Price-Driven Economic Cache Content Nash Bargaining Game in Wireless Multimedia Resource Allocation

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***Abstract*—In this paper, we propose a price-driven Nash Bargaining game solution to maximize Quality of Experience (QoE) with cache content optimization in wireless multimedia communications. By leveraging the cached multimedia content and the Smart Media Pricing (SMP) concept through device-to-device (D2D) communications, the economic-quality equilibrium is established between Service Provider (SP) and End Devices (EDs). The contribution of this paper is as follows. First, referring to the importance of multimedia packets, we develop a price-driven method to allocate cached multimedia resource on the seller EDs. Then a Nash Bargaining game is formulated between the seller and buyer EDs considering multimedia packet importance and content popularity. Referring to the two-player Nash Bargaining game theoretic model, a buying-caching-reselling strategy for multimedia content is proposed by deriving the Nash Bargaining Solution (NBS). Simulation results demonstrate that the proposed SMP cache allocation method has high efficiency and fairness in quality-driven wireless multimedia communications, leading to desirable utilities towards Pareto optimality.**

***Index Terms*—Smart Media Pricing, Quality of Experience, Cache Content Allocation**

I. INTRODUCTION

As the Quality of Experience (QoE) becomes an increasing important issue for wireless multimedia communication, leveraging cached content in an economics-friendly fashion becomes critically essential in future wireless networks [1] [2]. Device-to-device (D2D) strategy is widely studied for increasing the network throughput and transmission quality of service (QoS) of mobile devices that were located in a short distance area [3] [4]. In [5], authors examined the D2D transmissions in Wi-Fi by using different frequencies or time-sharing the channel. Experiment results shown that network performance gets significant improving, especially in dense environment. While the rational decisions for devices, when facing problems such as whether to cooperate with others or how to allocate the traffic load and available radio resources is one urgent problem need to be solved when considering D2D transmission. Extremely, a selfish device would exclusively occupy its resources to maximize its own profit rather than cooperative with others [6].

In addition, game theory has been recognizing as an important tool in studying, modeling and analyzing the interactions in different layers among mobile users [7] [8]. Lots of research work based on game theory has been published in the literature. For instance, to tackle the selfish device problem, authors in [9] proposed a low-complexity distributed device selection and power control scheme based on Stackelberg game. The proposed strategy combines base station and devices (acting reluctant because of limited energy and possible delays for their own data) together by providing profits to devices. In [10], authors investigated the utility maximization problem for carrier and payment minimization for end users. The interactions between end users are formulated as a non-cooperative game and system performed the optimality by deriving the sub-game Nash equilibrium. Both research results presented in [9] and [10] were based on non-cooperative game solution. Their model consists of two operators which controlled by multiple players and the objective is to prove the uniqueness and existence of equilibrium.

Cooperative games are also widely studied in the wireless transmission field. A fair scheme to allocate subcarrier, rate and power for multiuser OFDMA system is proposed in [11]. The new scheme considers a generalized proportional fairness based on Nash Bargaining solutions and coalition games. In cognitive radio wireless network, how to efficiency allocate the spectrum to mobile devices is discussed in [12] [14]. Authors in [12] proposed a novel multi-winner spectrum auction game. Attar A et.al developed an optimum resource allocation strategy which guarantees the primarys QoS request and allocate suitable rate to secondary by using cooperative game in [13]. A new spectrum access protocol is presented in [14] to address the problem where nodes in a multi-hop wireless network need to agree on a fair allocation of spectrum. Similar to the spectrum resource, storage space is another resource need to be considered for mobile devices. In [15], authors proposed the unequal error protection (UEP) based resource allocation method to optimize the energy using and channel coding rate. Authors in [16] presented frame level algorithm based on frame importance and dependency to determine the encryption block length, since the storage space was limited on wireless sensors. The importance level of multimedia has been considered in wireless multimedia communication and QoE resource allocations [21] [22].

