

Energy efficient power control for device to device communication in 5G networks

Mohamed Amine Charar, Zouhair Guennoun

Smart Communications (ERSC formerly known as LEC),

Research Center E3S Ecole Mohammadia d'Ingénieurs, Mohammed V University, Morocco

Article Info

Article history:

Received Sep 29, 2019

Revised Mar 3, 2020

Accepted Mar 12, 2020

Keywords:

5G

Device-to-device

Energy efficiency

Non-cooperative game theory

OFDMA

Power control

Resource allocation,

ABSTRACT

Next generation cellular networks require high capacity, enhanced efficiency of energy and guaranteed quality of service (QoS). To reach these goals, device-to device (D2D) communication is a candidate technology for future 5th Generation especially applications that require the reuse, the hop and the proximity gain. The present paper studies the energy efficient power control for the uplink of an OFDMA (orthogonal frequency-division multiple access) system composed of both regular cellular users and device-to-device (D2D) pairs. First, we analyze and model mathematically the prerequisites for D2D communications and classical cellular links in terms of minimum rate and maximum power requirement. Second, we use fractional programming in order to convert the initial problem into a concave one and we apply non-cooperative game theory in order to characterize the equilibrium. Then, we got the solution of the problem from the results of a water-filling power allocation. Moreover, we employ a distributed design for power allocation by means of three methods: a) Theory of fractional programming b) Closed form expression (the novelty is the use of Wright Omega function). c) Inverse water filling. Finally, simulations in both static and dynamic channel setting are realized to demonstrate the enhanced gain in term of EE, SE (spectral efficiency) and time of execution of the iterative algorithm (Dinkelbach) than the closed form algorithms.

Copyright © 2020 Institute of Advanced Engineering and Science.

All rights reserved.

Corresponding Author:

Mohamed Amine Charar,

Research Team in Smart Communications (ERSC formerly known as LEC),

Research Center E3S Ecole Mohammadia d'Ingénieurs,

Mohammed V University,

Avenue Ibn Sina B.P 765, Agdal Rabat 10090 Morocco.

Email: Mohamed.charar@gmail.com

1. INTRODUCTION AND ARTICLE CONTRIBUTIONS

Nowadays, numerous applications of wireless communications has emerged: Mobile broadband, smart grid, intelligent transportation systems, smart home, E-Health and are using an increasing number of devices: 18 billions are expected by 2022 [1]. The growth of the mobile internet is estimated to 46 percent annually from 2017 to 2022 [2] forecasted to reach 77 exabytes (EB) corresponding to a seven-fold increase every 5 years. The 5G systems are expected by 2020 and according to the wireless industry and academic, the 1000x capacity of 5G should be obtained using the same amount of energy of the previous cellular generation. Therefore, 5G have to increase energy efficiency by a factor 1000 or more [3].

From the perspective of the end user, battery autonomy is a decisive element in mobile data experience [4]. To match with the growth of mobile data, further enhancement in battery technology is needed. However, battery technology does not develop as quickly [5]. Therefore, improving the EE (energy efficiency) of mobile communication is essential to lessen the difference between increasing data consumption

and the relatively slow progress of battery technology. Although a major advance happens in battery technology, environmental, economic, and social concerns will continue to be an incentive for upper EE.

In spite of the limited contribution of ICT (information and communication technologies) to worldwide carbon dioxide emissions of around 2%, CO₂ emissions linked to ICTs are growing by 10% per year [6]. Furthermore, the energy spending of mobile broadband communications is increasing more rapidly than the entire ICT. Consequently, more efforts are needed in the area of energy efficient wireless communications to limit the environmental impact of the mobile broadband communications.

New distributed concepts are emerging such as cognitive radio [7] and device to device communications (D2D) [8], thanks to smarter equipment (UE). Besides, small cell are massively deployed and the cell size is continuously reduced which imply less UEs per base station (BS) especially in dense urban area. The feasibility of power control was studied in [9] is focused on a centralized femtocell network with a multi-channel user.

Therefore, reducing the processing load at the BS level is convenient and practical for increasing system scalability and reducing complexity, and distributed decisions should be made at the terminal level. Power control is of paramount importance in order to mitigate interference in the same channel and the near-far effect. The distributed energy efficient power control design give the wireless users the possibility to benefit from an improved quality of experience by rising their battery life for the same volume of data consumed while improving access to common resource and reducing complexity managed by the BS.

The D2D (device to device) that was introduced from version 13 of 3GPP [10] is a remarkable technology which aims to deliver, a direct connection between nearby users, underlying the cellular network. Thus, D2D improves the EE of the communication. This article discusses energy-efficient power control in the uplink of a wireless network that offers conventional cellular and D2D communications at the same time. The D2D communication mode allows nearby users to exchange data bypassing the operators' cellular infrastructure, which increases throughput, EE and reduces delay and paves the way to new usages such as disaster relief [11] and vehicle-to-vehicle communications (V2V) [12]. D2D has better ranges and better throughput than competitor technologies such as Wifi direct [13].

The technological techniques for resource allocation, interference handling, mobility management and other system-level component permit proficient D2D functioning [14]. In the vast majority of the related literature, D2D communication reuses spectral resource of cellular transmissions, which leads to more spectrum efficiency. The resource sharing between D2D communication and cellular one poses a major challenge in term of interference management, the power control is powerful tool to solve this problematic.

In the present paper, we study the uplink of a multi-carrier system with minimum QoS requirement composed of both cellular and D2D tiers. OFDM technology has several merits: low complexity, compatibility with MIMO. It thus strongly motivates 5G NR (new radio) still choosing OFDM as the basis of new waveform design [15]. Consequently, we believe that OFDMA technology will remain a foundation to 5G systems.

The framework of the non-cooperative games is applied to increase the EE. Three methods were compared for network EE maximization: a) Dinkelbach Method b) Form Expression c) Inverse Water-filling. As far as we know the comparison between these algorithms exists in the related paper in the literature but has never been evaluated and assessed.

The main contribution of this article is therefore the implementation and the evaluation of the closed expression-form algorithm and the use of Wright Omega instead of Lambert-W function. Whereas the closed expression of power was described in theory in [16], it was not implemented. Graphical comparison of the EE, SE, power and time execution was done for Dinkelbach and Closed form algorithms for cellular users and also for D2D users. A baseline algorithm was used: the Inverse waterfilling using exact minimum rate requirements.

2. RELATED WORKS

In the work of [17], the EE metric frequently encountered in later work, is defined as the data successfully transmitted (bit) over the energy consumed (Joule), also authors applied non-cooperative games theory to increase EE in the case of data transmission. This work was later extended by [18] using a linear pricing function corresponding to the power that is transmitted. The authors of [19] extended later the work of [17] to multi-carrier CDMA systems.

The authors of [20] studied the Games of power allocation for MIMO (multiple input multiple output). The authors of [21] used the potential games to tackle resource allocation for a multicell system using OFDMA (orthogonal frequency multiple access) technology. The authors of [22] proposed a cross-layer method for the control of distributed energy efficiency power in networks experiencing interference.

The authors of [5] study interference-limited environment employing non-cooperative games, then a trade-off between spectral efficiency and EE is obtained. The authors of [23] apply the concept of repeated game in order to handle decentralized power control. The uplink of an OFDMA based HetNet (heterogeneous network) composed of a macro cell and helped by a set of small cell was studied by the authors of [24] where the maximization of EE is done while respecting minimum QoS requirements. They define a solution based on Debreu Equilibrium that generalizes Nash equilibrium, which leads to a water filling like best response. The trade-off between spectral efficiency (SE) and energy efficiency (EE) is investigated for device-to-device (D2D) communications reusing uplink channel of cellular networks in [25].

The rest of the article is structured as following. The notations adopted are defined in the section 3. The system model is discussed in section 4. In the section 5 the power control game is described, then the Nash equilibrium solution is obtained using fractional programming theory in section 6. The practical aspect and the design of the algorithm are given in Section 7. The simulations results are commented in the section 8. We conclude finally in section 9.

3. NOTATIONS

The notation in the sequel of the present of the present paper are as follows:

- Bold letters are used for matrices and vectors
- Lambert W function is denoted $\mathcal{W}()$
- $\max(0, x)$ is denoted x^+
- The vector $(\alpha_1, \dots, \alpha_K)$ is written more compactly as (α_k, α_{-k}) with:

$$\alpha_{-k} = (\alpha_1, \dots, \alpha_{k-1}, \alpha_{k+1}, \dots, \alpha_K)$$

- $|A|$ is used for the cardinality of a set A

4. SYSTEM MODEL

The system we adopt is a single cell served by one BS (base station), K_c cellular UEs and K_d D2D transmitter/receiver pairs.

