Achieving Energy Efficiency for Device to Device Communications using Power Control: a Low Complexity Algorithm

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***Abstract*—In this article we investigate energy efficient power control in the context of D2D (Device to Device) communications. An approach based on game theory is used to implement a fully distributed power control scheme. We propose a practical implementation of a low complexity power allocation algorithm that we compare with an existing NLP (Non Linear Programming) power allocation algorithm. Simulations results show that the proposed algorithm has near optimal performance and reduced computational complexity comparing to NLP algorithm.**

***Index Terms*—Energy Efficiency, Power Control, D2D (Device To Device), Game Theory, Resource Allocation**

I. Introduction

Nowadays telecommunication industry is facing a continuous growth of data usage. As battery technology is not improving that fast, Energy efficiency (EE) is then a key aspect of quality of experience from end user perspective. This implies more efforts on uplink wireless energy optimization. The peer to peer concept, D2D (Device to Device) is a promising technology that is intended to offer, underlaying a cellular network, direct connection between close devices. By doing so, D2D enhances EE of communication. This article addresses the energy efficient power control in the uplink of a wireless network that offers at same time classical cellular and D2D communications. D2D is a promising technology that is planned for 3GPP Release 13 [1]. The D2D communication allows spatially close users to exchange data with each other without passing through operator's base stations which increases EE, throughput and reduces delay and allows new applications like disaster relief [2]. Comparing to other competitor technologies such as Wifi Direct D2D offers better ranges and better rates [3]. In most papers in the literature, D2D communication shares the same spectrum with regular cellular transmissions in order to achieve high spectral efficiency. As D2D communication uses the same resources as the cellular networking , interference handling is a challenge to face when using D2D communications and power control is one of the solutions to deal with interference.

EE is becoming a challenge in modern Wireless Networks. In one hand the mobile traffic is growing exponentially at a 57 percent CAGR from 2014 to 2019 [4], in the other hand the battery technology is growing relatively slowly at only 10 percent every two years [5]. Even if a breakthrough happened in battery technology, economical, environmental concerns and social responsibility of end users would continue to be a motivation of higher EE.

Efficient power control design allows all kind of wireless users, cellular and D2D ones, to enjoy a better quality of experience by increasing their battery lifetime.

II. Related Works & article contributions

In the seminal work of [6] authors define the EE metric often encountered in subsequent works, data successfully transmitted (bit) over energy consumed (Joule). In [7] authors studied enabling D2D communication and showed that D2D communication increase the total system throughput in case of an LTE-A. The work of [8] derives the tradeoff between EE and spectral efficiency (SE) in device-to-device communications underlaying cellular networks with uplink channel reuse. A distributed energy-efficient scheme was developed, given SE requirement and maximum power constraints.

In this article we propose an uplink Energy Efficient communications scheme of Device to Device underlaying cellular network. We used a non-cooperative game formulation to deal with the EE. We prove the existence and the uniqueness of Nash Equilibrium of that power control game. We compared two iterative power allocation algorithms dealing with EE of D2D network:

- A proposed Low complexity power allocation algorithm that calculates first the best power then verify if this power respects rate constraint.
- A Classical power allocation algorithm based on NLP (Non Linear Programming)

We compare both algorithms in terms of calculation time, Throughput and EE using computer simulations. Results shows that the proposed algorithm offers near optimal performance with less computational cost. For both algorithms we represent and compare graphically the EE and system throughput functions .
The remainder of this paper is organized as follows. In section III, we describe the system model. The proposed power control game is discussed in section IV and its Nash equilibrium