Motivated by the aforementioned work, a Smart Media Pricing (SMP) [2] [20] based cache content Nash Bargaining game-theoretic solution is proposed to improve the multimedia

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QoE of end devices (EDs) in wireless networks in this paper. For instance, considering the scenario shown in Figure 1, one service provider (SP) and two EDs are formulated in the model. First, SP serves EDs with same data price. But each ED gets different QoS because of their varying physical conditions, i.e., transmission distance and channel states. Then ED1 (who gets the better data service) caches certain popular data contents and prepares to resell the cached data for extra profits. Powered by the D2D scheme [17], we assume that ED1 resells data to ED2 through the D2D communication which operated in unlicensed spectrum. We first propose an unequal weight proportion method to allocate the storage space efficiency for ED1. It makes the data-selling decision be simple for primary player and ensures the data service quality at the same time. Second, the Nash bargaining game in proposed between the primary player (ED1) and secondary player (ED2). The degree of cooperation is decided by how much data to be sold between EDs. We prove the two-player bargaining game can be solved based on the Nash bargaining solution (NBS) when certain conditions are satisfied. This way, our proposed cross layer strategy can achieve an optimal system utility while keeping fairness and efficiency among players. The analyzing results are demonstrated by the computer simulations.

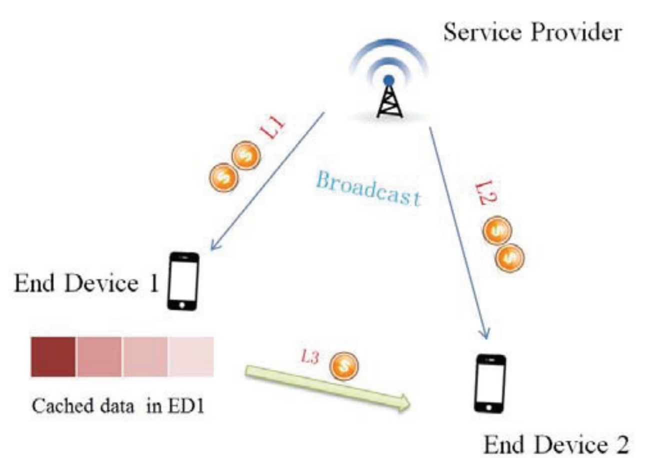

Fig. 1. Economic cache content Nash Bargaining in smart media pricing-driven wireless multimedia resource allocations.

The rest of this paper is organized as follows. Section II presents the system model and defines the utility functions for EDs. In section III, the unequal weight proportion method is proposed first. Then the cooperative game theory is addressed to help EDs find out their proper consuming data contents based on NBS. The simulation results which demonstrate the effectiveness of the proposed strategy are presented in section IV. We conclude this paper in section V. The key notations and nomenclature in this paper is summarized in TABLE I.

II. System Model

In this part, we construct our system model based on the scenario shown in Fig. 1. We consider single SP and two EDs

TABLE I
SUMMARY OF KEY NOTATIONS

Symbol	Comments
U_1, U_2	Utility of ED1 and ED2.
π_i	Selling strategies of ED1. When $i-th$ frame is resold to ED2, $\pi_1 = 1$.
N	The total number of packets sold by SP.
L_i	The length of $i-th$ frame.
L_{D2D}	Length of data that transmitted through D2D communication.
Q	Summation of frames distortion reduction.
α, β	System parameters in utility function.
M	Number of frames ED1 loads from SP.
K	Number of frames ED2 buys from SP.
C, ε	Costs coefficient for ED1 when providing data service.
p_i	Packet error rate of $i-th$ frame.
R_i	Dependency set of $i-th$ frame.
D_i	Distortion reduction of $i-th$ frame.
$w_{(i)}$	Importance level of frame i.
$H_{(i)}$	Descendent frame set for i frame.
N_f	Number of importance level.
s	Parameter for Zipfian distribution.

in our system to start. Let U_1,U_2 denote the utility of ED1 and ED2, respectively. Our system goal can be mathematically described as

$$\left\{\pi_{i[i=1,2,\ldots,N]}\right\} = argmax\left\{U_1, U_2\right\} \tag{1}$$

where $\pi_i \in \{0, 1\}$. When ED1 resells $i-th$ packet to ED2, we set $\pi_i = 1$, otherwise $\pi_i = 0$. The N denotes the total number of packets sold by SP. Let L_i denote the length of $i-th$ packet that ED1 loads from SP. The QoE maximization problem could be solved by determining how much data being sold (the degree of cooperation) between EDs.

