# **Energy Splitting for SWIPT in QoS-constraint MTC Network: A Non-Cooperative Game Theoretic Approach**

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#### ABSTRACT

This paper studies the emerging wireless energy harvesting algorithm dedicated for machine type communication (MTC) in a typical cellular network where one transmitter (e.g. the base station, a hybrid access point) with constant power supply communicates with a set of users (e.g. wearable devices, sensors). In the downlink direction, the information transmission and power transfer are conducted simultaneously by the base station. Since MTC only transmits several bits control signal in the downlink direction, the received signal power can be split into two parts at the receiver side. One is used for information decoding and the other part is used for energy harvesting. Since we assume that the users are without power supply or battery, the uplink transmission power is totally from the energy harvesting. Then, the users are able to transmit their measured or collected data to the base station in the uplink direction. Game theory is used in this paper to exploit the optimal ratio for energy harvesting of each user since power splitting scheme is adopted. The results show that this proposed algorithm is capable of modifying dynamically to achieve the prescribed target downlink decoding signal-to-noise plus interference ratio (SINR) which ensures the high reliability of MTC while maximizing the uplink throughput.

#### KEYWORDS

Energy harvesting, decoding SINR, uplink throughput maximization

# 1. INTRODUCTION

Recent years, wireless power transfer is emerging as a possible solution to address the power supply issue in wireless communications. Conventionally, terminals in wireless networks are powered by fixed energy supplies, e.g. power lines and batteries. But for most mobile terminals and remote deployed terminals (e.g. temperature sensor and wind speed monitor), they are mainly supplied by batteries, which extremely limits the lifetime [1]. However, sometimes because of the unreachable deployment location, it is impossible or extremely difficult to replace or charge the battery. Thus, wireless energy transfer is considered as an alternative solution to extend the working time of the network by transfer unlimited power via a wireless method.

#### 1.1. Related Works

In [2], Wireless power transfer techniques are summarized into three categories: RF energy transfer, resonant inductive coupling and magnetic resonance coupling. Compared with the other two coupling related techniques, RF energy transfer outperforms in terms of effective distance. Note that in this paper,

we only focus on this RF energy transfer technique. In [3], an orthogonal frequency division multiple access (OFDMA) system with simultaneous wireless information and power transfer is considered. The tradeoff between energy efficiency, system capacity, and wireless power transfer are achieved by developing suboptimal iterative resource allocation algorithms. In [4], the authors consider both delay and mobility with wireless energy harvesting. Three issues including optimal transmission policy for the mobile node, energy management strategy and deployment of wireless power sources are solved. In [5], a point-to-point wireless link over the narrowband flat-fading channel with time-varying co-channel interference is considered. Time switcher is used at the receiver side to switch between information decoding and energy harvesting based on the instantaneous channel and interference condition. Various trades-offs between wireless information transfer and energy harvesting are achieved.

Additionally, multiple-input multiple-output (MIMO) is widely used in wireless energy transfer to improve the performance of wireless energy transfer. In [6], an efficient channel acquisition method for a point-to-point MIMO wireless energy transfer system is designed by exploiting the channel reciprocity. The dedicated reverse-link training from the energy receiver is used by the energy transmitter to estimate the CSI. In [7], wireless energy transfer with MIMO is considered and a general design framework for a new type of channel learning method based on the energy receivers energy transfer and uplink for wireless information transmission and the optimal time allocation for downlink and uplink is obtained.

Game theory has been widely used as an effective approach to solving resource allocation problems. A Multiservice Uplink Power Control game (MSUPC) is formulated in [9] and the cost function of each user is designed to maximize its own utility. Besides, some optimal power allocation schemes using game theory are proposed in [10], [11] and [12] by considering different network scenarios. In addition, game theory is also used to handle joint resource allocation problems. [13] considers both utility-based uplink transmission power and rate allocation in a non-cooperative game model with pricing. [14] proposes a utility function representing its perceived satisfaction with respect to its allocated power and rate.