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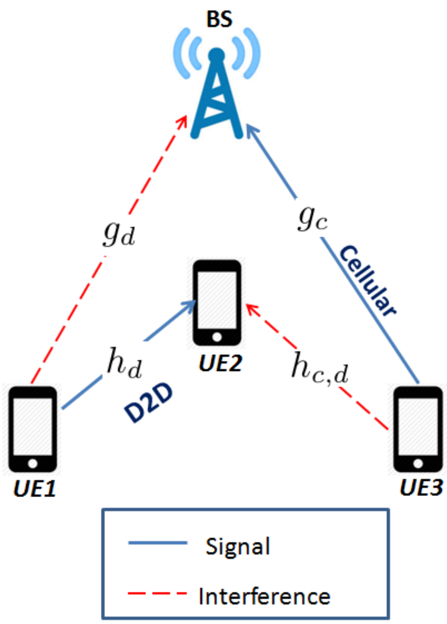

Fig. 1. Illustration of the system model

solution is derived. In section V practical considerations are described. Section VI results obtained from computer simulation are commented. Finally, we give conclusions in section VII.

III. System Model

Our model to analyze D2D uplink EE is based on a MAC (Multi Access Channel) system composed of one BS and 3 users: UE1 , UE2 and UE3 . Where UE1 and UE2 have a directional D2D communication where UE1 the transmitter and UE2 the receiver and where UE3 has an uplink with BS. The system has a total bandwith W shared by all users. To define channel gains, we suppose that all channels are experiencing flat fading:

- g_d , g_c are channel gains to BS from respectively UE1 and UE3,
- $h_{c,d}$ channel gain from the UE3 to UE2,
- h_d channel gain from the UE1 and UE2,

The power radiated from the D2D transmitter UE1 is noted p_d and the power radiated from the cellular user UE3 is noted p_c, both p_d and p_c cannot go beyond a maximum radiation power p_{max}. We suppose that both of UE1 and UE3 are consuming a fixed circuit power linked to electronics p_{cir} which is dissipated even during non-transmission periods.

The SINR of the D2D transmitter UE1 at the D2D receiver UE2 is :

$$\gamma_d = \mu_d p_d$$

With μ_d defined as the effective channel gain at the D2D receiver :

$$\mu_d = \frac{h_d}{h_{c,d} p_c + \sigma^2}$$

The noise power $\sigma^2 = W * N_0$, where N_0 is the noise spectral density and W the spectrum bandwidth.

Similarly the SINR of the cellular user at the base station :

$$\gamma_c = \mu_c p_c$$

With μ_c defined as the effective channel gain at the D2D receiver :

$$\mu_c = \frac{g_c}{g_d p_c + \sigma^2}$$

The utility function corresponding to the EE of D2D link is :

$$U_d(p_d, p_c) = \frac{f(\gamma_d)}{p_d + p_{cir}}$$

The utility function corresponding to the EE of cellular link is :

$$U_c(p_d, p_c) = \frac{f(\gamma_c)}{p_c + p_{cir}}$$

$f(\gamma)$ is an increasing function of SINR , with$f(0) = 0$ with utility function going to 0 when power goes to infinity. In this article, we choose to use the Shannon information rate:

$$f(\gamma) = W log_2(1 + \gamma)$$

As $\gamma = \mu p$, $f(\gamma)$ will go to 0 if p goes to ∞, meaning intuitively that user has no benefit when transmitting at high power.

IV. Game Theory Formulation

The strategy of each player (UE) is to adjust his power in order to enhance his EE. The utility of the D2D link (resp. cellular link) depends not only on the D2D power but also on the cellular power (resp. D2D power). The natural framework to study the interdependent interaction between rational agents is the non cooperative game theory. The considered non-cooperative game can be formally expressed as the triplet: $\mathcal{G} = \{\mathcal{K}, \{\mathcal{A}_k\}_{k\in\{d,c\}}, \{\mathcal{U}_k\}_{k\in\{d,c\}}\}$ where:

- Players: $\mathcal{K} = \{\text{UE1,UE3}\}$
- Actions: $\mathcal{A}_k = [0, p_{max}]$, $k = d$ for D2D user UE1 and $k = c$ for cellular user UE3.
- Utilities: $\mathcal{U}_k$, $k = d$ for D2D user UE1 and $k = c$ for cellular user UE3. The utility function corresponds to EE expressed in (bit/J).