The UEs of the system belong to the following set: $K_c = \{UE_1, UE_2, \dots, UE_{K_c}\}$

The set of D2D pairs in the system is denoted as: $K_d = \{D_1, D_2, \dots, D_{K_d}\}$

Spectral resource allocation is based on the OFDMA technology. One sub-carrier is allocated to each cellular user. Therefore, no interference exists in the cellular tier. By contrary, every D2D transmitter has the freedom to transmit on all sub-carriers. We assume no sub-carrier allocation to D2D pairs is performed, but rather D2D transmit randomly their powers over the subcarriers. The Table 1 gives the main notations adopted.

Table 1. Notations

Notation	Meaning
W	Bandwidth of the system
K_c	Number of equally spaced sub-carriers
$B = \frac{W}{K_c}$	Bandwidth per sub-carrier
h_k	Channel between the cellular k and the BS
$h_{k,l}$	Channel between the cellular k and the D2D receiver l
g_i^n	Channel of the D2D pair i
$g_{i,c}^n$	Channel over the Sub-carrier n between The BS and the D2D transmitter i
$g_{i,l}^n$	Channel over the sub-carrier n between the D2D receiver l and the D2D transmitter i
p_k^c	Power of the cellular k
$p_{i,n}^d$	D2D Power of transmitter i over the sub-carrier n
p_{\max}^c	Cellular maximum power
p_{\max}^d	D2D maximum power
p_{cir}^c	Cellular circuit power
p_{cir}^d	D2D circuit power
R_{\min}^c	Cellular minimum rate
R_{\min}^d	D2D minimum rate

Thus, the baseband signal is written for UE_k as:

$$y_k^c = h_k \sqrt{p_k^c} x_k^c + \sum_{i=1}^{K_d} g_{i,c}^k \sqrt{p_{i,k}^d} x_{i,k}^d + n_k \quad (1)$$

With n_k is an AWGN (Additive White Gaussian Noise) that is having a mean 0 and variance σ^2 . Similarly, the signal of the baseband is written for D2D_k in the sub-carrier n as:

$$y_k^d = g_{k,n}^n \sqrt{p_{k,n}^d} x_{k,n}^d + \sum_{i=1, i \neq k}^{K_d} g_{i,c}^k \sqrt{p_{i,k}^d} x_{i,k}^d + h_n \sqrt{p_n^c} + n_{k,n} \quad (2)$$

with $n_{k,n}$ is an AWGN having the same mean and variance as n_k .

The channels are assumed complex Gaussian: the real part and imaginary part are both Gaussians.

For each D2D pair i , its power vector is denoted (over all subcarriers):

$$\mathbf{p}_i^d = [p_{i,1}^d, p_{i,1}^d, \dots, p_{i,K_d}^d] \quad (3)$$

and the vector power of D2D pairs excluding the D2D pair i is:

$$\mathbf{p}_{-i}^d = [p_1^d, \dots, p_{i-1}^d, p_{i+1}^d, \dots, p_{K_d}^d] \quad (4)$$

The transmitting vector corresponding to all D2D pairs:

$$\mathbf{p}^d = [\mathbf{p}_i^d, \mathbf{p}_{-i}^d] \quad (5)$$

The total power of D2D pair i accounting the circuit related consumption:

$$P_{tot}(\mathbf{p}_i^d) = \sum_{n=1}^{K_d} p_{i,n}^d + p_{cir}^d \quad (6)$$

and the power vector of UEs except UE_k is:

$$\mathbf{p}_{-i}^c = [p_1^c, \dots, p_{k-1}^c, p_{k+1}^c, \dots, p_{K_c}^c] \quad (7)$$

The global power of cellular users is denoted:

$$\mathbf{p}^c = [p_k^c, \mathbf{p}_{-k}^c] \quad (8)$$

The total power of UE_k accounting the circuit related consumption:

$$P_{tot}(p_k^c) = p_k^c + p_{cir}^c \quad (9)$$

The SINR (Signal to Interference plus Noise Ratio) of UE_k at the n^{th} sub-carrier:

$$\gamma_k^c = \frac{|h_k|^2 p_k^c}{\sum_{i=1}^{K_d} |g_{i,c}^k|^2 p_{i,k}^d + \sigma^2} \quad (10)$$

We denote the SINR of D2D pair k at the n^{th} sub-carrier:

$$\gamma_{k,n}^d = \frac{|g_{k,n}^n|^2 p_{k,n}^d}{\sum_{i=1, i \neq k}^{K_d} |g_{i,k}^n|^2 p_{i,n}^d + |h_n|^2 p_n^c + \sigma^2} \quad (11)$$

Let us define the effective channel gain of the cellular user UE_k as following:

$$\nu_k^c = \frac{|h_k|^2}{\sum_{i=1}^{K_d} |g_{i,c}^k|^2 p_{i,k}^d + \sigma^2} \quad (12)$$

The effective channel gain of D2D pair k is defined as:

$$\nu_{k,n}^d = \frac{|g_k^n|^2}{\sum_{\substack{i=1 \\ i \neq k}}^{K_d} |g_{i,k}^n|^2 p_{i,n}^d + |h_n|^2 p_n^c + \sigma^2} \quad (13)$$

The SE (Spectral Efficiency) utility function of UE $_k$ is:

$$SE_k^c(p_k^c, \mathbf{p}_{-k}^c, \mathbf{p}^d) = \log_2 \left(1 + \frac{\gamma_k^c}{\Gamma} \right) \quad (14)$$

With Γ the SINR gap w.r.t BER as defined in [26]: $\Gamma = -\frac{\ln(5BER)}{1.5}$

The SE (Spectral Efficiency) utility function of the k^{th} D2D pair is:

$$SE_k^d(\mathbf{p}_k^d, \mathbf{p}_{-k}^d, \mathbf{p}^c) = \sum_{n=1}^{K_c} \log_2 \left(1 + \frac{\gamma_{k,n}^d}{\Gamma} \right) \quad (15)$$

The EE (Energy Efficiency) utility function of the uplink communication of UE $_k$ is:

$$EE_k^c(p_k^c, \mathbf{p}_{-k}^c, \mathbf{p}^d) = \frac{SE_k^c(p_k^c, \mathbf{p}_{-k}^c, \mathbf{p}^d)}{P_{tot}(p_k^c)} \quad (16)$$

The EE (Energy Efficiency) utility function of the k^{th} D2D pair:

$$EE_k^d(\mathbf{p}_k^d, \mathbf{p}_{-k}^d, \mathbf{p}^c) = \frac{SE_k^d(\mathbf{p}_k^d, \mathbf{p}_{-k}^d, \mathbf{p}^c)}{P_{tot}(p_k^d)} \quad (17)$$

Each UE will increase its energy efficiency and at the same time respect the minimum rate requirements. The UE $_k$ will try to maximize its global energy efficiency while respecting minimum rate constraint. Consequently, the following problem has to be solved for UE $_k$:

$$\begin{aligned} & \text{Maximize}_{p_k^c} EE_k^c(p_k^c, \mathbf{p}_{-k}^c, \mathbf{p}^d) \\ & \text{s.t. (C1A)} \quad p_k^c \in [0, p_{max}^c] \\ & \text{(C2A)} \quad SE_k^c(p_k^c, \mathbf{p}_{-k}^c, \mathbf{p}^d) \geq R_{min}^c \end{aligned} \quad (18)$$

Similarly, the following problem has to be solved for k^{th} D2D pair:

$$\begin{aligned} & \text{Maximize}_{\mathbf{p}_k^d} EE_k^d(\mathbf{p}_k^d, \mathbf{p}_{-k}^d, \mathbf{p}^c) \\ & \text{s.t. (C1B)} \quad \mathbf{p}_k^d \in [0, p_{max}^d]^{K_c} \\ & \text{(C2B)} \quad SE_k^d(\mathbf{p}_k^d, \mathbf{p}_{-k}^d, \mathbf{p}^c) \geq R_{min}^d \end{aligned} \quad (19)$$

Hence, there are $(K_c + K_d)$ optimization problems to be jointly solved in the system. The multivariate optimization cannot be applied; as there is no central entity that is controlling all variables of the system, instead each has partial control on his own variables, which leads to the application of Game Theory.

5. GAME THEORY FORMULATION

The non-cooperative game theory appears as the natural tool to tackle to problem as we have independent, rational players that control their variables. The following triplet defines the non-cooperative game formally as:

$$\mathcal{G} = \{\mathcal{K}, \{\mathcal{A}_k\}_{k \in \{1, \dots, K\}}, \{\mathcal{U}_k\}_{k \in \{1, \dots, K\}}\}$$

where :

- Players: $K = \{K_c, K_d\}$
- Actions: $\mathcal{A}_k = [0, p_{max}^c]$ if $k \in K_c$ or $[0, p_{max}^d]^{K_c}$ if $k \in K_d$
- Utilities: The EE utility function (bit/J/Hz).