#### 1.2. Contributions

In this paper, game theory is utilized to derive the balancing ratio for energy harvesting out of the total received power for future MTC networks. Most of the existing works discuss optimal time allocation, throughput maximization and various trades-offs between energy efficiency, capacity and wireless power transfer. Different from these existing papers, our main contributions are listed below.

- We first use game theory to address wireless energy transfer problem. Game theory enables us to obtain a balancing solution under various constraints. In this paper, in order to ensure the downlink received decoding SINR and the uplink throughput of each user, a non- cooperative game model is formed to seek a balancing solution between energy for decoding and energy for harvesting.
- We first design a wireless energy transfer algorithm dedicated for MTC networks. Different from common mobile communications, the base station broadcasts control signal, which is only several bits size, to the machines in the downlink direction while in the uplink direction the machines transmit large amount data to the base station periodically. So these require an extremely high decoding SINR level in the downlink direction. Based on these requirements, a target decoding SINR is set, upon which the uplink throughput is maximized.



Figure 1: System model

• Our solution indicates that in order to ensure the high reliability of MTC, a cell edge machine with poor channel condition utilizes the majority of received energy to do harvesting while a cell center machine with good channel condition utilizes majority of received energy to do information decoding. As a result, the uplink throughput of a cell edge machine is lower than that of a cell centre machine since the harvest-then-transmit protocol is used here. Additionally, the value of target decoding SINR affects the performance of this system as well. When the target decoding SINR increases, the uplink throughput decreases so that more received energy can be used for decoding.

The rest of this paper is organized as follows: Section 2 shows the system model of this wireless energy transfer MTC networks. In Section 3, the wireless energy transfer algorithm is derived based on game theory. The simulation results are presented in Section 4. Finally, this paper is concluded in Section 5.

## 2. SYSTEM MODEL

As shown in Fig. 1, this paper considers a wireless cellular network with mixed wireless information transmission and wireless energy transfer in the downlink direction and pure wireless information transmission in the uplink direction. The system consists of one base station and N devices denoted by  $MTCD_i$ ,  $i = 1, \dots, N$ . It is assumed that the base station and all devices operate on the same frequency band. Different from those MIMO systems, we assume that one single antenna is equipped at the base station and all devices. We further assume that all devices are without batteries or power supplies. Therefore, the devices have to harvest energy from the received signals transmitted by the base station in the downlink direction, upon which the devices use the harvested energy to transmit data to the base station in the uplink direction. The downlink and uplink channel gains of *i*th device are denoted as  $G_i^{DL}$ 



Figure 2: Energy harvesting frame

and  $G_i^{UL}$ , respectively. It is assumed that the downlink and uplink channels are Rayleigh fading. Since no battery embedded in the devices, the harvest-then-transmit protocol is used in this network. On the device side, power splitter is connected to two functionality units: energy harvester and information decoder as shown in Fig. 2. The power splitter splits the received power into two parts:  $\theta \times 100\%$ received power for information decoding.

It is known that MTC networks require high reliability. Therefore, the downlink decoding SINR  $\gamma_i^d$  is crucial because the downlink signal contains control message which may cause misoperation if decoding fails. Thus, a target decoding SINR, which ensures the high reliability, is prescribed as  $\gamma_i^{tar}$  which should satisfy

$$\gamma_i^d \ge \gamma_i^{tar} \tag{1}$$

where subscript *i* indicates the *i*th device. Since  $(1 - \theta_i) \times 100\%$  of the received power is used to decode the downlink signal, the downlink decoding SINR of *i*th device is written as

$$\gamma_{i}^{d} = \frac{P_{t}G_{i}^{DL}(1-\theta_{i})}{N_{0}}$$
(2)

where  $P_t$  is transmission power of base station and  $N_0$  is noise. And  $\theta_i \times \%$  of the received power is used for harvesting so after this harvesting, the power used for uplink transmission is  $P_i^{UL} = \eta_i P_t G_i^{DL} \theta_i G_i^{UL}$ where  $\eta_i$  represents the harvesting efficiency which is set to be a constant value in this paper. The corresponding uplink SINR is shown as

$$\gamma_i^{UL} = \frac{\eta_i P_i G_i^{DL} \theta_i G_i^{UL}}{I_i + N_0} \tag{3}$$

where Ii is the interference from other devices and it is written as  $I_i = \sum_{j \neq i} \eta_j P_t G_j^{DL} \theta_j G_j^{UL}$ . From (2) and (3), we can see that if  $\theta_i$  increases, the downlink decoding SINR  $\gamma_i^d$  decreases and uplink SINR  $\gamma_i^{UL}$  increases. And vice versa. Thus, there must be a  $\theta_i$  balancing this conflict.

