A Nash Bargaining Solution for Energy-Efficient Content Distribution over Wireless Networks with Mobile-to-Mobile Cooperation

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Abstract—A game theoretical formulation for energy minimization in mobile-to-mobile cooperative networks is provided. The problem is formulated as a Nash bargaining game, and the Nash bargaining solution is derived. Furthermore, a low complexity utility minimization algorithm is presented. Using the appropriate utilities, the proposed algorithm is used to implement both the proposed solution in addition to the greedy energy minimization solution. Results show that a good trade-off between energy reduction and fairness is obtained by the Nash bargaining solution. In addition, when Rayleigh fading is considered, the optimal greedy solution is shown to lead to long term fairness, although it is instantaneously unfair towards one of the mobile terminals.

I. INTRODUCTION

Cooperative wireless networks proved to have a lot of advantages in terms of increasing the network throughput [1], [2], [3], extending the network coverage [4], [5], decreasing the end user communication cost [6], [7], [8], decreasing the file download time [2], and decreasing energy consumption at mobile terminals (MTs) [9], [10], [11].

Studies show that the high energy consumption of battery-operated MTs will be one of the main limiting factors for future wireless communication systems. In order to tackle this limitation, mechanisms to reduce energy consumption appear extensively in the literature, e.g. see [9], [10], [12]. In [9], a cooperative network architecture composed of a long range (LR) link technology and a short range (SR) link technology is presented in order to reduce energy consumption among MTs during real-time video streaming. Results show promising opportunities to decrease the total energy consumed by increasing the number of collaborative MTs. In [13], preliminary experimental analysis for a collaborative video streaming architecture using test bed implementation is presented. A group of MTs interested in the same video are connected to a WLAN access point through which they pull one of the video descriptions that they share with other MTs using their Bluetooth interface. This collaborative scheme proved to be more energy efficient than pulling all the video over the WLAN interface. A comprehensive study is conducted in COMBINE [14] where experimental results are presented for a test bed composed of a GPRS LR interface and a WLAN SR interface. However, all these studies apply only to specific wireless technologies in specific scenarios and do not investigate optimal strategies.

Data sub-stream distribution and energy consumption are studied in an optimized way in [15], where energy minimization with mobile-to-mobile (M2M) collaboration was formulated and solved using integer linear programming (ILP), both in the cases of unicasting and multicasting. However, the optimal solution of [15] showed that the whole data stream is sent to a single MT on the LR link, and that MT is responsible for the distribution of the data on the SR, whether via unicasting or multicasting. Hence, although this solution leads to energy minimization in the network, it is unfair towards the MT selected for data distribution.

In this paper, we present a game theoretical formulation in order to add fairness to the greedy energy minimization problem with unicasting, formulated in [15]. Users are assumed to play a bargaining game and the Nash bargaining solution (NBS) is investigated. A novel low complexity heuristic algorithm that performs utility minimization is presented. With an appropriate choice of the utility, the algorithm can either retrieve the energy minimization approach of [15], or implement the NBS of the proposed Nash bargaining game model. In addition, it is shown that the cooperative approach allows distributing the content in less time than the non-cooperative scenario, with the NBS approach outperforming the greedy energy minimization approach. Furthermore, it is shown that, in the presence of Rayleigh fading, the optimal greedy solution leads to long term fairness between MTs.

This paper is organized as follows. Section II presents an overview of the system model and of the energy minimization formulation. In Section III, the game theoretical formulation
and solution are presented. Section IV presents the low complexity heuristic algorithm that can be applied to implement both the optimal solution and the fair solution. Results are presented and discussed in Section V. Finally, conclusions are drawn in Section VI.

II. SYSTEM MODEL

This section presents the system model and summarizes the problem formulation for minimizing the total consumed energy. The problem formulation is an extension to the approach of [15] where all MTs are assumed to have the same power consumption on the long range and short range. In this section, we present a general problem formulation where the energy consumption can be different on the LR and SR, in addition to different power consumption levels between MTs. The formulation of [15] thus becomes a special case of the presented formulation. The system model adopted in this work is depicted in Figure 1. The design consists of a number of cooperating MTs in the range of a base station (BS) or access point (AP). The BS is connected via wired LAN to the server that holds the content. Terminals can communicate with each other over SR links.