SP transmits multimedia data to EDs by broadcasting through downlinks, charging EDs at price $y_{(0)}$. Due to different channel conditions between SP and EDs, ED1 (the closer one to SP) gets better data service and consumes L_1 data content in total. While for ED2, it consumes L_2 data content with lower data service since the longer transmission distance (causes highly signal fading or bit error rate). To make up the inferior situation of ED2, we assume ED1 would take D2D communication scheme to resell certain amount of popular data with price $y_{(1)}$ ($y_{(1)} \leq y_{(0)})$) to ED2. Let β denote the benefit gain per unit of multimedia quality of ED1. C represents the incurred cost factor when ED1 sells data to ED2. ε denotes the SPs commission coefficient when ED2 purchases data through D2D communication. L_{D2D} denotes the length of data that ED1 resells to ED2.

$$L_{D2D} = \sum_{i=1}^{N} L_i \pi_i \tag{2}$$

Then, the utility function of U_1 is given as

$$\begin{gathered} U_1 = \beta lg Q_1 + y_{(1)} L_{D2D} - \\ \sum_{i=1}^{M} y_{(0)} L_{(SP,i)} - C L_{D2D} - \varepsilon y_{(1)} L_{D2D} \end{gathered} \tag{3}$$

The utility of ED1 is presented as the summation of its multimedia quality gain and profits from selling data to ED2, subtracted by the its cost which includes three parts: costs on buying data from SP, incurred cost to provide the D2D service, and commission to SP. The Q_1 here represents the summation of frames distortion reduction, more details about Q_1 will be discussed later.

Let α denote the benefit gain per unit of multimedia quality of ED2. We model the utility of ED2 as follows:

$$U_2 = \alpha * \sum_{S \in SP, ED} lgQ_S - \sum_{i=1}^{K} y_{(0)} L_{(SP,i)} - y_{(1)} L_{D2D} \quad (4)$$

where $S \in SP, ED$ implies that multimedia quality gain of ED2 contains two parts. Q_{SP} denotes the ED2s multimedia gain from SP and Q_{ED} denotes the multimedia gain from ED1. Q_{ED} equals 0 if ED2 does not buy any data from ED1 (that means $L_{D2D} = 0$). The utility of ED2 is represented as its multimedia quality subtracted by it costs. The multimedia quality Q in Equation (2) and (3) is represented as the summation of the distortion reduction of each individual multimedia frame, multiplied by the probability that it is successfully transmitted and decoded with regards to the frame encoding dependency inherited from the video codec [18]. The calculation of Q is shown as follows:

$$Q = \sum_{i=1}^{N} D_i(1-p_i) \prod_{K \in R_i} (1 - p_{(K,i)}) \quad (5)$$

where D_i denotes reduction distortion of $i-th$ frame. p_i represents the packet error rate of $i-th$ frame. Here we define R_i as the frame dependence set of $i-th$ frame. For example, considering in a multimedia flow, P1 represents I frame (Intra frame), P2 represents the B frame (Bidirectional frame) right after P1 and P3 represents the P frame (Predicted frame) right after P2. I frame is least compressible and does not require other video frames to decode at the receiver. While for P and B frames, it is necessary to ensure the previous dependent frames successfully transmitted when decoding them. So we get the P3's dependence set $\{P_1\}$ and P2's dependence set $\{P_1, P_3\}$. Let BER imply the bit error rate in physical channel. The packet error rate is explained as:

$$p_i = 1 - (1 - BER)^{L_i} \quad (6)$$

where L_i represents the length of $i-th$ frame.

To maximize the utilities of EDs, we address the problem with a strategy which can determine how to allocate the reasonable quantity of data L_{D2D} that ED1 sells to ED2. The main contribution of this paper includes: First we take unequal weight proportion method to allocate the multimedia data cached at ED1. Second we formulate the data contents reselling progress as a bargaining game and our goal is to prove the existence and uniqueness of NBS.

III. COOPERATIVE CACHE NASH BARGAINING GAME

In the proposed system, ED1 loads multimedia data with high quality and resells it to its neighbors. With the constraint of storage limitation on device, we propose the unequal weight proportion method to cache popular data (the popularity is determined by frames distortion reduction) from SP. The neighbor, we consider ED2, purchases certain data content with price $y_{(1)}$. We formulate Nash bargaining game between ED1 and ED2, to decide how much data should be sold for keeping optimality utility of both seller and buyer. The non-uniform storage allocation method and Bash bargaining game will be discussed in detail in the following sections.