## 3. GAME PROBLEM FORMULATION

In this section, we formulate the energy harvesting problem using non-cooperative game model, upon which the energy harvesting ratio iteration function is derived. In addition, we prove the existence of Nash equilibrium of this algorithm as well as the convergence of this iteration function with certain constraints.

#### 3.1. Utility Function and Nash Equilibrium Derivation

A game model consists of three essential elements: player, strategy and utility function. In this paper, each device is regarded as a player participating in this game. The energy harvesting ratio  $\theta_i$  is assumed

to be the strategy of *i*th device and the utility function of *i*th device is defined as  $U_i(\theta_i, I_i(\Theta_i))$ , where  $\Theta_i := [\theta_1, \dots, \theta_{i-1}, \theta_{i+1}, \dots, \theta_N]$ . Note that when the Nash equilibrium is achieved, the utility function is presented as  $U_i(\theta_i^*, I_i(\Theta_i^*))$ . The definition of Nash equilibrium indicates that no one can increase its utility by deviating from the Nash equilibrium solution  $\theta_i^*$ . Thus,  $\theta_i^*$  satisfies the following equation

$$U_{i}(\theta_{i}^{*}, I_{i}(\Theta_{i}^{*})) \geq U_{i}(\theta_{i}, I_{i}(\Theta_{i}^{*}))$$

$$\forall \theta_{i}, \forall i = 1, 2, \cdots, N$$
(4)

As we illustrated above, there exists a conflict between downlink decoding SINR and uplink throughput. So, the objective of the proposed algorithm in this paper is to find out a balancing energy harvesting ratio  $\theta_i$  for each device so that the uplink throughput of each device is maximized while the downlink decoding SINR of each device achieves the prescribed target SINR which ensures the reliability. Therefore, we take downlink decoding SINR  $\gamma_i^d$ , prescribed target SINR  $\gamma_i^{tar}$  and uplink throughput  $log(1 + \gamma_i^{UL})$  into consideration and propose the following utility function:

$$U_i(\theta_i, I_i(\Theta_i)) = a_i(\gamma_i^d - \gamma_i^{tar})^2 + b_i(log(1 + \gamma_i^{UL}))$$
(5)

where  $a_i$  and  $b_i$  is two non-negative coefficients. The value of this prescribed target decoding SINR  $\gamma_i^{tar}$  depends on reliability level, e.g. high level for military and industrial applications, low level for civil and home applications. Then the first order partial derivative of this utility function is derived as

$$\frac{\partial U_i}{\partial \theta_i} = 2a_i(\gamma_i^d - \gamma_i^{tar})\frac{\partial \gamma_i^d}{\partial \theta_i} + \frac{b_i}{ln2}\frac{1}{1 + \gamma_i^{UL}}\frac{\partial \gamma_i^{UL}}{\partial \theta_i} 
= -2a_i\frac{P_tG_i^{DL}}{N_0}(\frac{P_tG_i^{DL}(1 - \theta_i)}{N_0}) + \frac{b_i}{ln2}\frac{1}{\theta_i + \frac{I_i + N_0}{\eta_i P_i G_i^{DL}G_i^{UL}}}$$
(6)

then we let  $\frac{\partial U_i}{\partial \theta_i} = 0$  and obtain

$$\gamma_i^d = \gamma_i^{tar} + \frac{b_i}{2a_i ln^2} \frac{N_0}{P_i G_i^{DL} \theta_i + \frac{I_i + N_0}{n_i G_i^{UL}}}$$
(7)