Now we have to determine the equilibrium of the game $\mathcal{G}$. The existence and uniqueness of equilibrium is very important for distributed system design because when agents reach equilibrium they have stable and predicable behavior. It is at the equilibrium that network will effectively operate.

Definition. *Nash Equilibrium*
A joint power strategy vector of the two UE, $\mathbf{p}^* = (p_d^*, p_c^*)$ is a Nash equilibrium if:

$$\forall k \in \{d, c\}, \forall p_k \in \mathcal{A}_k : U_k(\mathbf{p}^*) \geq U_k(p_k, p_{-k}{}^*)$$

Where p_{-k} is the strategy of the other player. In other words , when the users are playing a NE no user has interest to deviate unilaterally from this equilibrium.

The D2D transmitter tries to solve the following optimization problem by adjusting his power level p_d:

$$\begin{aligned} \underset{p_d}{\text{Max}} \quad & U_d(p_d, p_c) \\ \text{s.t} \quad & 0 \leq p_d \leq p_{max} \\ & f(\gamma_d) \geq R^d_{min} \end{aligned} \tag{1}$$

If $R_{min} = 0$, we say that EE optimization of D2D link is unconstrained. If $R_{min} > 0$, we say that the EE optimization of D2D link is Rate Constrained. The cellular user tries to solve the following optimization problem by adjusting his power level p_c:

$$\begin{aligned} \underset{p_c}{\text{Max}} \quad & U_c(p_d, p_c) \\ \text{s.t} \quad & 0 \leq p_c \leq p_{max} \\ & f(\gamma_c) \geq R^c_{min} \end{aligned} \tag{2}$$

For cellular link also we have either constrained rate communication or uncontrained one.

Pratically, each of the two UE will reach equilibrium and hence solve (2), (1) by giving his best reponse to the strategy of the other player. Hereafter the Best Response function of the D2D user UE1 which is the best action p_d to adopt knowing the action of the other play p_c:

$$\forall p_c \in [0, p_{max}], \mathrm{BR_d}(p_c) = \mathrm{argmax}_{p_d} U_d(p_d, p_c)$$

Similarly, the Best Response function of the cellular user UE3 which is the best action p_c to adopt knowing the action of the other play p_d:

$$\forall p_d \in [0, p_{max}], \mathrm{BR_c}(p_d) = \mathrm{argmax}_{p_c} U_c(p_d, p_c)$$

Theorem 1. *The BR functions of D2D user and cellular user verify the following properties:*

- *Concavity:* $\mathrm{BR_i}(\mathbf{p_{-i}})$ *is strictly concave in* $\mathbf{p_{-i}}$
- *Positivity:* $\mathrm{BR_i}(\mathbf{p_{-i}}) > 0$
- *Monotonicity: if* $\mathbf{q_{-i}} > \mathbf{p_{-i}}$ *then* $\mathrm{BR_i}(\mathbf{q_{-i}}) > \mathrm{BR_i}(\mathbf{p_{-i}})$
- *Scalability: For all* $\alpha > 1$, $\alpha \mathrm{BR_i}(\mathbf{p_{-i}}) > \mathrm{BR_i}(\alpha \mathbf{p_{-i}})$

Hence, BR functions are standard: The existence and uniqueness of Nash Equilibrium are guaranteed.

Proof. Let first that our BR functions verify the properties cited above.