For each $k \in \{1, \dots, K\}$ the action space corresponding to other players: $\mathcal{A}_{-k} = \prod_{\substack{i=1 \\ i \neq k}}^K \mathcal{A}_i$

In order to get a solution, we have to find the equilibrium of the game. Indeed, the importance of the equilibrium in game is important as agents will become predictable and stable. The network operates effectively when reaching equilibrium [27]. The power strategy of each user must be feasible by respecting minimum QoS (quality of service) conditions. This leads us to use a different Game theory solution that allows each player to choose its strategy knowing the strategy of other players while respecting feasibility conditions: the GNE (generalized Nash equilibrium). By supposing that each player's strategy may depend on the other players', the GNE goes beyond the common NE (Nash equilibrium) [28]. Not only utility functions are dependent but also the players' action sets are couple, which is different from classical non-cooperative games [29].

We will denote by $\mathcal{A}_k^G(\mathbf{p}_{-k})$ the set of user UE_k actions respecting the minimum rate and the maximum power requirements with respect to other players' strategy:

$$\mathcal{A}_k^G(\mathbf{p}_{-k}) = \{\mathbf{p}_k \in \mathcal{A}_k : (\mathbf{p}_k, \mathbf{p}_{-k}) \text{ respects (C1) \& (C2)}\}$$

Definition. Generalized Nash equilibrium

The matrix of power $\mathbf{p}^* = (\mathbf{p}_k^*, \mathbf{p}_{-k}^*)$ is a Generalized Nash equilibrium if: $\mathbf{p}_{-k}^* \in \mathcal{A}_k^G(\mathbf{p}_{-k})$ and:

$$\forall \mathbf{p}_k \in \mathcal{A}_k^G(\mathbf{p}_{-k}^*) : EE_k(\mathbf{p}^*) \geq EE_k(\mathbf{p}_k, \mathbf{p}_{-k}^*) \quad (20)$$

Which means that no player has the interest to deviate unilaterally from a GNE to another feasible point (respecting the constraints).

6. FRACTIONAL PROGRAMMING FORMULATION AND GAME SOLUTION

The EE objective function in (18) and (19) are fractional and non-convex. The most suitable mathematical framework to tackle the optimization of such functions is the fractional programming, which provide polynomial complexity algorithms when the numerator is concave and denominator is convex [29].

First, let us give a formal definition of Fractional programming:

Definition. Fractional programming

Let $C \in \mathbb{R}^n$ convex subset and let $C \rightarrow \mathbb{R}$ the following functions:

$$f: x \rightarrow f(x) \text{ and } g: x \rightarrow g(x) \quad (21)$$

A fractional program is the optimization problem:

$$\text{Maximize}_{x \in C} \frac{f(x)}{g(x)} \quad (22)$$

The fractional programming allows us to solve equivalent form of the problem that is less complex than the original one:

Proposition 1. The vector $x^* \in C$ solves the (22) if and only if: $(f(x^*) - \lambda^* g(x^*)) = 0$, λ^* the zero of the function:

$$H(\lambda) = \text{Maximize}_{x \in C} f(x) - \lambda g(x) \quad (23)$$

For a given value, λ_k^c the UE_k will solve the following transformed fractional programming problem instead of (18):

$$\begin{aligned} &\text{Maximize}_{\mathbf{p}_k^c} SE_k^c(\mathbf{p}_k^c, \mathbf{p}_{-k}^c, \mathbf{p}^d) - \lambda_k^c P_{\text{tot}}(\mathbf{p}_k^c) \\ &\text{s.t. (C1A) \& (C2A)} \end{aligned} \quad (24)$$

For the optimal value, $\lambda_k^{c,*}$ we get:

$$SE_k^c(\mathbf{p}_k^c, \mathbf{p}_{-k}^c, \mathbf{p}^d) - \lambda_k^{c,*} P_{\text{tot}}(\mathbf{p}_k^c) = 0 \quad (25)$$

This means that the best response power $p_k^{c,*}$ given other transmitters $(\mathbf{p}_{-k}^c, \mathbf{p}^d)$ verifies the following expression:

$$\lambda_k^{c,*} = \frac{SE_k^c(\mathbf{p}_k^c, \mathbf{p}_{-k}^c, \mathbf{p}^d)}{P_{tot}(\mathbf{p}_k^c)} \quad (26)$$

Similarly, for a given value λ_k^d the equivalent problem of optimization that the k^{th} D2D pair will solve instead of (19):

$$\begin{aligned} & \text{Maximize}_{\mathbf{p}_k^d} SE_k^d(\mathbf{p}_k^d, \mathbf{p}_{-k}^d, \mathbf{p}^c) - \lambda_k^d P_{tot}(\mathbf{p}_k^d) \\ & \text{s.t. (C1B) \& (C2B)} \end{aligned} \quad (27)$$

For the optimal value, $\lambda_k^{d,*}$ we get:

$$SE_k^d(\mathbf{p}_k^d, \mathbf{p}_{-k}^d, \mathbf{p}^c) - \lambda_k^{d,*} P_{tot}(\mathbf{p}_k^d) = \mathbf{0} \quad (28)$$

This means that the best response power \mathbf{p}_k^d given other transmitters $(\mathbf{p}_{-k}^d, \mathbf{p}^c)$ verifies the following expression:

$$\lambda_k^{d,*} = \frac{SE_k^d(\mathbf{p}_k^d, \mathbf{p}_{-k}^d, \mathbf{p}^c)}{P_{tot}(\mathbf{p}_k^d)} \quad (29)$$

Practically, the solution of (24) and (27) is got when the players are giving their best response to each other. As follows, the k^{th} user best response function which is the best action \mathbf{p}_k to adopt when the strategy of the other players is $\mathbf{p}_{-k} \in \mathcal{A}_{-k}^G(\mathbf{p}_k)$:

$$BR_k(\mathbf{p}_{-k}) = \mathbf{argmax}_{\mathbf{p}_k \in \mathcal{A}_k^G(\mathbf{p}_{-k})} EE(\mathbf{p}_k, \mathbf{p}_{-k}) \quad (30)$$

The necessary conditions are more easily obtained in the case of a single carrier.

Proposition 2. In the single carrier case, the uniqueness and existence of Generalized Nash equilibrium are guaranteed, as the BR functions of the user k are standard and verify the following properties:

- Concavity: $BR_k(\mathbf{p}_{-k})$ is concave strictly in \mathbf{p}_{-k}
- Positivity: $BR_k(\mathbf{p}_{-k}) > \mathbf{0}$
- Monotonicity: if $\mathbf{q}_{-k} > \mathbf{p}_{-k}$ then $BR_k(\mathbf{q}_{-k}) > BR_k(\mathbf{p}_{-k})$
- Scalability: For all $\alpha > 1$, $\alpha BR_k(\mathbf{p}_{-k}) > BR_k(\alpha \mathbf{p}_{-k})$

Proof. The proof is given in [30]

In the case of multi-carrier, the equilibrium can be characterized by giving the expression of power for each sub-carrier and for each user as in the following proposition.

Proposition 3. The best power of the UE $_k$ is given by the following when the game admits a GNE:

$$p_k^{c,*} = \min \left(p_{\max}^c, \left(\frac{1}{\lambda_k^{c,*}} - \frac{1}{v_{k,n}^c} \right)^+ \right) \quad (31)$$

The optimal value $\lambda_k^{c,*}$:

$$\lambda_k^{c,*} = \min(\lambda_k^c, \lambda_k^{c,max}) \quad (32)$$

$$\lambda_k^c = \frac{\omega(\log(B_k^c \exp(A_k^c - 1)))}{B_k^c} \quad (33)$$

$$\text{With: } A_k^c = \log(v_k^c) \quad (34)$$

$$B_k^c = \left(p_{cir}^c - \frac{1}{v_{k,n}^c} \right) \quad (35)$$

p_{\max}^c is calculated when the rate requirements are active:

$$\lambda_k^{c,max} = v_{k,n}^c 2^{-R_{min}^c} \quad (36)$$

Proposition 4. The following formula gives the optimal power of the D2D_k for each sub-carrier n:

$$\forall n \in K_c: p_{k,n}^{d,*} = \min \left(p_{max}^d, \left(\frac{1}{\lambda_k^{d,*}} - \frac{1}{v_{k,n}^d} \right)^+ \right) \quad (37)$$

$$\text{The optimal value } \lambda_k^{d,*} : \lambda_k^{d,*} = \min(\lambda_k^d, \lambda_k^{d,max}) \quad (38)$$

$$\lambda_k^d = \frac{\omega(\log(B_k \exp(A_k^d - 1)))}{B_k^d} \quad (39)$$

N_k is the set of active subcarriers (i.e. with strictly positive power) of D2D_k when:

$$\begin{aligned} \lambda_k^{d,*} &= \lambda_k^d \\ N_k^* &= \left\{ n \in K_c \mid \left(\frac{1}{\lambda_k^d} - \frac{1}{v_{k,n}^d} \right) > 0 \right\} \end{aligned} \quad (40)$$

with:

$$A_k^d = \frac{\log(\prod_{n \in N_k^*} v_{k,n}^d)}{|N_k^*|} \quad (41)$$

$$B_k^d = \frac{\left(p_{cir}^d - \sum_{n \in N_k^*} \frac{1}{v_{k,n}^d} \right)}{|N_k^*|} \quad (42)$$

When the normalized rate constraints are active, $\lambda_k^{d,max}$ has the following formulation

$$\lambda_k^{d,max} = \left(2^{-|N_k^{max}| R_{min}^d} \prod_{n \in N_k^{max}} v_{k,n}^d \right)^{\frac{1}{N_k^{max}}} \quad (43)$$

$$\text{with: } N_k^{max} = \left\{ n \in K_c \mid \left(\frac{1}{\lambda_k^{d,max}} - \frac{1}{v_{k,n}^d} \right) > 0 \right\} \quad (44)$$

Proof. The proof is given in [31] applied to our model.