it is clear that when  $b_i = 0$ ,  $\gamma_i^d = \gamma_i^{tar}$  holds. This indicates that if the uplink throughput is not taken into consideration or we put no emphasize on uplink throughput, the solution is achieved by  $\gamma_i^d = \gamma_i^{tar}$ . Recalling (2), we obtain

$$\theta_{i} = 1 - \frac{N_{0}}{P_{t}G_{i}^{DL}}\gamma_{i}^{tar} - \frac{b_{i}}{2a_{i}ln2}\frac{N_{0}^{2}}{(P_{i}G_{i}^{DL})^{2}\theta_{i} + \frac{P_{i}G_{i}^{DL}(I_{i}+N_{0})}{\eta_{i}G_{i}^{UL}}}$$
(8)

Here we define  $\frac{P_i G_i^{DL}}{N_0} = \gamma_i^{DL}$  and associated with (3), we can get

$$\frac{\gamma_i^{DL}}{\gamma_i^{UL}} = \frac{I_i + N_0}{\eta_i G_i^{UL} N_0 \theta_i} \tag{9}$$

So that (8) can be written as

$$\theta_{i} = 1 - \frac{\gamma_{i}^{tar}}{\gamma_{i}^{DL}} - \frac{b_{i}}{2a_{i}ln2} \frac{1}{(\gamma_{i}^{DL})^{2}\theta_{i}(1 + \frac{1}{\gamma_{i}^{UL}})}$$
(10)

It can be seen that  $\theta_i = f(\gamma_i^{DL}, \gamma_i^{UL})$  with a given  $\gamma_i^{tar}$ .

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#### 3.2. Energy Harvesting Algorithm

Providing that the interference and noise can be measured at the receiver side, we can get

$$\theta_i^{(k+1)} = 1 - \frac{\gamma_i^{(ar)}}{\gamma_i^{DL}} - \frac{b_i}{2a_i ln^2} \frac{1}{(\gamma_i^{DL})^2 \theta_i^{(k)} (1 + \frac{1}{(\gamma_i^{(L)})^{(k)}})}$$
(11)

where  $\theta_i^{(k)}$  represents the energy harvesting ratio of the *i*th device at the *k*th iteration, and  $(\gamma_i^{UL})^{(k)}$  represents the SINR of the *i*th device at the *k*th iteration which includes the  $I_i^{(k)}$  experienced by the *i*th device at the *k*th iteration. Note that if and only if  $\theta_i^{(k)} > 0$ , this algorithm makes sense. Otherwise, there is no received energy for harvesting at all. In order to analyze the convergence, we define the iteration function as  $\theta_i^{(k+1)} = f_i^{(k)}(\theta_i^{(k)})$  and rewrite it as

$$f_i^{(k)}(\theta_i^{(k)}) := \theta_i^{(k+1)} = 1 - \frac{\gamma_i^{lar}}{\gamma_i^{DL}} - \frac{b_i}{2a_i ln^2} \frac{1}{(\gamma_i^{DL})^2 \theta_i^{(k)} (1 + \frac{1}{(\gamma_i^{UL})^{(k)}})}$$
(12)

So far, we have obtained the energy harvesting control iteration function and the convergence is proved in the next subsection.

#### 3.3. Convergence

For an iterative algorithm, it needs to achieve a stable value after some iterations. In [15], the authors show that when convergence is achieved, three properties need to be satisfied. The proof of convergence is showed as follows

• Positivity:  $f(\theta) > 0$ 

Since  $\theta$  represents the energy harvesting ratio, it needs to follow a more strict constraint,  $0 < \theta < 1$ . By putting (10) into this constraint, we obtain

$$0 < \frac{\gamma_i^{tar}}{\gamma_i^{DL}} + \frac{b_i}{2a_i ln^2} \frac{1}{(\gamma_i^{DL})^2 \theta_i^{(k)} (1 + \frac{1}{(\gamma_i^{UL})^{(k)}})} < 1$$
(13)

in order to satisfy this inequality, the ratio value between  $a_i$  and  $b_i$  need to be

$$-\gamma_i^{tar}\theta_i \left(\gamma_i^{DL} + \frac{\gamma_i^{DL}}{\gamma_i^{UL}}\right) < \frac{b_i}{2a_i ln2} < \left(\gamma_i^{DL} - \gamma_i^{tar}\right)\theta_i \left(\gamma_i^{DL} + \frac{\gamma_i^{DL}}{\gamma_i^{UL}}\right)$$
(14)