- Concavity: let us prove that the second derivative of the D2D best response function is negative: $\frac{\partial^2 \mathrm{BR_d}(p_c)}{\partial p_c^2} < 0$ To simplify calculation we adopt the following notations: $\mathrm{BR_d}^2(p_c) = p_d^0$ and $I = \frac{h_{c,d}p_c + \sigma^2}{h_d}$ as I is linear combination of p_c proving that the best response is concave is equivalent to demonstrate that $\frac{\partial^2 p_d^0}{\partial I^2} < 0$. p_d^0 maximizes the utility function which is quasi-concave then: $\frac{\partial U_d(p_d^0, p_c)}{\partial p_d^0} = 0$ That implies that:

$$\frac{\partial f(\gamma_d)}{\partial p_d^0} = \frac{f(\gamma_d)}{p_d^0 + p_{cir}}$$

Exploiting the fact that: $\partial p_d^0 = I \partial \gamma_d^0$

$$\frac{1}{(1+\gamma_d)I} = \frac{log(1+\gamma_d)}{p_d^0 + p_{cir}}$$

Which implies:

$$p_d^0 = (I + p_d^0) log(1 + \frac{p_d^0}{I}) - p_{cir}$$

The first derivative formula is the following:

$$\frac{\partial p_d^0}{\partial I} = \frac{\gamma_d - log(1+\gamma_d)}{log(1+\gamma_d)}$$

The Second derivative formula is the following:

$$\frac{\partial^2 p_d^0}{\partial I^2} = -\frac{log(1+\gamma_d)(1+\gamma_d) - \gamma_d}{I(I+p_d^0)log(1+\gamma_d)}$$

. Since :

$$\forall x > 0 : (1+x)log(1+x) - x > 0$$

The concavity of the best reponse function is proved.
- Positivity: Given a value of p_{-i}, we have that if $p_i = 0$ then $U_i(0, p_{-i}) = 0$, if $p_i > 0$ then $U_i(p_i, p_{-i}) > 0$. So, given a value p_{-i} the value $p_i = 0$ is never a best response.

$$\forall p_{-i} \in [0, p_{max}], \mathrm{BR_i}(p_{-i}) > 0$$

That proves the positivity property.
- Monotonicity: We suppose that at the beginning, D2D user adopts a power level p_d as a best response to cellular user power level p_c, then : $p_d = \mathrm{BR_d}(\mathbf{p_c})$. Now if the cellular user increases his power to new value p'_c greater than p_c, the D2D user cannot stay at the same power level because the structure of the SINR. Actually, the increase of the power of cellular user will decrease the SINR and then will decrease the utility function of D2D user. Hence, the D2D user will adopt a power level p'_d greater than p_d: $p'_d = \mathrm{BR_d}(\mathbf{p'_c})$.The same reasoning applies to the best response function of cellular user. That proves the monotonicity property.
- Scalability: For a given cellular power p_c , let us define the following function:

$$\forall \alpha > 1 : g(\alpha) = \alpha \mathrm{BR_d}(p_c) - \mathrm{BR_d}(\alpha p_c)$$

Proving scalability is equivalent to the following statement:

$$\forall \alpha > 1 : g(\alpha) > 0$$

Let express first and second order derivatives of this function:

$$g'(\alpha) = \mathrm{BR_d}(p_c) - p_c \mathrm{BR'_d}(\alpha p_c)$$

and

$$g''(\alpha) = -p_c \mathrm{BR''_d}(\alpha p_c)$$

By concavity of best response function it is obvious that g is a convex function on α. When $\alpha = 1$,

$$g'(1) = \mathrm{BR_d}(p_c) - p_c \mathrm{BR'_d}(p_c)$$

Again by concavity of best response function we have that :

$$\mathrm{BR_d}(0) \geq \mathrm{BR_d}(p_c) - \mathrm{BR'_d}(p_c)$$

Using the positivity of best response function : $g'(1) > 0$. As the function g is convex its first order derivative is monotonically increasing. Then $\forall \alpha > 1 : g'(\alpha) > 0$. That proves that g is monotonically increasing on α as we remark that: $g(1) = 0$ we conclude that $\forall \alpha > 1 : g(\alpha) > 0$. The same reasoning applies to the best response function of cellular user. That proves the Scalability property.

From [5] if the best response function of user i verifies the properties cited above, ($-i$ denotes the other players): Then the existence and uniqueness of NE are guaranteed.