7. ALGORITHMS DESIGN AND ANALYSIS

7.1. Practical design

From practical point of view, each player give its best response to solve EE maximization problem knowing other players' strategy. We consider a scheme that is asynchronous as the user chooses its power strategy at time t based on the other players' strategy of $t - 1$. Indeed, an instantaneous feedback is very difficult in practice. We consider that each player knows his individual CSI (channel state information) within the SINR on each subcarrier. As initial value, the cellular users choose p_{init}^c and D2D users choose p_{init}^d . In each iteration, the user UE_k estimates the effective channel gain based on the previous value and based on the previous SINR:

$$\widehat{v}_k^c(t) = \frac{\gamma_k^c(t-1)}{p_k^c(t-1)} \quad (45)$$

The user UE_k estimates the EE as following and tries to increase it w.r.t to conditions (C1A) and (C2A):

$$\widehat{EE}_k^c(t) = \frac{\widehat{SE}_k^c(t)}{p_{k,n}^c(t) + p_{cir}^c} \quad (46)$$

with:

$$\widehat{SE}_k^c(t) = \log_2(1 + \widehat{v}_k^c(t) p_k^c(t)) \quad (47)$$

As in proposition 3:

$$p_{k,n}^{c,*}(t+1) = \min \left(p_{max}^c, \left(\frac{1}{\lambda_k^{c,*}(t+1)} - \frac{1}{v_k^c(t+1)} \right)^+ \right) \quad (48)$$

Similarly, the user D2D_k estimates the EE as following and tries to increase it w.r.t to conditions (C1A) and (C2A):

$$\widehat{v}_{k,n}^d(t) = \frac{\gamma_{k,n}^d(t-1)}{p_{k,n}^d(t-1)} \quad (49)$$

The user D2D_k estimates the EE as following and tries to increase it w.r.t to conditions (C1B) and (C2B):

$$\widehat{EE}_k^d(t) = \frac{\widehat{SE}_k^d(t)}{\sum_{n=1}^{K_c} p_{k,n}^d(t) + p_{cir}^d} \quad (50)$$

with:

$$\widehat{SE}_k^d(t) = \sum_{n=1}^{K_c} \log_2(1 + v_{k,n}^d(t) p_{k,n}^d(t)) \quad (51)$$

As in proposition 4:

$$\forall n \in K_c: p_{k,n}^{d,*}(t) = \min \left(p_{max}^d, \left(\frac{1}{\lambda_k^{d,*}(t)} - \frac{1}{v_{k,n}^d(t)} \right)^+ \right) \quad (52)$$

The challenge here is to find $\lambda_k^{c,*}(t)$ and $\lambda_k^{d,*}(t)$, for that we use three methods:

- The first method that was used by [24] relies on Dinkelbach algorithm: algorithm 3.
- The second method is the proposed in this article relies on the closed form expression as in algorithm 4.
- The third method is the IWF (Inverse Water Filling) is applied using algorithm 2 which aims to have exactly the minimum normalized SE (R_{min}).

Algorithm 1: Iterative Power control

- 1) **Input** : $t = 0$, $p_k^c(t) = p_{init}^c$ for $k \in \{1, \dots, K_c\}$
 $p_k^d(t) = p_{init}^d$ for $k \in \{1, \dots, K_d\}$
 - 2) **Loop over UE** for $k \in \{1, \dots, K_c\}$
 - a) Receive $\gamma_k^c(t)$
 - b) Calculate $v_k^c(t+1)$
 - c) Calculate $\lambda_k^{c,max}$ using Algorithm 2-A
 - d) Calculate λ_k^c using Algorithm 3-A or Algorithm 4-A
 - e) Calculate $\lambda_k^{c,*}$ as in (32)
 - f) Calculate $p_k^c(t+1)$ as in (48)
 - 3) **Loop over D2D transmitters** for $k \in \{1, \dots, K_d\}$
 - a) Receive $\gamma_{k,n}^d(t)$ for $n \in \{1, \dots, K_c\}$
 - b) Calculate $v_{k,n}^d(t+1)$ for $n \in \{1, \dots, K_c\}$
 - c) Calculate $\lambda_k^{d,max}$ using Algorithm 2-B
 - d) Calculate λ_k^d using Algorithm 3-B or Algorithm 4-B
 - e) Calculate $\lambda_k^{d,*}$ as in (38)
 - f) Calculate $p_k^d(t+1)$ as in (52)
 - 4) **Increment**: $t = t + 1$
 - 5) **Repeat until convergence**
-

Algorithm 2-A: Inverse Water Filling for Cellular UE_k

- 1) Calculate $\lambda_k^{c,max}$ as in (36)
 - 2) Return $\lambda_k^{c,max}$
-

Algorithm 2-B: Inverse Water Filling for $D2D_k$

- 1) Initialize $N_k^* = K_c$
 - 2) Initialize $\lambda_k^{d,max}$ as in (43)
 - 3) Loop over subcarrier for $n \in \{1, \dots, K_c\}$
 - a) Calculate $p_{k,n}^d$ as in (31)
 - b) If $p_{k,n}^d = 0$, $N_k^* = K_c \setminus \{n\}$
 - c) Else continue
 - 4) Update $\lambda_k^{d,max}$ as in (43)
 - 5) Return $\lambda_k^{d,max}$
-

Algorithm 3-A: Dinkelback method to find λ_k^c

- 1) Tolerance $\epsilon \ll 1$
 - 2) While $(SE_k^c(p_k^c) - \lambda_k^c P_{tot}(p_k^c)) < 0$
 - a) Select Random $\lambda_k \in \mathbb{R}^+$
 - b) Calculate p_k^c as in (48)
 - c) Compute $SE_k^c(p_k^c)$ and $P_{tot}(p_k^c)$
 - d) Update $(SE_k^c - \lambda_k^c P_{tot}(p_k^c))$
 - 3) End While
 - 4) While $(SE_k^c(p_k^c) - \lambda_k^c P_{tot}(p_k^c)) > \epsilon$
 - a) set $\lambda_k^c = SE_k^c(p_k^c) / P_{tot}(p_k^c)$
 - b) Calculate p_k^c as in (48)
 - c) Update $SE_k^c(p_k^c)$ and $P_{tot}(p_k^c)$
 - 5) End While
 - 6) Return λ_k^c
-

Algorithm 3-B: Dinkelback method to find λ_k^d

- 1) Tolerance $\epsilon \ll 1$
 - 2) While $(SE_k^d(p_k^d) - \lambda_k^d P_{tot}(p_k^d)) < 0$
 - a) Select Random $\lambda_k^d \in \mathbb{R}^+$
 - b) Calculate (Loop over subcarriers) $p_{k,n}^d$ as in (52)
 - c) Compute $SE_k^d(p_k^d)$ and $P_{tot}(p_k^d)$
 - d) Update $(SE_k^d(p_k^d) - \lambda_k^d P_{tot}(p_k^d))$
 - 3) End While
 - 4) While $(SE_k^d(p_k^d) - \lambda_k^d P_{tot}(p_k^d)) > \epsilon$
 - a) set $\lambda_k^d = SE_k^d(p_k^d) / P_{tot}(p_k^d)$
 - b) Calculate (Loop over subcarriers) $p_{k,n}^d$ as in (52)
 - c) Update $SE_k^d(p_k^d)$ and $P_{tot}(p_k^d)$
 - 5) End While
 - 6) Return λ_k^d
-

Algorithm 4-A: Closed-form expression to find λ_k^c

- 1) Initialize λ_k^c as in (33)
 - 2) Return λ_k^c
-

Algorithm 4-B: Closed-form expression to find λ_k^d

- 1) Initialize $N_k^{max} = K_c$
 - 2) Initialize λ_k^d as in (39)
 - 3) Loop over subcarrier for $n \in \{1, \dots, K_c\}$
 - a) Calculate $p_{k,n}^d$ as in (52)
 - b) If $p_{k,n}^d = 0$, $N_k^{max} = K_c \setminus \{n\}$
 - c) Else continue
 - 4) Update λ_k^d as in (39)
 - 5) Return λ_k^d
-

7.2. Complexity analysis

The different algorithms comprise two loops: the inner and the outer loop. Superlinearity convergence characterize the outer loop iteration; hence, the inner loop dominate the two-loop power control algorithm [32]. The complexity of the Dinkelbach algorithm is calculated as $O((KcKd + Kc)^{3.5})$ the algorithm IWF has superlinear convergence properties both in the inner and in the outer loops. For the Closed-Form algorithm we use the Wright-Omega [33] and the Lambert-W functions embedded [34] in MATLAB Software.