A. Unequal Weight Proportion Method for Caching

The priority of frames in Group Of Picture (GOP) is determined by their video distortion reduction and reference relationship. The high priority frames mean better media quality and play a major role in term of users utility (according to Equations 3 and 4). The first contribution of our work is to propose the unequal weight proportion scheme when ranking and caching frames in the limited memory. Similar to [16], let w_i denote the perceptional importance level of frame i in the GOP. H_i represents descendent frame set for i frame in the decoding dependency graph. We get w_i expressed as

$$w_i = \sum_{\forall j | j \in H_{(i)}} D_j \quad (7)$$

When ED1 loads multiple multimedia streams from SP, we calculate the importance level for each frame based on Equation (7) repeatedly. We consider there are many GOPs in each stream. Then, we allocate storage space for cached multimedia data according to the importance level, details are shown in Fig. 2.

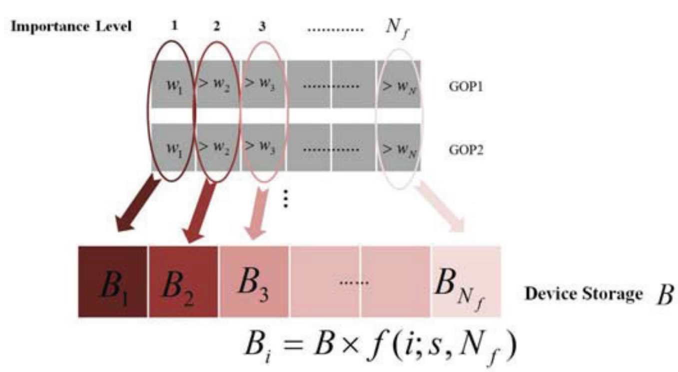

Fig. 2. The ranking and caching scheme of multimedia data storage based on Zipfan distribution.

Let B denote the device's storage capacity. Here we take the empirical law (Zipfian distribution) to make full use of storage resource [19]. In Figure 2, $f(i; s, N_f)$ represents the probability of the $i-th$ element being requested by at least one user, which is defined as:

$$f(i;s,N_f)=\frac{1/i^s}{\sum_{n=1}^{N_f}1/n^s} \tag{8}$$

where N_f is the number of perceptional importance level we calculated before. s denotes the parameter of the exponent characterizing the distribution. We unevenly separate the storage space into N blocks based on the data importance level. In this way, it is ensured that theres enough space for highly distortion reduction data. It is worth noting that when ED1 resells data to ED2, the highly ranked data in storage space should be sold first, for the purpose of keeping ED2 gets the best data service.

The allocation process of unequal weight proportion method is shown in algorithm 1. First, based on the distortion reduction and reference relationship, the importance level is determined for each individual GOP. The importance level is a vital factor for the storage allocation. In step 7, we choose the maximum number of importance level in all GOPs, as it ensures all data contents have chance to be stored for future reselling. In step 10, we take the Zipfian distribution to allocate storage resource based on the frame ranking sequence. It is worth pointing out when the parameter $s \geq 4$, more than 90 percent storage space is occupied by most important data (within the importance level 1), which satisfies the strictly quality-driven transmission case very well. Under proper parameter s, we can achieve the resource allocating process with highly efficiency and fairness.

Algorithm 1 The Unequal Weight Proportion Algorithm for ED1

1: **Inputs:** (1) The distortion reduction D_i of frames in each GOP. (2) The reference relationship among frames. (3) Other parameters such as the number of GOP (denoted as N_G), the storage capacity B, the parameter s for Zipfian distribution.
2: **Outputs:** (1) The importance level ($1 \sim N_f$) of frames. (2) The storage allocation strategy.
3: For i=1:N_G
4: Calculate the $w_{(i)}$ for each frame based on its reference relationship and Equation (7).
5: Rank frames based on $w_{(i)}$, record the importance level $N_{(i)}$. The $N_{(i)}$ maybe different since it varies from GOP.
6: End For
7: Set the global importance level N_f = maxN_i. Record N_f for next step.
8: For j=1:N_f
9: Based on the Equation (8) and input parameter s, calculate the probability of $f(i;s,N_f)$.
10: Taking $B_j = B * f(i;s,N_f)$ to calculate subspace for storing data contents which belong to importance level j.
11: End For
12: Check the $w_{(i)}$ for each GOP and output the storage allocation strategy.