□

V. Practical considerations

This section describes the practical considerations adopted to allow UE learn equilibrium. A sequential best response scheme will be used.

At time $t+1$, a user reacts to action that happened in time t of the other player. Actually, each user transmitter receives the interference information from its corresponding receiver. The D2D transmitter receives the interference value of the previous step as feedback information from the D2D receiver: $I_d(t) = h_{c,d} p_c(t) + \sigma^2$, this allows us to calculated the estimated effective channel gain $\widehat{\mu_d}(t+1) = \frac{h_d}{I_d(t)}$. Consequently, the estimated utility function :

$$\widehat{U_d}(p_d(t+1), I_d(t)) = \frac{f(\widehat{\mu_d}(t+1) p_d(t+1))}{p_d(t+1) + p_{cir}} \tag{3}$$

The same way, the BS feeds back the cellular receiver the past interference value: $I_c(t) = g_d p_d(t) + \sigma^2$. Similarly, $\widehat{\mu_c}(t+1) = \frac{h_c}{I_c(t)}$, the estimated utility function is then :

$$\widehat{U_c}(p_c(t+1), I_c(t)) = \frac{f(\widehat{\mu_c}(t+1) p_c(t+1))}{p_c(t+1) + p_{cir}} \tag{4}$$

Each user tries to maximize his utility function selfishly at time $t+1$ given the measured interference at time t , by changing his transmit power with respect to minimum power constraint. We first find $p_c(t+1) = \mathrm{argmax}_{p_c} \widehat{U_c}(t+1)$ and $p_d(t+1) = \mathrm{argmax}_{p_c} \widehat{U_d}(t+1)$.

We choose a tolerance level $\Delta = 10^-3$ when the difference between two successive values of power level in time t and in time $t+1$ is below this level we consider that algorithm has converged.

A. Algorithm 1 (proposed): post-check of rate constraint

Each user tries to maximize his utility function selfishly at time $t+1$ given the measured interference at time t at its receiver, by changing his transmit power with respect to minimum rate objective. The user first find the power that maximizes his estimated utility function, then verifies his chosen power value satisfy the rate constraint. Furthermore, the proposed algorithm chooses the power that achieves the R_{min} without going beyond p_{max}.

Algorithm 1: Iterative Power control , **Post-Check**

1) **Input** : $t = 0$, $p_c(t) = 0$, $p_d(t) = 0$, $\Delta = 10^{-3}$
2) **While** $|p_d(t+1) - p_d(t)| > \Delta$ or $|p_c(t+1) - p_c(t)| > \Delta$
   a) **Calculate** the effective gains $\widehat{\mu_d}(t+1)$ and $\widehat{\mu_c}(t+1)$ from the interference $I_d(t)$ and $I_c(t)$
   b) **Find** $p_c(t+1) = \mathrm{argmax}_{p_c} \widehat{U_c}(t+1)$
   c) **Find**$p_d(t+1) = \mathrm{argmax}_{pc} \widehat{U_d}(t+1)$
   d) **Check** if $f(\widehat{\mu_d}(t+1) p_d(t+1)) < R_{min}$: $p_d(t+1) = min(p_{max}, \frac{2^{R_{min}/W} - 1}{\widehat{\mu_d}(t+1)})$, Else continue
   e) **Check** if $f(\widehat{\mu_c}(t+1) p_c(t+1)) < R_{min}$: $p_c(t+1) = min(p_{max}, \frac{2^{R_{min}/W} - 1}{\widehat{\mu_c}(t+1)})$, Else continue
3) **Output** p_c^* and p_d^*,

Algorithm 2: Iterative Power control , **NLP**

1) **Input** : $t = 0$, $p_c(t) = 0$, $p_d(t) = 0$, $\Delta = 10^{-3}$
2) **While** $|p_d(t+1) - p_d(t)| > \Delta$ or $|p_c(t+1) - p_c(t)| > \Delta$
   a) **Calculate** the effective gains $\widehat{\mu_d}(t+1)$ and $\widehat{\mu_c}(t+1)$ from the interference $I_d(t)$ and $I_c(t)$
   b) **Find** $p_d(t+1)$ solution of (3), $p_c(t+1)$ solution of (4)
3) **Output** p_c^* and p_d^*,

B. Algorithm 2 (Classical NLP)

An alternative way of obtaining best power values, is to solve directly the optimization problems with respect to minimum rate and maximum power constraints to the constraints using NLP methods usually encountered to optimize EE utility as we can find in [9].