![Fig. 1. General system model.](image)

In a traditional setup, the server either separately streams the complete content to each requesting MT or multicasts the content once to all requesting MTs. In both cases, the communication interface of each MT remains active for the whole reception duration, which depends on the length of the content. This results in high energy consumption due to the required processing during data reception.

In this work, we assume the establishment of a M2M network between the MTs over SR wireless links that are more energy-efficient than the LR wireless link. In this scheme, the content is divided into $N$ parts. If $K$ MTs are requesting the content, then, each will be receiving a subset of the $N$ data parts from the server. Over the SR wireless links, each MT receives the remaining data subsets from the other cooperating MTs in the M2M network. Being exchanged over an energy-efficient SR wireless technology, the SR exchanged subsets require lower reception power at the communication interface of the MTs. However, an additional overhead in this case is that each MT needs to spend additional energy to transmit its received data subset to the other cooperating MTs.

A. Energy Minimization Formulation

In this paper, multicasting is assumed. With multicasting, every MT transmits with a data rate that is equal to the minimum one among its neighbors, so that all other MTs can correctly receive the data. Thus $R_{S,j} = \min_j R_{S,j'}$. $j' = 1, \ldots, K$ and $j' \neq k$, with $R_{S,kj}$ the transmission rate on the SR links from MT $k$ to MT $j$. Denoting by $S_T$ the size of the content divided into $N$ parts, $K$ the number of requesting MTs, $x_k$ the number of parts received by MT $k$ over the LR link, $R_{L,k}$ the transmission rate on the LR links from the BS to MT $k$, $P_{Rx,L,k}$ and $P_{Rx,S,k}$ the powers consumed by MT $k$ during reception on the long range and short range, respectively, and $P_{Tx,S,k}$ the power consumed by MT $k$ during transmission on the SR, the total energy consumed by MT $k$ is:

$$E_k = \frac{x_k S_T}{N} R_{L,k} + \frac{x_k S_T}{N} P_{Tx,S,k} \min_j R_{S,j} \frac{1}{R_{L,k}} + \frac{S_T}{N} P_{Rx,S,k} \sum_{j=1,j\neq k}^{K} x_j \min_{j'} R_{S,j'}$$

In (1), the first term corresponds to energy consumption while receiving the content on the LR link, the second corresponds to transmitting the content on the SR links, and the third corresponds to receiving the other content parts from the other MTs on the SR links.

To minimize the total consumed energy, the optimization problem can be formulated as follows:

$$\min_{x} E_{\text{coop}} = \frac{S_T}{N} \sum_{k=1}^{K} x_k \cdot \frac{P_{Rx,L,k}}{R_{L,k}} + \frac{S_T}{N} \sum_{k=1}^{K} x_k \cdot (P_{Tx,S,k} + \sum_{j=1,j\neq k}^{K} P_{Rx,S,j}) \min_j R_{S,j} \tag{2}$$

s.t.

$$\sum_{k=1}^{K} x_k = N \tag{3}$$

$$x \in Z^K_+ \tag{4}$$

The problem in (2) is a linear integer optimization problem in the optimization variables $x_k$, since the objective function $E_{\text{coop}}$ is linear, and the constraints are also linear as shown by (3) which guarantees that the whole content is transmitted on the LR and by (4) which guarantees that the decision variable is integer and positive. Such an integer linear program (ILP) can be solved using the CPLEX solver. This can be done similarly to [15], where the optimal solution was shown to be unfair: all the content is sent to a single MT, and that MT is responsible for transmitting the whole content to the other cooperating MTs. Although this solution is optimal in terms of minimizing the total consumed energy, it is unfair towards the selected MT, whose energy consumption would exceed its consumption in the non-cooperative scenario.
It should be noted that $P_{\text{Rx},L,k}$, $P_{\text{Rx},S,k}$, and $P_{\text{Tx},S,k}$ correspond to the power consumed by MT $k$, i.e. drained from its battery, during reception and transmission, respectively. They are not to be confused with $P_t$ and $P_r$, the respective receive and transmit powers over the air interface, measured at the antenna.