The sorting and caching problem of popular data contents has been solved by means of unequal weight proportion method. With the non-uniform allocation method, ED1 would keep providing high quality data service. Next, we will discuss the transmission work between EDs in high level, which directly affects the overall system performance.

B. Cooperative Game Approach

Cooperative games request players in games to reach an agreement on how to fairly and efficiently share the available resources. First, we will briefly review the fundamental concepts and theorems for Nash Bargaining game and axioms which ensure the existence of Nash Bargaining Solution. Then we will discuss how to implement the bargaining game in our work.

Definition 1: The state of source allocation $(u_1, ..., u_k)$ is **Pareto optimality**, if and only if there is no other source allocation u_i^* such that $u_i^* \geq u_i, \forall i$, and $u_j^* > u_J, \exists j$, i.e., there does not exist other allocation to make any one individual player better off without making at least one another player worse off.

The Pareto optimality axiom must be satisfied when seeking NBS. But there might be more than one allocation set of Pareto optimality. We need further axioms to select a bargaining result which considering the fairness for each player and providing a unique Pareto optimal operation allocation simultaneously. For convenience, we consider the two-player bargaining game in our following definition and theorem (study case shown in Fig. 1), while it can be extended more players straightforwardly. Let U denote the feasibility set, it is the set of all possible source allocation $(u_1^i, u_2^i)_{[i=1,...,N]}$. The initial of negotiation process denoted by (u_1^0, u_2^0), which represents no bargaining game between two players.

Definition 2: Source allocation $(u_1^* = u_2^*)$ is said to be NBS. The solution should satisfy following axioms [7][11].

1) Individual rationality: $u_1^* > u_1^0$ and $u_2^* > u_2^0$.
2) Feasibility set: $(u_1^* > u_1^0) \in U$
3) Pareto optimality: If $(u_1, u_2), (u_1^i, u_2^i) \in U, \forall i$, and $u_1 > u_1^i, u_2 > u_2^i$. Then $(u_1, u_2) = (u_1^*, u_2^*)$
4) Symmetry: The allocation strategies are symmetric in the feasibility set. i.e., $(u_1, u_2) \in U \Leftrightarrow (u_2, u_1) \in U$. And if $u_1^0 = u_2^0$, then $u_1^* = u_2^*$.
5) Independence of irrelevant alternatives: If $(u_1^*, u_2^*) \in U' \subset U$, then (u_1^*, u_2^*) is also the NBS in U'.
6) Invariant to affine transformations: We consider the independence of linear transformations, let U_c be obtained from U by the linear transformation $u_1^c = c_1 u_1^0 + c_2$ and $u_2^c = c_3 u_2^0 + c_4$ with $c_1, c_3 > 0$. Then, $(c_1 u_1^* + c_2, c_3 u_2^* + c_4)$ is the NBS on U_c

Theorem 1: There is a unique NBS (u_1^*, u_2^*) which satisfies all the axioms above. And it is given by

$$(u_1^*, u_2^*) = argmax(u_1 - u_1^0)(u_2 - u_2^0)_{[(u_1^*, u_2^*) \in U, u_1 > u_1^0, u_2 - u_2^0]} \tag{9}$$

Next, we will discuss how to implement NBS into our work. As we can notice from Equations (1) and (9), the cooperative (Nash bargaining) game between ED1 and ED2 can be defined as follows. Both players have their objective functions, i.e., Equations (2) and (3). The goal of our model is to maximize all EDs simultaneously.The $(u_1^0, u_2^0) = (U_1, U_2)|L_{D2D} = 0$ represents the minimal performance and is called the initial agreement status of bargaining game. Furthermore, we define

$$U = \{L_i \pi_{i[i=1,...,N]} | \pi_i = 1, u_1^i > u_1^0, u_2^i > u_2^0\} \tag{10}$$

as the feasible set. The problem is simplified to choose the proper reselling strategy in U for ED1 and ED2, such that both players get maximum utility (QoE). The Nash bargaining between ED1 and ED2 gets a unique and efficient solution since it satisfies the six axioms.