The NLP method find directly the optimal power vector that must satisfy the Karush-Kuhn-Tucker (KKT) conditions more details can be found in [10].

VI. Simulation and comments

The main parameters adopted to perform simulation are synthesized in Table-I:

The propagation exponent α serves to calculate the channel gain as follow: $h = \frac{cte}{d^\alpha}$ which accounts the path-loss. We have worked on a single cell environment where the BS is located at center of the cell $(0, 0)$ that has 500 meters radius.

TABLE I
MAIN SIMULATION PARAMETERS

Notation	Meaning	Value
N_0	Noise power spectral density	$10^{-17}W/Hz$
W	Bandwidth	$1MHz$
p_{cir}	Power circuit	$100mW$
α	Propagation exponent	4
cte	Constant of propagation	$7.75 * 10^{-3}$
R^c_{min}	Min. Rate Cellular	$5Mbps$
R^d_{min}	Min. Rate D2D	$10Mbps$
p_{max}	Max. transmission power	$2W$

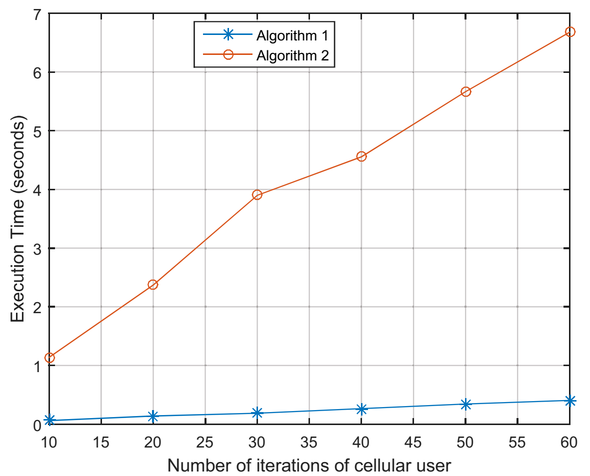

Fig. 2. Comparison between algorithm 1 and algorithm 2 : time of execution

A. Execution time analysis

In this simulation, we put the D2D receiver in the point $R = (50, 100)$ and the D2D transmitter in the point $T = (50, 110)$. Thus, the distance between the D2D receiver and the D2D transmitter 10 meters. we change randomly the position of the cellular user N times and we perform an average calculation for N having the following values $\{5, 10, 15, 20, 25, 30, 35, 40\}$. We perform the simulation for execution time as a function of number of iteration of the cellular user N .

Results in Figure (2) show that the algorithm 1 gives at least 10 times faster time execution than algorithm 2. In this article we consider the power dissipation as a constant, but in reality if terminal executes heavy calculations, this imply an increase of p_{cir} also. An increased execution time and higher number of calculations decrease the communication EE. Consequently, algorithm 1 outperforms algorithm 2 in term of overall low complexity.