Since  $a_i$  and  $b_i$  are both positive, (14) can be rewritten as

$$0 < \frac{b_i}{a_i} < 2ln2\left(\gamma_i^{DL} - \gamma_i^{tar}\right)\theta_i\left(\gamma_i^{DL} + \frac{\gamma_i^{DL}}{\gamma_i^{UL}}\right)$$
(15)

This constraint indicates that  $\frac{b_i}{a_i}$  has to be carefully designed and it need to be a very small value so that this positivity is guaranteed.

• Monotonicity:  $\theta > \theta' \rightarrow f(\theta) > f(\theta')$ 

In order to prove this monotonicity, we have to prove  $f(\theta_i)$  is a monotonically increasing function. So

$$\frac{\partial f(\theta_i)}{\partial \theta_i} = \frac{b_i}{2a_i ln^2 \left(\theta_i \gamma_i^{DL}\right)^2 \left(1 + \frac{1}{\gamma_i^{UL}}\right)} \tag{16}$$

Since  $\frac{b_i}{a_i} > 0$ ,  $\frac{\partial f(\theta_i)}{\partial \theta_i} > 0$  holds.

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• Scalability:  $f(\alpha\theta) < \alpha f(\theta), \forall \alpha > 1$  In order to determine the scalability, we use (10) and obtain

$$f(\alpha\theta_i) - \alpha f(\theta_i) = (\alpha - 1) \left( \frac{\gamma_i^{tar}}{\gamma_i^{DK}} + \frac{b_i}{2a_i ln 2(\gamma_i^{DL})^2 \left(1 + \frac{1}{\gamma_i^{UL}}\right)} \frac{\alpha + 1}{\alpha\theta_i} - 1 \right)$$
(17)

It is clear that the first term  $\alpha - 1 > 0$ . Thus we need to prove the latter term is negative so that  $f(\alpha\theta) < \alpha f(\theta), \forall \alpha > 1$  is ensured. So we need to solve this following inequality

$$\frac{b_i}{2a_i ln 2(\gamma_i^{DL})^2 \left(1 + \frac{1}{\gamma_i^{UL}}\right)} \frac{\alpha + 1}{\alpha \theta_i} < 1 - \frac{\gamma_i^{lar}}{\gamma_i^{DK}}$$
(18)

After several mathematical derivations, the solution of this inequality is shown as

$$\frac{b_i}{a_i} < \ln 2 \left( \gamma_i^{DL} - \gamma_i^{tar} \right) \theta_i \left( \gamma_i^{DL} + \frac{\gamma_i^{DL}}{\gamma_i^{UL}} \right)$$
(19)

So far, in order to satisfy the convergence requirements, we have discussed three properties and derive constraints of  $\frac{b_i}{a_i}$ . Combined with (15) and (19), we limit  $\frac{b_i}{a_i}$  as

$$0 < \frac{b_i}{a_i} < \ln 2 \left( \gamma_i^{DL} - \gamma_i^{tar} \right) \theta_i \left( \gamma_i^{DL} + \frac{\gamma_i^{DL}}{\gamma_i^{UL}} \right)$$
(20)

#### 3.4. Existence of Nash Equilibrium

In this section, the Implicit Function Theorem [14] is used to prove the existence of a unique solution for this iterative function. According to the Implicit Function Theorem, a new function is established by moving the left-hand side term of (8) to the right-hand side and obtain

$$F_{i}(\theta_{i}, I_{i}, G_{i}^{DL}, G_{i}^{UL}, a_{i}, b_{i}, N_{0}) = 1 - \theta_{i} - \frac{N_{0}}{P_{t}G_{i}^{DL}}\gamma_{i}^{tar} - \frac{b_{i}}{2a_{i}ln2} \frac{N_{0}^{2}}{(P_{i}G_{i}^{DL})^{2}\theta_{i} + \frac{P_{i}G_{i}^{DL}(I_{i}+N_{0})}{\eta_{i}G_{i}^{UL}}}$$
(21)