7.3. Convergence analysis

The methods used to calculate the value of λ are iterative (algorithm 1), which leads to an increasing serie of λ and converge to an optimal value. The algorithms got the optimal power value for a given λ , which is obtained from previous power values. The algorithms stop running whenever the resultant is relatively small [31]. The algorithms used are asynchronous: using the past strategy of the competitor in order to react to take a present action. The repeated games framework guarantees the convergence in the long-term. Indeed, players decide about the future based on their experiences in the previous stages of the game [23].

8. SIMULATION AND COMMENTS

For simulations, we choose a single cell system having a radius of 300 meters radius and $K_c=3$ cellular users and $K_d=5$ D2D pairs. The Algorithm 4 was implemented using two different ways using Lambert-W function and Wright-Omega function.

In the figures, we adopt the following notations:

- DBK for the algorithm 3 (Dinkelbach)
- CF for the algorithm 4 (Closed form) with Lambert-W function
- CF_{OM} for the algorithm 4 (Closed form) with Wright Omega function
- IWF for the algorithm 2 for Inverse Water-filling algorithm

We choose $p_{init} = 1|_N \frac{p_{max}}{2}$ to initiate power for all users

8.1. Static channel: number of iterations

The Table 2 presents main parameters adopted for the simulations to compare algorithm 3 (Dinkelbach) and algorithm 4 (Closed-form). The channel gain is expressed using the parameter α to calculate the path-loss: $h = \frac{cte}{d^\alpha}$

Table 2. List of parameters

Notation	Meaning	Value
K_c	Number of Cellular users	3
K_d	Number of D2D pairs	5
N_0	Spectral density of Noise	$3.98 \times 10^{-19} W/Hz$
B	Bandwidth for each subcarrier	1M Hz
p_{cir}^c	Circuit consumption power for cellular	300mW
p_{cir}^d	Power circuit for D2D	200mW
p_{max}	Maximum power per sub-carrier	2W
α_c	Propagation exponent for cellular	3.6
α_d	Propagation exponent for cellular	2
cte	Constant of propagation	2.57399×10^{-2}
d_{min}^c	Min. Distance form BS	20 meters
d_{min}^d	Min. between D2D	5 meters
R_{Min}^c	Min. Normalized Rate for Cellular	0.2 bit/s/Hz
R_{Min}^d	Min. Normalized Rate for D2D	2 bit/s/Hz
Γ	The BER Gap in the SINR	1

We perform 10 iterations to be sure that the users will end by learning equilibrium by executing the interative algorithms 3 and 4. We average the energy efficiency, spectral efficiency and power per subcarrier of the reference user to obtain the results of simulation. The position of the reference user was averaged 100 times. The simulations show that equilibrium of the game exist and converge before the 10th iteration. We do not have a saturated equilibrium, which does not reach the maximum power. For the subsequent simulations, static and flat fading channel model was choosen. The algorithm 3 and 4 both respect minimum SE and consequently converge to a solution that respect the minimum rate requirement.

The IWF (inverse water filling) algorithm respects the minimum rate requirement by its construction to achieve the minimum rate exactly. Hence, the conditions in the maximization problem (C1) and (C2) are respected. The flat fading assumption leads to the users to choose the same power over all the sub-carriers. We give below our comments on results obtained:

EE: The Energy efficiency corresponds to the EE utility times the bandwidth.

- Cellular: The simulations in Figure 1 that represent the EE of a reference cellular user shows that the DBK algorithm is 800% better than CF algorithm. CF_{OM} algorithm realizes the same EE as CF algorithm. Unsurprisingly, the IWF algorithm has the least EE.
- D2D: The simulations in Figure 2 that represent the EE of a reference D2D user shows that the DBK algorithm is 20% better than CF algorithm. CF_{OM} algorithm realizes the same EE as CF algorithm. The IWF algorithm has the least EE.
- Comparison Cellular and D2D: The D2D communication brings proximity gain in, the EE of D2D is at least 2.5 times the EE of Cellular.

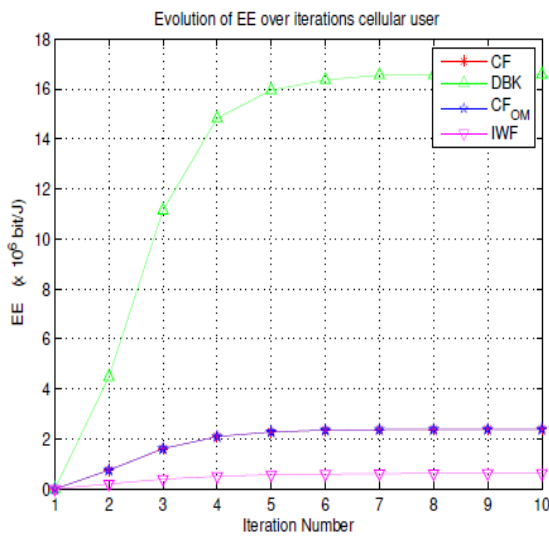


Figure 1. Comparison in term of EE, cellular user static channel

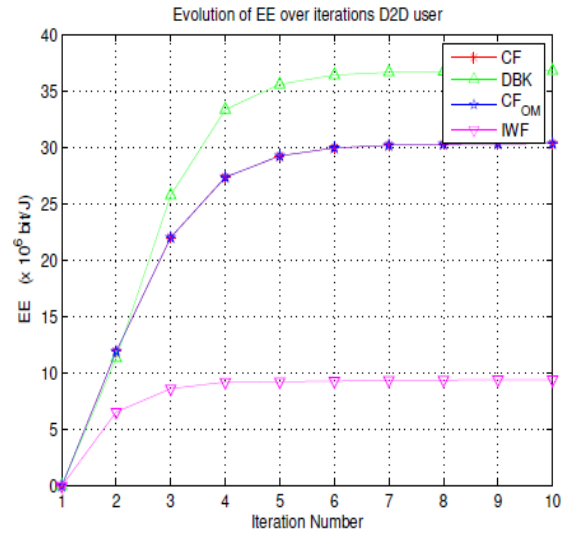


Figure 2. Comparison in term of EE Static, D2D user static channel

SE: the SE expressed in bit/s/Hz

- Cellular: the simulations in Figure 3 that represent the SE of a reference cellular user shows that the DBK algorithm is 10% better than CF algorithm. CF_{OM} algorithm realizes the same EE as CF algorithm. The IWF algorithm has the least EE.
- D2D: the simulations in Figure 4 that represent the EE of a reference D2D user shows that the DBK algorithm is slightly better than CF algorithm. CF_{OM} algorithm realizes the same EE as CF algorithm. The IWF algorithm has the least EE.
- Comparison Cellular and D2D: The D2D communication brings proximity gain; the SE of D2D is at least 8.3 times the SE of Cellular.

Power: the instant consumed power

- Cellular simulations in Figure 5, that represent the power of a reference Cellular user shows that the CF algorithm consumes 75% more power than DBK algorithm. The IWF algorithm consumes the least power.
- D2D simulations in Figure 6, that represent the power of a reference Cellular user shows that the CF algorithm consumes 25% more power than DBK algorithm. The IWF algorithm consumes the least power.

Time of execution: simulations in Figure 7 shows the cumulative time of execution expressed in millisecond. In the 6 first iterations the DBK algorithm consumes more time than the CF algorithm. The CF_{OM} algorithm based on Wright Omega function has slightly less complexity than Lambert W function starting from the seventh iteration the DBK algorithm join the closed form. The least time execution belongs to IWF algorithm.