B. Throughput and EE Analysis

In this simulation we compare performances in terms of Throughput and EE of algorithm 1 and algorithm 2 when the distance changes between the D2D receiver and transmitter . To simulate the distance variation, we put the D2D receiver in a fixed location $R = (50, 100)$ and we we change the location the D2D transmitter in the point $T = (50, 100 + d)$ with:

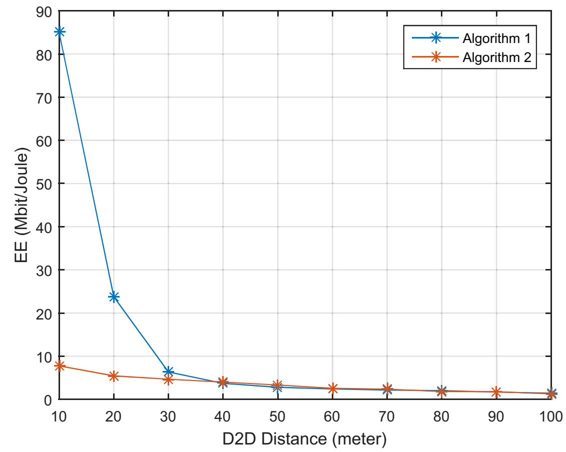

Fig. 3. EE as a function of D2D distance for algorithm 1 and 2

$d \in \{10, 20, ..., 100\}$ expressed in meters represents the distance between the D2D receiver and transmitter. For each D2D distance d, we set randomly the position of the cellular user 50 times and we perform an average calculation.

We perform the simulation for both algorithm 1 and 2.

Simulations in figure 3, that represent the EE variation in terms of distance, show naturally that the nearest distance is the highest EE is.

Simulations in figure 4, that represent Throughput as a function of distance, the throughput is low at long distances, which is quite expected as the terminal with high distance can transmit its data in longer duration in order to maintain his EE and also as the path-loss is high.

From these results we can distinguish three regions for D2D communication: short ranges (up to 30 meters), medium ranges (from 30 to 60 meters), and long ranges (above 60 meters).

i. Short ranges: algorithm 2 outperforms algorithm 1 in Throughput, it is at least 15% better. But Algorithm 1 offers better much higher EE especially in very short distances. Algorithm 1 gives 400% more EE than Algorithm 2 at 20 meters distance.
ii. Medium ranges: in one hand the gap of Throughput between algorithm 1 and algorithm 2 is reduced , but still algorithm 2 offers better Throughput (up to 10%). In the other hand the EE of both algorithms are very close. Algorithm 1 is near optimal in these ranges.
iii. Long ranges: for both algorithm neither EE nor throughput are meeting expectations it may be better to switch off from D2D mode to cellular mode.

For All cases, the algorithm 1 offers better EE/Throughput/Complexity trade-off than algorithm 2.

VII. CONCLUSION & FUTURE WORKS

This work investigated the problem of energy efficient power allocation of D2D communication. The non-cooperative game theory tools are used to find a solution to the power

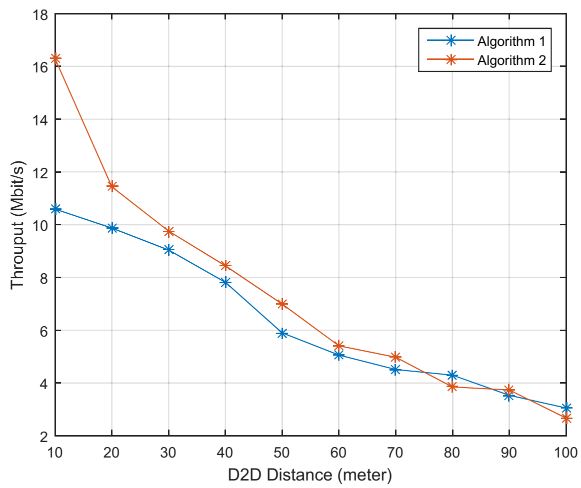

Fig. 4. Throughput as a function of D2D distance for algorithm 1 and 2

allocation problem, and to derive an iterative and decentralized algorithm. Furthermore, simulations show that the proposed algorithm (Post-check) offers lower complexity than the classical algorithm based on NLP and gives near optimal results in terms of Throughput and EE. Yet, the complexity reducing results found by simulations must be proven analytically, for that goal closed form complexity expressions for both algorithms must be obtained. Then will come the extension of the proposed model for more sophisticated cases such as multi carrier OFDMA and multi cell environment.

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