UEs associated to different receivers, but only between a receiver and its associated UEs. Finally, as for the other parameters α_k and ϕ_k, they can be locally computed as they only depend on the k-th UE's own channel coefficient. Bearing this in mind, the formal pseudo-code for the proposed distributed power allocation algorithm is stated as in Algorithm 1, which is guaranteed to converge to the unique NE of $\mathcal{G}$, by virtue of Proposition 3.

Algorithm 1 Distributed Power Control

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Initialize p_k to feasible values for k = 1, ..., K;
Compute α_k and φ_k for k = 1, ..., K;
repeat
  for k = 1 to K do
    ω_k = α_k p_k / γ_k − φ_k p_k;
    p_k = min{P_max, max{P_min,k, p̄_k}};
  end for
until Convergence
```

IV. Numerical results

Numerical results are now used to assess the performance of the proposed solution. To this end, we consider a multi-cell system with $L = 4$ cells, and 3 users per-cell. Therefore, we have that $K = 12$. Each cell is a square with edge 500 m which is served by a base station (BS) with $N = 128$ antennas. In each cell, the users are randomly distributed, with a minimum distance of 50 m from the service BS. All users have the same maximum feasible power $P_{\max}$ and hardware-dissipated power $P_c = 10$ dBm. The receive noise power is $\sigma^2 = FB\mathcal{N}_0$, wherein $F = 3$ dB is the receive noise figure, $B = 180$ kHz is the communication bandwidth, and $\mathcal{N}_0 = -174$ dBm/Hz is the noise spectral density at the receiver. All channels are generated according to the Rayleigh fading model with path-loss model as in [21]. Both hardware impairments at the mobile users, and channel estimation errors at the BSs are assumed and modeled following [11], with the channel estimation accuracy factor $\tau = 0.3$ and the hardware impairment factor $\epsilon = 0.1$. It was shown in [11] that such a scenario leads to an SINR expression in the same form as in (1), for particular expressions of the coefficients $\{\alpha_k\}_k$, $\{\phi_k\}_k$, $\{\beta_{k,j}\}_{k,j}$. The exact formulae can be found in [11]. Here it suffices to remark that, according to the general assumptions made in Section II, $\{\alpha_k\}_k$ and $\{\phi_k\}_k$ depend only on the k-th user's own channel and on global system parameters, whereas $\{\beta_{k,j}\}_{k,j}$ depend on the interfering users' channels. For all $k = 1, \ldots, K$, the delay parameter is set to $\lambda_k = \lambda = 0.5$, the weight factor to $\rho_k = \rho = 1$ J/s, while the adopted efficiency function is:

$$RS_k(\gamma_k) = R(1 - e^{-\gamma_k}) \tag{18}$$

with $R = 100$ kbit/s.

Fig. 1 compares the cost function (6), averaged over the K users, versus $P_{\max}$, for the following schemes:

(a) Algorithm 1 with $\theta_k = \theta = 1 - 10^{-6}\ \forall k$. If a best-response is unfeasible, we relax the QoS constraint to $\theta = 0$;
(b) Algorithm 1 with $\theta_k = \theta = 1 - 10^{-4}\ \forall k$. If a best-response is unfeasible, we relax the QoS constraint to $\theta = 0$;
(c) Algorithm 1 without QoS constraints, i.e. $\theta = 0$.