According to Implicit Function Theorem, if there exists an unique Nash Equilibrium, the Jacobian matrix must be non-singular. Then, we obtain

$$\frac{\partial F_{i}(\theta_{i}, I_{i}, G_{i}^{DL}, G_{i}^{UL}, a_{i}, b_{i}, N_{0})}{\partial \theta_{k}} = \begin{vmatrix} \frac{\partial F_{1}}{\partial \theta_{1}} & \frac{\partial F_{1}}{\partial \theta_{2}} & \cdots & \frac{\partial F_{1}}{\partial \theta_{N}} \\ \frac{\partial F_{2}}{\partial \theta_{1}} & \frac{\partial F_{2}}{\partial \theta_{2}} & \cdots & \frac{\partial F_{2}}{\partial \theta_{N}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial F_{N}}{\partial \theta_{1}} & \frac{\partial F_{N}}{\partial \theta_{2}} & \cdots & \frac{\partial F_{N}}{\partial \theta_{N}} \end{vmatrix} = \begin{vmatrix} A_{1} & B_{12} & \cdots & B_{1N} \\ B_{21} & A_{2} & \cdots & B_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ B_{N1} & B_{N2} & \cdots & A_{N} \end{vmatrix}$$
(22)

where

$$A_{i} = -1 + \frac{b_{i}}{2a_{i}ln^{2}} \frac{1}{\frac{P_{i}G_{i}^{DL}}{N_{0}}\theta_{i} + \frac{I_{i}+N_{0}}{\eta_{i}G_{i}^{UL}N_{0}}}$$
(23)

and

$$B_{ij} = \frac{b_i}{2a_i ln2} \frac{\eta_j P_t^2 G_i^{DL} G_j^{DL} G_j^{UL}}{\left( \left(\frac{P_t G_i^{DL}}{N_0}\right)^2 + \frac{P_t G_i^{DL} (l_i + N_0)}{\eta_i G_i^{UL} N_0^2} \right)^2}$$
(24)

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It is clear that the value of this matrix is determined by each element. In order to make this matrix non-singular, the ratio value  $\frac{b_i}{a_i}$  should be carefully defined. Otherwise, this matrix cannot be ensured to be non-singular. So far, we have proved the convergence as well as the existence of the unique solution of this energy harvesting iterative algorithm under constraint of  $\frac{b_i}{a_i}$ .



Figure 3: Convergence of energy harvesting ratios

### 4. NUMERICAL RESULTS

In this section, the simulation results of this proposed algorithm are presented in Matlab. We consider a cell with one base station communicating with *N* randomly located MTC devices denoted by  $MTCD_i$ ,  $i = 1, \dots, N$ . The channel that every device experiences is defined as quasi-static flat-fading. The available bandwidth is 20MHz and the transmission power at the base station, which is denoted as Pt, is 30dBm. The energy harvesting efficiency  $\eta_i$  is set to be 0.8. The ratio value of  $\frac{b_i}{a_i}$  is set to be 0.025, which is small enough to ensure the convergence and existence of the unique Nash solution of this iterative algorithm.

Fig. 3 shows the convergence of  $\theta_i$  with N = 50. It is the core parameter of this iterative algorithm since it directly determines how much received energy is used for energy harvesting. The initial  $\theta_i^{(0)}$  is set to be 0.001. It is very clear that after 3 iterations, the  $\theta_i$  of each device achieves a stable state. Note that when reaching values within 0.01% of the steady state values the convergence of the iterative algorithm is obtained. There are 50 lines representing the 50 devices, respectively.  $\theta$  varies from 0 to 1 because each device experiences a different channel so that each individual device needs different energy to reach the prescribed target SINR.

Fig. 4 shows the downlink decoding SINR gap between the average downlink decoding SINR and target decoding SINR with different number of devices (N) in terms of different target decoding SINR.