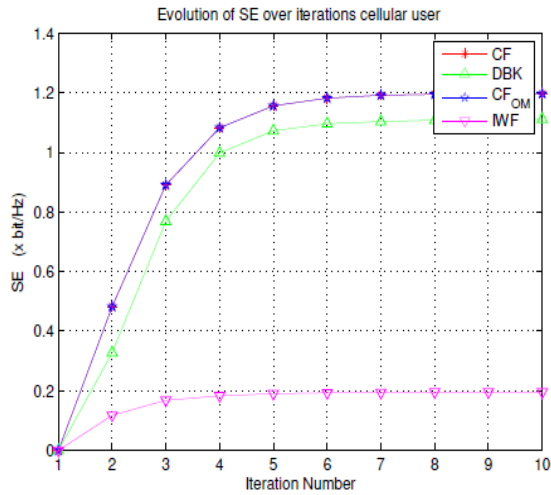


Figure 3. Comparison in term of SE, cellular user static channel

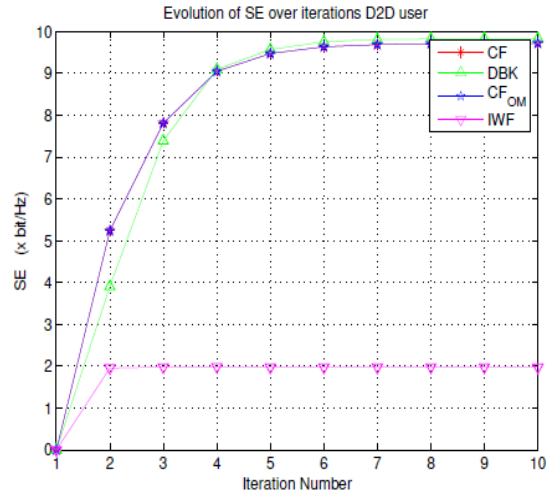


Figure 4. Comparison in term of SE static, D2D user static channel

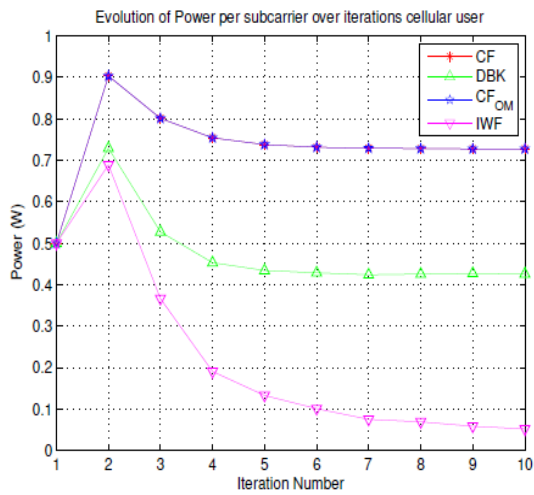


Figure 5. Comparison in term of power, cellular user static channel

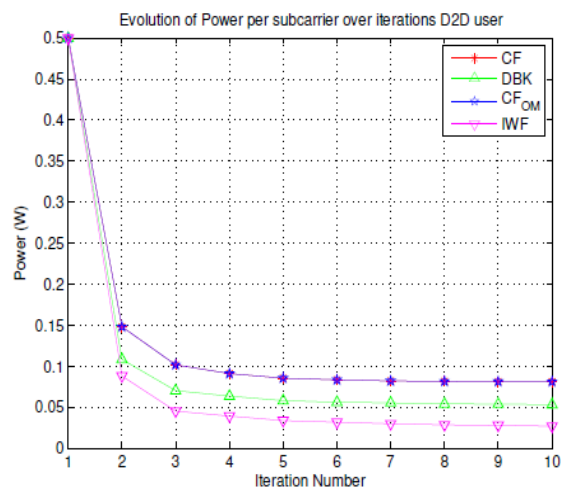


Figure 6. Comparison in term of power static, D2D user static channel

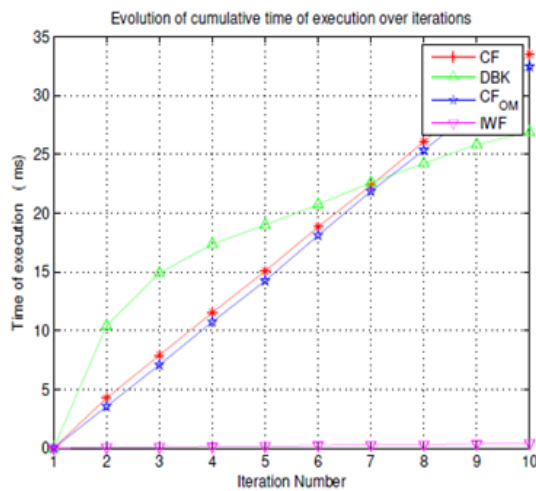


Figure 7. Comparison in term of time execution

8.2. Rayleigh channel: number of iterations

In this subsection, we perform simulations with Rayleigh channel instead of static channel considered for the previous simulations. For the subsequent simulations, static and flat fading channel model was chosen. The algorithm 3 and 4 both respect minimum SE and consequently converge to a solution that respect the minimum rate requirement.

The IWF (inverse water filling) algorithm respects the minimum rate requirement by its construction to achieve the minimum rate exactly. Hence, the conditions in the maximization problem (C1) and (C2) are respected. The flat fading assumption leads to the users to choose the same power over all the sub-carriers. We give below our comments on results obtained:

EE: The Energy efficiency corresponds to the EE utility times the bandwidth.

- Cellular the simulations in Figure 8 that represent the EE of a reference cellular user shows that the DBK algorithm is 800% better than CF algorithm. CFOM algorithm realizes the same EE as CF algorithm. Unsurprisingly, the IWF algorithm has the least EE.
- D2D the simulations in Figure 9 that represent the EE of a reference D2D user shows that the DBK algorithm is 20% better than CF algorithm. CFOM algorithm realizes the same EE as CF algorithm. The IWF algorithm has the least EE.
- Comparison cellular and D2D: The D2D communication brings proximity gain, the EE of D2D is at least 2:25 times the EE of Cellular.

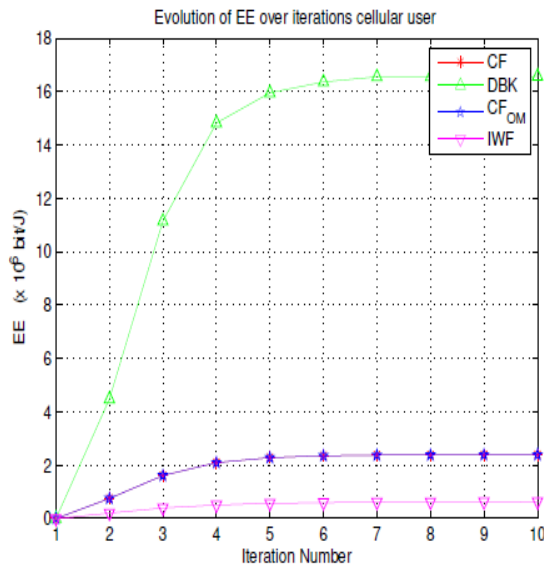


Figure 8. Comparison in term of EE, cellular user rayleigh channel

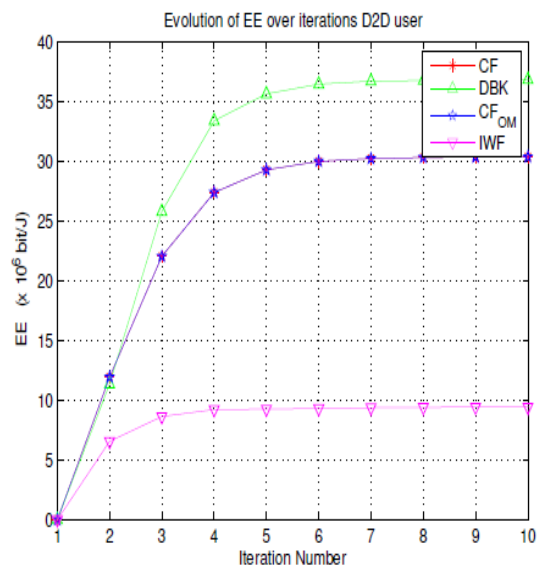


Figure 9. Comparison in term of EE static, D2D user rayleigh channel

SE: the SE expressed in bit/s/Hz

- Cellular the simulations in Figure 10 that represent the SE of a reference cellular user shows that the CF algorithm is 20% better than DBK algorithm. CFOM algorithm realizes the same EE as CF algorithm. The IWF algorithm has the least EE.
- D2D The simulations in Figure 11 that represent the EE of a reference D2D user shows that the DBK algorithm is slightly better than CF algorithm. CFOM algorithm realizes the same EE as CF algorithm. The IWF algorithm has the least EE.
- Comparison cellular and D2D: The D2D communication brings proximity gain, the EE of D2D is at least 8.33 times the EE of Cellular.