As expected, the minimum cost function is achieved when no QoS constraints are enforced. In fact, enforcing QoS constraints inevitably degrades the performance in terms of

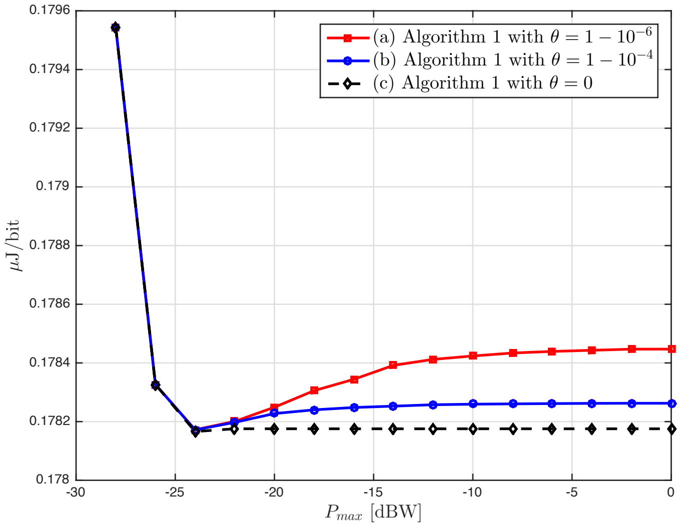

Fig. 1. $K = 12; N = 128; \epsilon = 10^{-1}; \tau = 0.3$. Average cost versus $P_{\max}$ for: (a) Algorithm 1 with $\theta = 1 - 10^{-6}$; (b) Algorithm 1 with $\theta = 1 - 10^{-4}$; (c) Algorithm 1 with $\theta = 0$.

TABLE I
$K = 12; N = 128; \epsilon = 10^{-1}; \tau = 0.3$. AVERAGE NUMBER OF REQUIRED ITERATIONS TO REACH CONVERGENCE VERSUS $P_{\max}$ FOR: (A) ALGORITHM 1 WITH $\theta = 1 - 10^{-6}$; (B) ALGORITHM 1 WITH $\theta = 1 - 10^{-4}$; (C) ALGORITHM 1 WITH $\theta = 0$.

QoS	$\theta = 1 - 10^{-6}$	$\theta = 1 - 10^{-4}$	$\theta = 0$
$P_{\max} = -28$ [dBW]	3.11	3.11	3.11
$P_{\max} = -24$ [dBW]	3.91	3.91	3.91
$P_{\max} = -20$ [dBW]	4.38	4.36	4.34
$P_{\max} = -16$ [dBW]	4.93	4.90	4.80
$P_{\max} = -12$ [dBW]	5.20	5.10	5.06
$P_{\max} = -8$ [dBW]	5.35	5.41	5.29
$P_{\max} = -4$ [dBW]	5.89	5.71	5.74
$P_{\max} = 0$ [dBW]	6.17	6.01	5.83

(6). In particular, it is seen that for low values of $P_{\max}$, all schemes perform similarly. This happens because when $P_{\max}$ is small the QoS cannot be met and therefore are relaxed - falling back to the unconstrained case. On the other hand, for larger values of $P_{\max}$, the cost function increases as the QoS constraint becomes more demanding. This is because the more demanding the QoS constraint is, the more the feasible sets of the best-response problems shrink. However, enforcing the QoS constraints allows one to guarantee minimum probabilities of correct packet reception to each user in the system. For the case at hand, Scheme (a) and (b) ensure a probability of error lower than 10^{-6} and 10^{-4}, respectively.

Next, we analyze the computational complexity of Algorithm 1. A similar scenario as in Fig. 1 is considered, reporting in Table I the average number of iterations required by Algorithm 1 to converge, for Schemes (a), (b), and (c). The rule $\|\mathbf{p}^{(n)} - \mathbf{p}^{(n-1)}\|^2 / \|\mathbf{p}^{(n)}\|^2 \leq 10^{-4}$ is used to declare convergence, with $\mathbf{p}^{(n)}$ the vector of the players' powers after iteration n of Algorithm 1. It is seen that convergence occurs after a handful of iterations, which tends to increase for larger $P_{\max}$, since increasing $P_{\max}$ results in a larger feasible set. This shows that the proposed non-cooperative approach has a very limited computational complexity, thereby lending itself to a simple implementation in practical systems.

V. Conclusions

The problem of energy-efficient and delay-aware power control in wireless networks has been studied. A distributed scenario has been considered, and the problem has been formulated as a generalized non-cooperative game in normal form, in which each mobile aims at minimizing its own cost function subject to power and QoS constraints. Under feasibility conditions which have been derived in closed-form, the game admits a unique generalized NE, which can be reached by implementing the game BRD. This result enabled the development of a distributed power control algorithm which requires minimum feedback overhead. The numerical analysis indicates that the algorithm converges in a limited number of iterations, and that the performance degrades as the QoS constraints become more demanding.

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