Figure 4: Downlink decoding SINR gap with different number of devices in terms of different target decoding SINR

In MTC networks, the control information is carried by the downlink transmission. And at the receiver side, the device has to successfully decodes this control information so that functionality of the device can be conducted correctly. This requires a high reliability for the decoding part. Here we define a target decoding SINR denoted as  $\gamma_i^{tar}$ . We can see that all these six lines are positive regardless of the target decoding SINR. In another word, this proposed algorithm is capable of dynamically modifying the energy for decoding so that the reliability requirement can be satisfied. With the increase of target decoding SINR, the SINR gap is becoming narrow. This is because compared with a high target decoding SINR, a lower target decoding SINR is much easier to achieve. In this paper, the downlink received energy at the UE side is split into two parts.  $\theta_i \times 100\%$  of received energy is used for energy harvesting and  $(1-\theta_i) \times 100\%$  is used for information decoding. So  $\theta_i$  actually represents the amount of energy for harvesting. Further more, the value of  $\theta_i$  is affected by its corresponding channel gain, which is shown in Fig. 5. Note that stable theta means  $\theta_i$  achieves its stable state after several iterations. It is clear that with the improvement of channel gain, the stable  $\theta_i$  increases regardless of the different target decoding SINR. The reason is that when the channel is good, the device is capable of reaching the target decoding SINR with less energy (low  $(1 - \theta_i)$ ). Therefore, more energy (high  $\theta_i$ ) can be used for energy harvesting. On contrary, when channel is poor, the device has to assume more energy (high  $(1 - \theta_i)$ ) to do information decoding so that the target decoding SINR is ensured. In this case, less energy (low  $\theta_i$ ) is used for energy harvesting. In addition, target decoding SINR also make an influence on  $\theta_i$ . As we can see that when channel gain is fixed, a higher  $\theta_i$  is obtained with a lower target decoding SINR. It is straightforward that reaching a low target decoding SINR always assumes less energy (low  $(1 - \theta_i)$ ) compared with reaching a high target decoding SINR.

In this proposed algorithm,  $\theta_i$  not only determines the energy splitting for both information decoding



Figure 5: Achievable stable  $\theta_i$  under different channel gain in terms of target decoding SINR

and energy harvesting but also affects the uplink throughput of each device. Fig. 6 shows the effects that  $\theta_i$  makes on throughput. As it is discussed before,  $\theta_i$  actually represents the amount of energy for harvesting. And all of this harvested energy is used for uplink transmission since there is no battery for energy storage. So it is clear that with the increase of  $\theta_i$ , the throughput increases as well. It is worth noting that  $\theta_i$  varies in different regions under different target decoding SINRs. This is because a device experiencing a poor channel with a high target decoding SINR has to utilize more received energy to reach this target decoding SINR compared with a device experiencing a poor channel with a low target decoding SINR. This explains the starting points locations of these five lines. Additionally, for the devices with good channels, regardless of the target decoding SINRs, all these five lines achieve similar throughput. This is because for a device with a good channel, the target decoding SINR can be easily achieved by consuming little-received energy. As a result, most of the received energy is used for uplink transmission. Therefore, they are capable of achieving the same throughput. This explains the endpoints locations of these five lines.

## 5. CONCLUSION

In this paper, an energy harvesting control algorithm is proposed for future wireless powered MTC networks by involving a non-cooperative game model. This algorithm takes both downlink and uplink transmission into consideration. In the downlink direction, the device splits the received energy into two parts: the information decoding part and the energy harvesting part. Because of the harvest-then-transmit protocol, the harvested energy is in turn used for uplink transmission. Since the high reliability of MTC has to be satisfied with the highest priority, we firstly ensure the downlink decoding SINR achieve the prescribed target decoding SINR, and then we improve the uplink throughput as much as



Figure 6: Individual throughput under stable  $\theta_i$  in terms of different target decoding SINR

possible. The simulation and numerical results show that the decoding SINR of each individual device is slightly greater than the target decoding SINR. By varying the target decoding SINR, we evaluate the algorithm performance with different channel gain in terms of stable  $\theta$  which represents the amount of received energy for harvesting. And also this algorithm reveals the potential relation between the stable  $\theta$  and throughput with different target decoding SINR. For wireless powered MTC networks, this algorithm is capable of providing a solution which satisfies the reliability of MTC and maximizes the throughput of each device.