Time of execution: simulations in Figure 12 shows the cumulative time of execution expressed in millisecond. In this case the DBK algorithm has clearly better complexity than the CF algorithms.

Robustness: Although the algorithms DBK and CF do not converge but they show a good robustness as the power, EE, SE are smooth, stable, and slowly varying after few iterations.

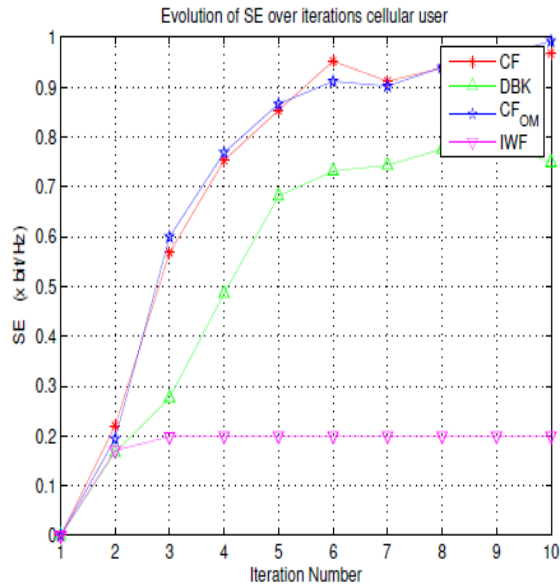


Figure 10. Comparison in term of SE, cellular user rayleigh channel

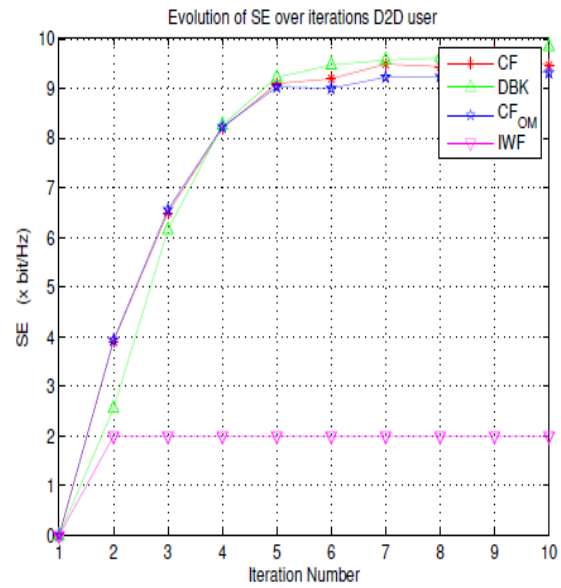


Figure 11. Comparison in term of SE static, D2D user rayleigh channel

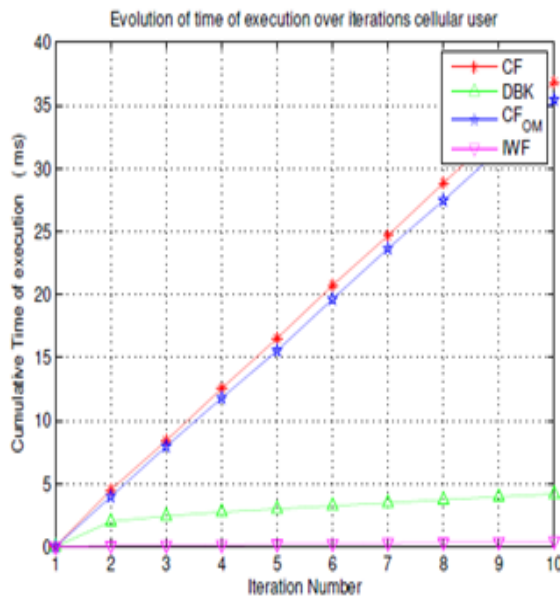


Figure 12. Time of execution rayleigh

8.3. Impact of minimum rate

In this subsection, we examine the impact of the minimum rate constraint on the SE and EE of the D2D pair. We take a fixed minimum rate constraint for cellular users $R_{min}^c = 0.2 \text{ bit/s/Hz}$ and we vary the minimum rate for the D2D users from 0 to 30bit/s/Hz As in Figure 13 and Figure 14:

- EE: The energy efficiency grows steadily for IWF algorithm until around 7 bit/s/Hz while it is higher for the other algorithm. Then the EE drops beyond 10bit/s/Hz for all algorithms.
- SE: The spectral efficiency steadily for IWF algorithm until around 10 bit/s/Hz while it is higher for the other algorithm. Then the SE is stable beyond 15 bit/s/Hz for all algorithms.

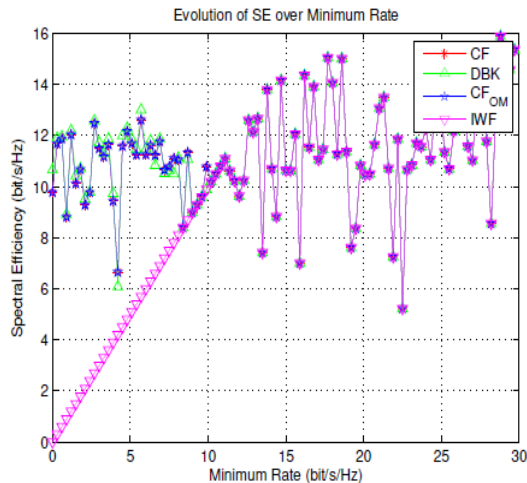


Figure 13. Comparison of SE as function of minimum rate

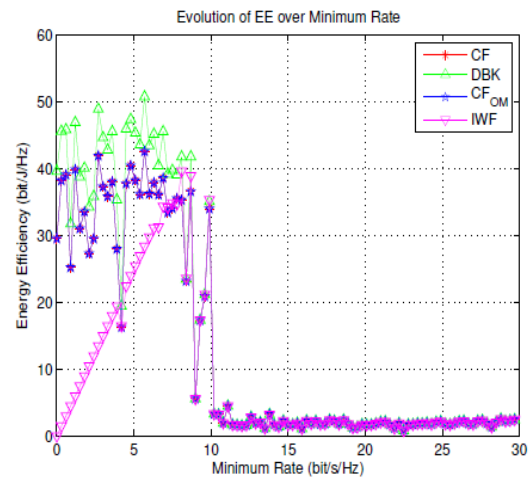


Figure 14. Comparison of EE as function of minimum rate

9. CONCLUSION AND FUTURE WORKS

In this work, we compare closed-form expression of the power allocation to Dinkelbach algorithm applied to a D2D communication underlying a cellular network. Results shows that Dinkelbach algorithm provides more EE than the Closedform algorithm. Furthermore, in term of SE Dinkelbach algorithm is equivalent to closed form when it comes to D2D communication type. However, closed form algorithm outperforms the Dinkelbach for cellular type communication, which is in line with our previous work [31]. In term of time of execution, we remark that the Dinkelbach Algorithm suffers from a slow start in the first iterations then it becomes faster than closed form algorithms. Due to its simplicity, the Inverse Waterfilling algorithm has excellent convergence, lowpower and complexity properties but its EE is very limited and its SE is just the minimum rate. This algorithm (IWF) can be applied to fixed rate application that are not ambitious in term of rate: for instance VoNR (voice over new radio). Despitethe non-convergence in the dynamic channel conditions, the proposed algorithms show good stability and very similar results to the static case in terms of EE, SE, and power. However, the time of execution in the dynamic case of Dinkelbach algorithm is much lower than closed form. Although the usage of the Wright Omega function compared to Lambert Wfunction brought some reduction of time execution, but it was not enough to get better results than Dinkelbach algorithm was. Whatever the used algorithms, thanks to proximity and hoptgain, D2D communication bring significant improvement of energy efficiency compared to cellular communication. Yet, more investigation needs to be done in order to increase Energy Efficiency. Another possible future work is the application to more sophisticated scenarios such as MIMO and Small Cells.

REFERENCES

- [1] "Internet of Things forecast," *Ericsson Mobility Report*, Nov. 2018. [Online]. Available: <https://www.ericsson.com/en/mobility-report/internet-of-things-forecast>
- [2] "Cisco Visual Networking Index: Forecast and Trends, 2017–2022," *Cisco*, pp. 38, 2018.
- [3] S. Buzzi, C. I. T. E. Klein, H. V. Poor, C. Yang, and A. Zappone, "A survey of energy-efficient techniques for 5G networks and challenges ahead," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 4, pp. 697–709, Apr. 2016.
- [4] D. Feng, C. Jiang, G. Lim, J. Cimini, L. J., G. Feng, and G. Li, "A survey of energy-efficient wireless communications," *IEEE Communications Surveys Tutorials*, vol. 15, no. 1, pp. 167–178, 2013.
- [5] G. Miao, N. Himayat, G. Li, and S. Talwar, "Distributed interference-aware energy-efficient power optimization," *IEEE Transactions on Wireless Communications*, vol. 10, no. 4, pp. 1323–1333, Apr. 2011.
- [6] G. Bacci, E. V. Belmega, and L. Sanguinetti, "Distributed energy efficient power and subcarrier allocation for OFDMA-based small cells," in *Communications Workshops (ICC), 2014 IEEE International Conference on. IEEE*, pp. 647–652, 2014. [Online]. Available: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6881272
- [7] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," *IEEE Personal Communications*, vol. 6, no. 4, pp. 13–18, Aug. 1999.
- [8] S. Mumtaz, K. M. S. Huq, and J. Rodriguez, "Direct mobile-to-mobile communication: Paradigm for 5G," *IEEE Wireless Communications*, vol. 21, no. 5, pp. 14–23, Oct. 2014.