The total energy consumption spent when no cooperation takes place is:

$$E_{\text{NoCoop}} = S_T \sum_{k=1}^{K} \frac{P_{\text{Rx},L,k}}{R_{L,k}}$$

(5)

The normalized energy consumption $\eta$ can be calculated as follows:

$$\eta = \frac{E_{\text{coop}}}{E_{\text{NoCoop}}}$$

(6)

The value of $\eta$ indicates whether the cooperation is beneficial in terms of energy consumption or not; if $\eta < 1$, then the cooperation results in a gain of energy consumption while $\eta > 1$ reflects a non-beneficial cooperation.

### B. Channel Model

The channels on the LR and SR links are assumed to be orthogonal and are modeled by pathloss, shadowing and fading. Thus, the received power $P_r$ can be linked to the transmitted power $P_t$ by a pathloss model as in [16]:

$$P_r\text{ (dB)} = 10\log_{10}\left(\frac{P_t}{P_0}\right) + h + f(a)$$

(7)

where $\kappa$ is a unitless constant which depends on the antenna characteristics and the average channel attenuation, $\nu$ is the path loss exponent, $d_0$ is a reference distance, $d$ is the distance where the received power is calculated, $h$ is a Gaussian random variable representing shadowing or slow fading having a zero mean and a variance $\sigma_f^2$, and $f$ is a random variable representing Rayleigh or fast fading with a Rayleigh parameter $a$.

### C. Data Rates

Assuming that the channels are orthogonal, and given for each MT: the transmit power $P_t$ the sender is transmitting with, the pathloss and shadowing on the channel, and the thermal noise power $\sigma^2$, the received signal-to-noise ratio (SNR) $\gamma$ can be calculated following $\gamma = \frac{P_t}{\sigma^2}$. Given the target bit error rate $P_e$ and the SNR, the bit rates on the LR and SR links can be calculated according to the following:

$$R = B \cdot \ln(1 + \beta \gamma)$$

(8)

In (8), $B$ is the passband bandwidth of the channel, and $\beta$ is called the SNR gap. It indicates the difference between the SNR needed to achieve a certain data transmission rate for a practical M-QAM system and the theoretical limit (Shannon capacity) [16], [17]. It is given by: $\beta = \frac{-1.5}{\ln(5P_e)}$

III. INCORPORATING FAIRNESS: BARGAINING GAME

In this section, in order to ensure a more fair allocation of data parts, we model the problem as a bargaining game. We consider that each MT is a player (in this section, both terms MT and player are used interchangeably) who wants to minimize its payoff, considered to be its energy savings, or equivalently, who wants to minimize its energy consumption. Cooperation is assumed between players. Consequently, players should share the resources in an optimal way, i.e., a way they cannot jointly improve on. The resources to be shared are the $N$ data parts that the content is divided into. Allocating the shared resources in a way to maximize the players’ payoffs is equivalent to allocating the $N$ data parts to MTs in a way to minimize each MT’s energy, given the shares allocated to the other MTs. With each MT wanting to selfishly minimize its consumed energy, the MTs engage in a “bargaining” process. It is a well known result in game theory that the solution to the cooperative bargaining problem maximizes the Nash product $N_P$ [18]:

$$N_P = \prod_{k=1}^{K} \left(W_k(y_k) - F_k\right)$$

(9)

where $y_k$ represents the fraction of resources allocated to player $k$, $W_k(y_k)$ corresponds to the payoff of player $k$ when $y_k$ is allocated to it, and $F_k$ is the payoff of player $k$ in the case where no agreement is reached in the bargaining process. In the energy minimization problem, the objective of each player is to minimize its consumed energy, or equivalently, maximize it energy savings, and thus has a payoff of $(E_{k,\text{NoCoop}} - E_{k,\text{coop}})$. In case no agreement is reached, each MT obtains its data on the LR link and thus consumes $E_{k,\text{NoCoop}}$, which leads to a payoff (or energy savings) of zero. Hence, the optimization problem becomes

$$\max_{k=1}^{K} \prod_{k=1}^{K} \left(E_{k,\text{NoCoop}} - E_{k,\text{coop}}\right)$$