We propose a fast algorithm between two players for the optimization goals by iteratively increasing the data content which ED2 purchases from ED1, as shown in algorithm 2. First, the initial agreement (u_1^0, u_2^0) is on the table to start the bargaining game. Then the negotiating process is illustrated from step 3 to step 10. The most high quality data will be sold in the first or second iteration due to the advanced property of Zipfs law.

Algorithm 2 The Unequal Weight Proportion Algorithm for ED1

1: **Inputs:** (1) Initial agreement (u_1^0, u_2^0). (2) The feasible set U. (3) Else parameters we defined in Equations (2) and (3).
2: **Outputs:** (1) The Nash Bargaining Solution (u_1^*, u_2^*).
3: For i=1:N
4: If number of frame > 1
5: Gradually adding data frame into current agreement (u_1^i, u_2^i);
6: Calculate $U^{i^{'}}$ based on function $U = (u_1^i - u_1^0)(u_2^i - u_2^0)$;
7: Let $U^i = max\{U^{i^{'}}\}$
8: End if
9: If $U^i < U^{i-1}$, it means U cannot be increased by updating the u_1 and u_2. The iteration ends and return U^{i-1};
10: End for
11: It is worth mentioning that if U still keep rising when ED1 sells out all its cached data, we consider the final agreement (u_1^N, u_2^N) is the NBS.

IV. NUMERICAL SIMULATIONS AND RESULTS

In this section, we perform our simulations to evaluate the system performance based on the unequal weight proportion and cooperative game model which we proposed in this paper. The *Foreman* video srouce stream with H. 264 encoder is utilized in our simulations. The Peak Signal-to-Noise Ratio (PSNR) considered as the performance metric to evaluate the multimedia quality. Some vital parameters and their value ranges are shown in TABLE II.

TABLE II
PARAMETERS USED IN THE SIMULATION

Symbol	Value	Comments
α, β	$0.5 \sim 1$	Benefits gain per unit of multimedia quality.
ε	$0.1 \sim 0.5$	D2D transmission Commission coefficient for SP.
C	$0.5 \sim 1$	Incurred cost factor when ED1 selling data.
y_0, y_1	$0.5 \sim 2$	Purchasing price per unit length media data.
D_i	$35.92 \sim 36.27$	Distortion reduction of frames.
e	$10^{-7} \sim 10^{-5}$	Channel bit error rate.
N	30	Number of frames.

First, we evaluate the performance of the proposed unequal weight proportion method. We take streams $IPPPIPPP...$ and $IPBIPB...$ into our simulation to explore the effects of different reference relationships. Sequence $IPBIPB...$ is more complex comparing with the previous one, the results are shown in Fig. 3 and Fig. 4. From the results we can notice that when the multimedia frames have highly dependency (in Fig. 3), the smaller parameter s for Zipfian distribution serves the media quality request better. The rationale behind this result is that with highly dependency, the multimedia gain is leveraged into each frame. When $s = 0$, the storage space will be allocated evenly. It is the special case called equal weight proportion method in the simulation. P or B frame keep nearly the same multimedia gain but with shorter (one-third or even less) packets length, which will significantly save the bandwidth and transmission resources when providing the same level of video service. With the smaller s, the storage space is divided like to be evenly.

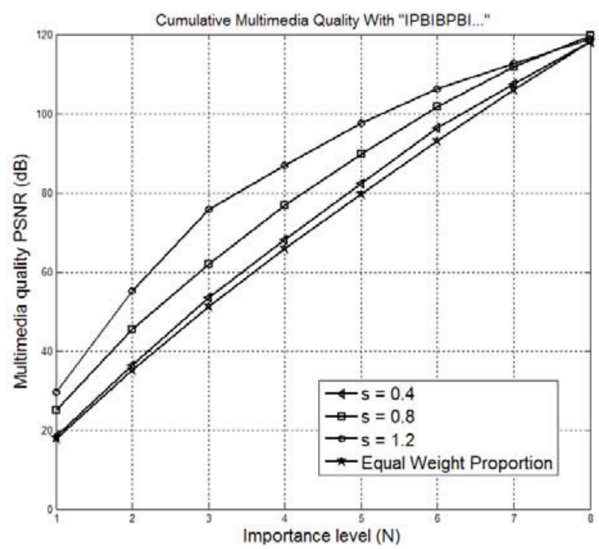

Fig. 3. Performances of different Zipfian parameters and equal weight proportion scheme, under complex reference relationship (with stream $IPBIBPBI$)