### References

- P. T. The, B. H. Mai, N. T. Tuan and T. C. Hung, (2017) Improving Distributed Energy-efficient Clustering Algorithm to Save Lifetime for Heterogeneous WSN, *International Journal of Computer Networks Communications*, Vol. 9, No. 7, pp. 81-96.
- [2] X. Lu, P. Wang, D. Niyato, D. I. Kim, and Z. Han, (2015) Wireless networks with rf energy harvesting: A contemporary survey, *IEEE Communications Surveys & Tutorials*, Vol. 17, No. 2, pp. 757-789.
- [3] D. W. K. Ng, E. S. Lo, and R. Schober, (2013) Wireless information and power transfer: Energy efficiency optimization in ofdma systems, *IEEE Transactions on Wireless Communications*, Vol. 12, No. 12, pp. 6352-6370.
- [4] D. Niyato and P. Wang, (2014) Delay-limited communications of mobile node with wireless energy harvesting: performance analysis and optimization, *IEEE Transactions on Vehicular Technology*, Vol. 63, No. 4, pp. 1870-1885.

- [5] L. Liu, R. Zhang, and K.-C. Chua, (2013) Wireless information transfer with opportunistic energy harvesting, *IEEE Transactions on Wireless Communications*, Vol. 12, No. 1, pp. 288-300.
- [6] Y. Zeng and R. Zhang, (2015) Optimized training design for wireless energy transfer, *IEEE Transactions on Communications*, Vol. 63, No. 2, pp. 536-550.
- [7] J. Xu and R. Zhang, (2016) A general design framework for mimo wireless energy transfer with limited feedback, *IEEE Transactions on Signal Processing*, Vol. 64, No. 10, pp. 2475-2488.
- [8] H. Ju and R. Zhang, (2014) Throughput maximization in wireless powered communication networks, *IEEE Transactions on Wireless Communications*, Vol. 13, No. 1, pp. 418-428.
- [9] Tsiropoulou, E. E., Katsinis, G. K., Papavassiliou, S, (2012) Distributed uplink power control in multiservice wireless networks via a game theoretic approach with convex pricing, *IEEE Transactions on Parallel and Distributed Systems*, Vol. 23, No. 1, pp. 61-68.
- [10] Zheng, J., Wu, Y., Zhang, N., Zhou, H., Cai, Y., Shen, X, (2017) Optimal power control in ultra-dense small cell networks: A game-theoretic approach, *IEEE Transactions on Wireless Communications*, Vol. 16, No. 7, pp. 4139-4150.
- [11] Liu, Z., Li, S., Yang, H., Chan, K. Y., Guan, X, (2017) Approach for power allocation in two-tier femtocell networks based on robust non-cooperative game, *IET Communications*, Vol. 11, No. 10, pp. 1549–1557.
- [12] Kang, K., Ye, R., Pan, Z., Liu, J., Shimamoto, S, (2017) Game-Theory-Based Distributed Power Splitting for Future Wireless Powered MTC Networks, *IEEE Access*, Vol. 5, pp. 20124–20134.
- [13] Tsiropoulou, E. E., Vamvakas, P., Papavassiliou, S Energy efficient uplink joint resource allocation non-cooperative game with pricing, in *Proc. 2012 Wireless Communications and Networking Conference (WCNC 2012)*, 2012, 2352–2356.
- [14] Tsiropoulou, E. E., Vamvakas, P., Papavassiliou, S, (2017) Supermodular game-based distributed joint uplink power and rate allocation in two-tier femtocell networks, *IEEE Transactions on Mobile Computing*, Vol. 16, No. 9, pp. 2656–2667.
- [15] R. D. Yates, (1995) A framework for uplink power control in cellular radio systems, *IEEE Journal on selected areas in communications*, Vol. 13, No. 7, pp. 1341-1347.