(10)

Since the logarithm is a continuous strictly increasing function, solving the problem in (10) is equivalent to finding the solution of the following problem:

$$\ln \left( \max \left( \prod_{k=1}^{K} (E_{k,\text{NoCoop}} - E_{k,\text{coop}}) \right) \right) = \max \ln \left( \prod_{k=1}^{K} (E_{k,\text{NoCoop}} - E_{k,\text{coop}}) \right)$$

(11)

$$= \max \sum_{k=1}^{K} \ln (E_{k,\text{NoCoop}} - E_{k,\text{coop}})$$

Maximizing the sum in (11) is equivalent to maximizing the product in (10) and is easier to implement numerically. This approach represents a notion of “proportional fairness” (PF) in energy, since it has analogies with PF scheduling, a well known resource allocation approach in wireless communications systems. PF scheduling is known to correspond to a sum of the logarithms of the user rates, and represents the NBS equivalent in the rate maximization problem [19], [20].
In the following section, we present a low complexity utility minimization algorithm that can be used to implement the PF approach in addition to the traditional energy minimization approach.

IV. LOW COMPLEXITY HEURISTIC ALGORITHM

The proposed algorithm consists of allocating part $n$ to MT $k$ in a way to minimize the difference

$$\Lambda_{n,k} = U_k(E_k|I_{N,k} \cup \{n\}) - U_k(E_k|I_{N,k})$$

(12)

where the marginal utility, $\Lambda_{n,k}$, represents the increase in the utility function $U_k$ when part $n$ is allocated to MT $k$, compared to the utility of MT $k$ before the allocation of $n$. In addition, $I_{N,k}$ denotes the set of parts allocated to MT $k$ among the $N$ available parts, such that $|I_{N,k}| = x_k$, where $| \cdot |$ denotes set cardinality. The algorithm is described as follows:

- Consider the set of available parts $I_N \subseteq \{1, 2, ..., N\}$.
- **Step 1:** Find the MT that has the lowest marginal utility defined in (12) among all MTs when the first available part in $I_N$ is allocated to it. In other words, for each part $n$, find the MT $k^*$ such that:

$$k^* = \arg \min_k \Lambda_{n,k}$$

(13)

- **Step 2:** Allocate part $n$ to MT $k^*$: $I_{N,k^*} = I_{N,k^*} \cup \{n\}$
- **Step 3:** Delete part $n$ from the set of available parts:

$$I_N = I_N - \{n\}$$

(14)

- Repeat Steps 1, 2, and 3, until all parts are allocated.

After the allocation of data parts to MTs, each MT sends the parts it received to the other MTs via multicasting.

A. Complexity Analysis

The proposed algorithm allocates each data part after performing a linear search on the MTs in order to find the MT that minimizes the marginal utility. Consequently, the total complexity of the algorithm is $O(NK)$, i.e., the algorithm has linear complexity in the number of MTs and in the number of data parts, and thus could be easily implemented in real-time.

B. Utility Selection

Selecting the utility to be equal to the consumed energy, i.e., $U_k = E_k$, the algorithm performs a greedy minimization of the sum of the energy consumed by the MTs. This solution was shown in [15] to be unfair to one of the MTs to which all the data is forwarded on the LR link so that it distributes it on the SR links. However, setting the utility of each MT as the total energy in the network, i.e., $U_k = E_{coop}$, the algorithm will lead to the same energy minimization approach as when setting $U_k = E_k$, due to the use of the marginal utility in (12). But in the case when $U_k = E_{coop}$, the MT utility is forced to be equal to the network utility, and thus each MT is led to act altruistically by seeing a benefit to the whole network as its own benefit, although this solution is actually unfair to one of the MTs. Assuming the utilities can be hardwired in the mobile devices, this approach can be followed in a distributed scenario in order to reach the minimum energy consumption in the network, even in the framework of a bargaining game. In fact, with $U_k = E_{coop}$, maximizing the Nash product is equivalent to maximizing:

$$\prod_{k=1}^{K} (E_{NoCoop} - E_{coop}) = (E_{NoCoop} - E_{coop})^K$$

(15)

which is equivalent to maximizing $(E_{NoCoop} - E_{coop})$ or minimizing $E_{coop}$, thus retrieving the greedy minimization of the total consumed energy in the network through the game theoretical formulation itself.

On the other hand, when each MT wants to selfishly maximize its energy savings using the bargaining model of Section III, we set the utility to: $U_k = -\ln(E_{NoCoop} - E_{coop})$. In this case, minimizing $\sum_{k=1}^{K} U_k$ is equivalent to maximizing $\sum_{k=1}^{K} \ln(E_{k, NoCoop} - E_{k, coop})$, which in turn is equivalent to maximizing the product $\prod_{k=1}^{K} (E_{k, NoCoop} - E_{k, coop})$, i.e., the Nash product.

C. Centralized vs. Distributed Implementation

The proposed algorithm can be applied with a wide range of utility functions, thus being able to achieve various objectives, with each objective represented by a certain utility function.

The proposed algorithm can be applied in a centralized way by the BS or AP. In this case, the BS is assumed to be aware of the channel state information (CSI), and hence of the achievable rates $R_{k, j, k}$ on the SR links in addition to the CSI and rates $R_{k, k, k}$ on the LR link. Furthermore, due to its low complexity, distributed protocols can easily be derived in order to implement the algorithm by the various MTs in a distributed way. In this case, an exchange of CSI information on the SR links needs to be performed between MTs. Although in this paper we assume a centralized scenario with perfect knowledge at the BS, it has been shown that results close to those with full CSI information can be achieved with the exchange of a very limited number of feedback bits on the SR links [19]. Implementing a quantized CSI exchange approach as in [19] with the proposed algorithm remains a topic for future investigation.

V. RESULTS AND ANALYSIS

In the numerical results presented in this section, the properties of the MTs are assumed to be similar to the HP iPAQ Pocket PC h6300 Series. Its specifications as given in [21] are shown in Table I. To ensure a fair comparison with [15], we adopt the same assumption of identical MTs with $P_{Rx,S,k} = P_{Rx,L,k} = P_{Rx}$ and $P_{Tx,S,k} = P_{Tx}$ for all $k$. The channel parameters are given in Table II [19], [20]. MTs are assumed to be uniformly distributed in a rectangular area of size $X \times Y$, whose origin is at a distance $d_{LR}$ from the BS.
TABLE I
HP iPAQ POCKET PC H6300 SERIES SPECIFICATIONS

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{Tx}$</td>
<td>1.015 W</td>
</tr>
<tr>
<td>$P_{Rx}$</td>
<td>0.66 W</td>
</tr>
</tbody>
</table>

TABLE II
CHANNEL PARAMETERS

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\kappa$</td>
<td>-128.1 dB</td>
</tr>
<tr>
<td>$\nu$</td>
<td>3.76</td>
</tr>
<tr>
<td>$d_0$</td>
<td>1000 m</td>
</tr>
<tr>
<td>$\sigma_{h0}$</td>
<td>8 dB</td>
</tr>
</tbody>
</table>

A. Average Results with Shadowing

In this section, lognormal shadowing is considered in addition to the pathloss, similarly to [15], where Rayleigh fading is not included. This channel model corresponds to a very low mobility or static scenario where fading is averaged out, and where the proposed M2M approach is easily applicable. The results are shown in Fig. 2 for different sizes of the short range area and different values of the long range distance.