Next, we evaluate the impacts of physical channel factors on system performance. According to Equations (5) and (6), we understand that the multimedia quality depends on channel Bit Error Rate (BER). We assume the BER in D2D transmission is lower than it is between SP and EDs. The rationale behind this is that the BER between SP and EDs is mainly determined by the distance and channel fading, while distance between devices in D2D transmission is relative short and the channel fading has rarely effects on media quality. Three scenarios are considered in the simulation to explore the cache and non-cache strategies performance. The BER in each scenario is shown in TABLE III.

TABLE III
PARAMETERS FOR THERE SCENARIOS

Scenario	1	2	3
$BER(SP-ED)$	$e = 10^{-4}$	$e = 10^{-5}$	$e = 10^{-6}$
$BER(ED-ED)$	$e = 10^{-5}$	$e = 10^{-6}$	$e = 10^{-7}$

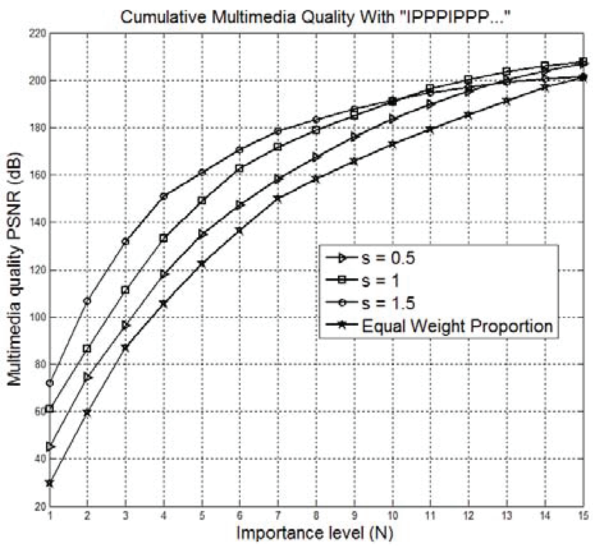

Fig. 4. Media quality performances under simple reference relationship (with stream $IPPPIPPP$)

Simulation results of the PSNR in varying BER are shown in Fig. 5. We observe that ED2 gets better multimedia if it buys data from ED1 instead of SP. Scenario 3 shows the best performance since its BER is the smallest. In further simulations, we will choose the optimal parameters, i.e., $e = 10^{-6}$ and $e = 10^{-7}$ for SP-ED, ED-ED scenarios respectively.

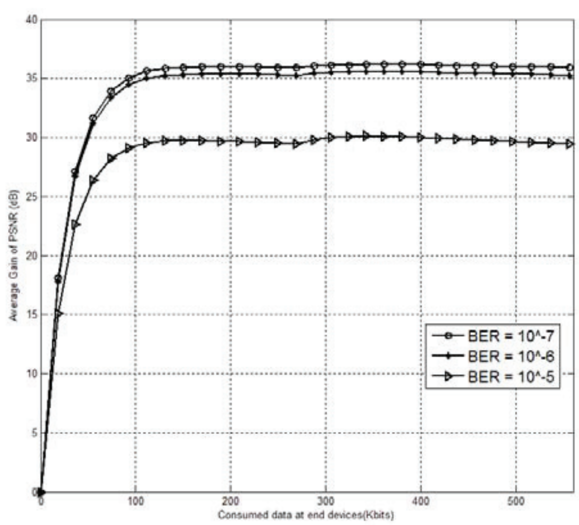

Fig. 5. ED2s media quality gains in cache (ED2 buys data from ED1) and non-cache (ED2 buys data from SP) cases