- [9] A. F. Isnawati, R. Hidayat, S. Sulistyono, and I. W. Mustika, "Feasibility of power control for multi-channel user in inter-femtocell network," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 6, no. 4, pp. 1685-1694, 2016.
- [10] Dino Flore, "Evolution of LTE in Release 13," *3GPP, The Mobile Broadband Standard*, 2014. [Online]. Available: <http://www.3gpp.org/news-events/3gpp-news/1628-rel13>
- [11] J. Liu, N. Kato, J. Ma, and N. Kadowaki, "Device-to-device communication in LTE-advanced networks: A Survey," *IEEE Communications Surveys Tutorials*, vol. PP, no. 99, pp. 1-1, 2014.
- [12] W. Sun, E. G. Ström, F. Brännström, Y. Sui, and K. C. Sou, "D2d-based V2v communications with latency and reliability constraints," in *2014 IEEE Globecom Workshops (GC Wkshps)*, pp. 1414-1419, Dec. 2014.
- [13] D. Feng, L. Lu, Y. Yuan-Wu, G. Li, S. Li, and G. Feng, "Device-to device communications in cellular networks," *IEEE Communications Magazine*, vol. 52, no. 4, pp. 49-55, Apr. 2014.
- [14] T. B. Iliev, Gr. Y. Mihaylov, E. P. Ivanova, and I. S. Stoyanov, "Power control schemes for device-to-device communications in 5G mobile network", in *2017 40th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*, pp. 416-419, 2017.
- [15] S. Lien, S. Shieh, Y. Huang, B. Su, Y. Hsu, and H. Wei, "5G new radio: Waveform, frame structure, multiple access, and initial access," *IEEE Communications Magazine*, vol. 55, no. 6, pp. 64-71, Jun. 2017.
- [16] G. Bacci, E. V. Belmega, and L. Sanguinetti, "Distributed energy efficient power optimization in cellular relay networks with minimum rate constraints," in *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 7014-7018, May 2014.
- [17] D. Goodman and N. Mandayam, "Power control for wireless data," *IEEE Personal Communications*, vol. 7, no. 2, pp. 48-54, Apr. 2000.
- [18] C. Saraydar, N. B. Mandayam, and D. Goodman, "Efficient power control via pricing in wireless data networks," *IEEE Transactions on Communications*, vol. 50, no. 2, pp. 291-303, Feb. 2002.
- [19] F. Meshkati, M. Chiang, S. Schwartz, H. Poor, and N. B. Mandayam, "A non-cooperative power control game for multi-carrier CDMA systems," in *2005 IEEE Wireless Communications and Networking Conference*, vol. 1, pp. 606-611, Mar. 2005.
- [20] E. Belmega and S. Lasaulce, "Energy-efficient precoding for multiple-antenna terminals," *IEEE Transactions on Signal Processing*, vol. 59, no. 1, pp. 329-340, Jan. 2011.
- [21] S. Buzzi, G. Colavolpe, D. Saturnino, and A. Zappone, "Potential games for energy-efficient power control and subcarrier allocation in uplink multicell OFDMA systems," *IEEE Journal of Selected Topics in Signal Processing*, vol. 6, no. 2, pp. 89-103, Apr. 2012.
- [22] V. S Varma, s. Lasaulce, y. hayel, and S. EddineEleyoubi, "A cross-layer approach for distributed energy-efficient power control in interference networks," *IEEE Transactions on Vehicular Technology*, vol. PP, no. 99, pp. 1-1, 2014.
- [23] M. Le Treust and S. Lasaulce, "A repeated game formulation of energy-efficient decentralized power control," *IEEE Transactions on Wireless Communications*, vol. 9, no. 9, pp. 2860-2869, Sep. 2010.
- [24] G. Bacci, E. V. Belmega, P. Mertikopoulos, and L. Sanguinetti, "Energy-aware competitive power allocation for heterogeneous networks under QoS constraints," *IEEE Transactions on Wireless Communications*, vol. 14, no. 9, pp. 4728-4742, Sep. 2015.
- [25] Z. Zhou, M. Dong, K. Ota, J. Wu, and T. Sato, "Energy efficiency and spectral efficiency tradeoff in device-to-device (D2D) communications," *IEEE Wireless Communications Letters*, vol. 3, no. 5, pp.485-488, Oct. 2014.
- [26] A. Goldsmith and S.-G. Chua, "Variable-rate variable-power MQAM for fading channels," *IEEE Transactions on Communications*, vol. 45, no. 10, pp. 1218-1230, Oct. 1997.
- [27] S. Lasaulce, M. Debbah, and E. Altman, "Methodologies for analyzing equilibria in wireless games," *IEEE Signal Processing Magazine*, vol. 26, no. 5, pp. 41-52, Sep. 2009.
- [28] G. Scutari, D. Palomar, F. Facchinei, and J.-S. Pang, "Convex optimization, game theory, and variational inequality theory," *IEEE Signal Processing Magazine*, vol. 27, no. 3, pp. 35-49, May 2010.
- [29] A. Zappone and E. Jorswieck, "Energy efficiency in wireless networks via fractional programming theory," *Foundations and Trends in Communications and Information Theory*, vol. 11, no. 3-4, pp. 185-396, Jun. 2015. [Online]. Available: <https://www.nowpublishers.com/article/Details/CIT-088>
- [30] M. A. Charar, Z. Guennoun, and G. Aniba, "Achieving energy efficiency for Device to Device communications using power control: A low complexity algorithm," in *2015 10th International Conference on Intelligent Systems: Theories and Applications (SITA)*, pp. 1-6, Oct. 2015.
- [31] M. A. Charar, Z. Guennoun, and G. Aniba, "Assessment of a closed-form iterative water filling energy efficient power control algorithm in multi-carrier context," in *The International Conference on Wireless Networks and Mobile Communications (WINCOM'17) (WINCOM'17)*, Rabat, Morocco, Nov. 2017.
- [32] K. Yang, S. Martin, C. Xing, J. Wu, and R. Fan, "Energy-efficient power control for device-to-device communications," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 12, pp. 3208-3220, Dec. 2016.
- [33] R. M. Corless and D. J. Jeffrey, "The wright omega function," in *AISC '02/Calculus '02: Proceedings of the Joint International Conferences on Artificial Intelligence, Automated Reasoning, and Symbolic Computation*, UK: Springer-Verlag, pp. 76-89, 2002. [Online]. Available: <http://dl.acm.org/citation.cfm?id=648168.750650>
- [34] R. M. Corless, G. H. Gonnet, D. E. G. Hare, D. J. Jeffrey, and D. E. Knuth, "On the LambertW function," *Advances in Computational Mathematics*, vol. 5, no. 1, pp. 329-359, Dec. 1996.

BIOGRAPHIES OF AUTHORS

Mohamed Amine Charar received the Dipl.-Ing. Degree from Ecole Nationale Supérieure de Télécommunications Bretagne -France With Major in wireless Communication, in 2008 after a consultant position in BT Services in Paris France, he joined Maroc Telecom as Networks Development Engineer in 2010, from 2015 to present he is the core network engineering Manager at the same company. He is currently pursuing the Ph.D. degree at École Mohammadia d' Ingénieurs (EMI) where he is member of the ERSC formerly known as LEC, working on Energy Efficiency Power control for Wireless Networks.



Zouhair Guennoun received the B.Eng. degree in electrical engineering in 1987 from ULG, Liege Belgium, M.Sc. degrees in electrical and computer engineering in 1993 from École Mohammadia d' Ingénieurs (EMI), Rabat, and the Ph.D. degree in applied science in 1996 from EMI. He is currently a Professor of Computer and electronic Engineering at École Mohammadia d' Ingénieurs (EMI) where he is member of the ERSC formerly known as LEC, and member of the spatial research center (CRES). His research interests include wireline and wireless networks, advanced communications systems, signal Processing, audio and image compression, audio cryptography. He is a senior member of IEEE.