Fig. 2 shows that greedy minimization of the total energy in the network leads to better results than PF energy minimization. However, the use of PF in the proposed algorithm still allows to achieve significant savings compared to the non-cooperative scenario. Increasing the size of the SR area leads to an increase in the normalized energy consumption for both greedy and PF scenario, although the increase is very reduced in the greedy case, as seen on the figure when the area is increased from $20 \times 20$ m to $100 \times 100$ m, while keeping $d_{LR} = 1000$ m. This increase is expected, since MTs on the SR have to spend more energy to transmit the available data to all the other MTs, since the separation between MTs has significantly increased.

For a $20 \times 20$ m SR area, varying $d_{LR}$ from 1000 m to 400 m leads to a significant increase in efficiency, even for the greedy case. The reason is not an increased energy consumption with the proposed approach, but a reduced consumption on the LR link, due to the significantly reduced LR distance, which leads to an increase in the ratio $\eta$. In fact, the results obtained show that the increase in energy consumption with the greedy approach is significantly small when the distance increases from 400 m to 1000 m, whereas the increase is huge in the non-cooperative scenario. However, the energy consumption results without normalization are not shown due to space limitations. The results of Fig. 2 are conforming with those obtained in [15]. In fact, the greedy algorithm was able to find the optimal ILP solution obtained in [15], where all the data parts are allocated to a single MT which is responsible of distributing this data over the SR links. However, the results of Fig. 2 do not show the enhanced fairness obtained by the proposed game theoretical approach neither the unfairness that affects the MT selected for data transmission on the SR in the greedy case. This is investigated in Section V-B where the results of a single snapshot are presented.

B. Snapshot Results with Rayleigh Fading

In Sections V-B, V-C, and V-D, we consider $K = 5$ MTs located at a constant distance $d_{LR} = 1$ km from the BS, with a 5 m separation between an MT and its neighbor MTs. We consider Rayleigh fading with a Rayleigh parameter $a$ such that $E[a^2] = 1$. In this section, we present a snapshot result corresponding to a single fading realization. We present results in the presence of fading, averaged over multiple fading realizations, in Section V-C. Fig. 3 shows the energy consumed by each of the five MTs at a given snapshot, whereas Fig. 4 shows the number of parts allocated to each MT. It can be clearly seen from Fig. 4 that the greedy approach allocates all data parts to a single user. This result is in line with the results of [15] and of Section V-A. An interesting conclusion is that the solution obtained by the low complexity algorithm
presented in Section IV is the same as the optimal ILP CPLEX solution.

Fig. 3 shows that the energy for the last MT with the optimal greedy solution exceeds its consumed energy in the non-cooperative case. However, the energy for all other MTs is significantly reduced. The PF approach achieving the NBS leads to energy savings for all MTs, although the total energy consumed is clearly higher than the greedy case. With the PF approach, MT 5 consumes the least energy. In fact, Fig. 4 shows that with PF, the parts are subdivided among all MTs, with MT 5 receiving the smallest part. The results show that the MT to which all parts are allocated with the greedy approach is the one that receives the least parts with the PF approach. This is in line with the NBS, since MT 5 has the most favorable conditions and in case of no cooperation, can obtain the required data with minimal energy consumption compared to the other MTs. Hence, MT 5 stands in a good bargaining position that keeps its consumption minimal in the cooperative case.

C. Average Results with Rayleigh fading

Fig. 5 shows the average energy consumed by each of the five MTs, whereas Fig. 6 shows the average number of parts allocated to each MT. It can be clearly seen that Rayleigh fading helped in ensuring fairness over time. In other words, although at a given time instant a single MT is selected to multicast all the data on the SR links, different MTs are selected at different instants, due to multiuser diversity ensured by the fading fluctuations. Hence, in the presence of fading, the greedy approach ensures long term fairness while guaranteeing energy minimization. However, to implement it, MTs need to be altruistic and act in the benefit of the network as a whole.

D. Delay Results

In this section, we present results that show that the proposed approach leads to not only savings in the energy consumption of the MTs, but also to less delay in the delivery of the content. Fig. 7 shows the time needed to receive the file by each of the MTs of Section V-B. We assume that all content is received on the LR before transmission starts on the SR; i.e., with the greedy case, MT 5 waits to receive all the content on the LR before starting transmission on the SR. With the PF case, all MTs wait until the last data part is sent on the LR to the last MT in the cooperative group, before starting the transmission on the SR. We assume that MTs transmit their data sequentially on the SR; hence we do not consider simultaneous transmissions from multiple MTs. Clearly, these assumptions correspond to a worst-case scenario for both the greedy and PF techniques, in terms of delay calculations. Nevertheless, both the greedy and PF methods outperform the non-cooperative scenario. Although this result might seem surprising at first glance, this is not the case: during long range transmission, the rates achievable on the links between the MTs and the BS are lower than those achievable on the short range MT-MT communications. Thus, the time needed to receive all the content on the LR is significantly larger than the time needed to distribute this content on the SR. For the greedy case, the MTs wait until the last data part is sent on the LR to the last MT in the cooperative group, before starting the transmission on the SR. Therefore, for MT 5, the waiting time is the same as in the non-cooperative case. Afterwards, MT 5 sends the content to MTs 1-4 via multicasting. Due to the high rates achievable on the SR, the reception time by MTs 1-4 is small. Thus, for MT \( k \) with \( k = 1, \ldots, 4 \): (Reception time of MT 5 on the LR) + (Reception time of MT \( k \) on the SR) < (Reception time of MT \( k \) on the LR in the non-cooperative case).

The PF case leads to shorter delays than the greedy case. In fact, the content on the LR is sent to several MTs with PF, not just one as with the greedy case. Thus, the limitation is in the time needed by the last MT to receive its share on the
LR. From the considered example, it can be seen on Fig. 3 that MT 1 has the worst LR channel conditions since it needs the most energy to receive the content on the LR in the non-cooperative case. In addition, it is allocated the highest number of parts in the PF case (8 parts), as seen on Fig. 4. Thus, with PF, for MT $k$ with $k = 1, ..., 5$: (Reception time of MT 1 on the LR) + (sum of reception times of MT k from the other MTs on the SR) $<$ (Reception time of MT k on the LR in the non-cooperative case). This applies also for MT 1, since with PF it is receiving only eight parts on the LR whereas it should receive the whole 25 parts in the non-cooperative case.

Consequently, it was shown in this section that SR cooperation leads to enhanced delay performance in addition to the reduction in energy consumption. In addition, the PF approach was shown to lead to shorter delays compared to the optimal greedy case, in addition to achieving more fairness in energy consumption, although at the cost of a slight increase of the total energy consumption in the network. It should be noted that the greedy approach is optimal in terms of total energy consumption, not in terms of delay reduction, since the greedy optimization problem is formulated as an energy minimization problem. Thus, although the greedy approach leads to the best results in minimizing total energy consumption, it is not surprising that it is outperformed by PF in terms of other metrics such as fairness and delay.

VI. CONCLUSIONS

A game theoretical formulation for energy minimization in M2M cooperative networks was provided. The problem was formulated as a Nash bargaining game, and the Nash bargaining solution was derived. A low complexity heuristic algorithm was presented to implement the proposed solution. The algorithm is a utility minimization algorithm that can retrieve the greedy sum-energy minimization solution when the utility used is the energy itself. The greedy energy minimization was also modeled as a utility maximization game where the players act altruistically in the benefit of the total network. Simulation results showed a good tradeoff obtained by the Nash bargaining solution. In addition, an interesting result was obtained when Rayleigh fading was considered: the optimal greedy solution is shown to lead to long term fairness, although it is always instantaneous unfair towards one of the MTs. It was also shown, via simulations, that content distribution with short range cooperation leads to less delay than the non-cooperative case.

Possible extensions of this work include grouping the requesting MTs such that only MTs within the same group can cooperate. In addition, the proposed approach can be applied to a various combination of systems, with an appropriate choice of the parameters, e.g., LTE or WiMAX on the LR, Bluetooth or WiFi on the SR. Another extension would be a distributed implementation of the heuristic algorithm by the MTs, where the overhead of exchanging information is taken into account.

REFERENCES