We set up simulations with $\alpha = 0.8, \beta = 1, \varepsilon = 0.2, C = 1$, and $y_{(0)} = 2$ for two EDs scenario to test the utility performance. In Fig. 6 and Fig. 7, we show utility of individual end device versus the D2D transmission data with different buying-selling prices. Referring to the proposed system model, the utilities of EDs are decided by factors such as BER, buying-selling price, data content sold through D2D etc. Because the optimal BER (10^{-6} and 10^{-7}) is implemented in simulations, EDs get almost same multimedia quality no matter from SP or D2D. Experimental results in this section explore the effects of buying-selling price ratio on EDs' utilities. As we can notice from the figures, as the primary end device, ED1 gets more benefit (in terms of utility) when reselling cached important data with higher price. But for ED2, his overall gain decreases with the higher selling price. This is because as the secondary ED, the cost of ED2 to experience high quality data service is buying data from ED1. The cheaper reselling price ED1 sets, the better gain ED2 gets.

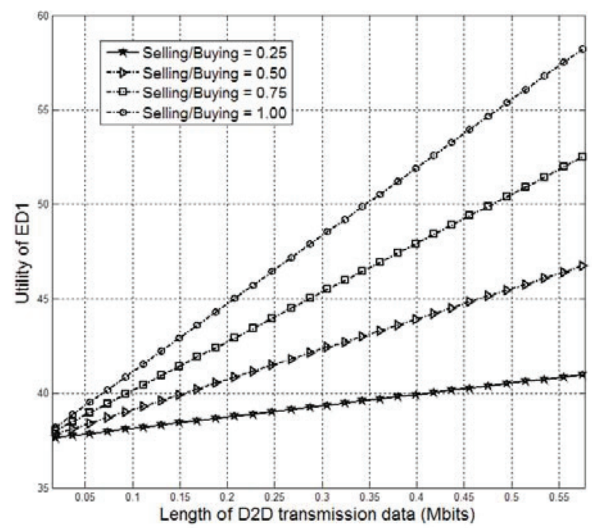

Fig. 6. Utility gain of ED1 versus quantity of D2D transmission data, under different reselling price strategies.

It can be concluded from the previous simulations that both EDs have different trends to choose the reselling strategies. i.e., ED1 trends to choose higher reselling price to improve its profit, which will decrease ED2s utility. Thats the reason a Nash bargaining model is presented in this paper. During the bargaining process, individual players have the opportunity to reach a mutually beneficial agreement even though they have conflicts of interest. In Fig. 8, we show the system utility performance starts at the first agreement (u_1^1, u_2^1) where $L_{D2D} = 0.0171Mbits$. When EDs do not cooperate ($L_{D2D} = 0$), $(u_1^i - u_1^0) * (u_2^i - u_2^0)$ is always equals zero, since both EDs' utilities will be the initial agreement (u_1^0, u_2^0). With varying reselling strategies in the feasible set, as we can notice from the figure, objective function $U = (u_1^i - u_1^0) * (u_2^i - u_2^0)$ achieves the NBS when selling data around 0.45 Mbits .

V. Conclusion

In this paper, an economic price-driven Nash Bargaining game solution is proposed to improve the QoE of EDs in wireless multimedia resource allocation. By leveraging SMP

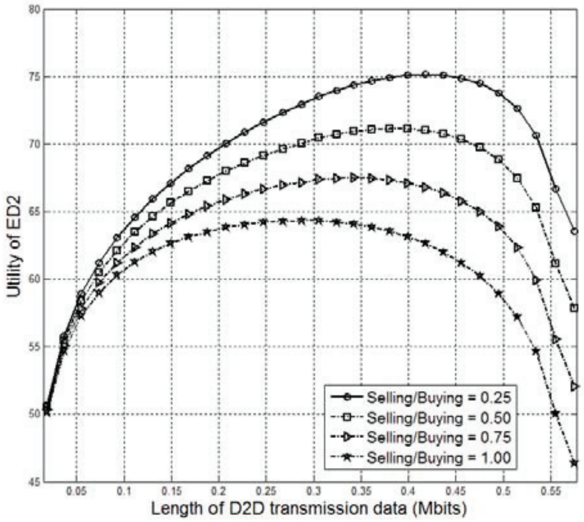

Fig. 7. Utility gain of ED2, in different reselling strategies and length of consumed data.

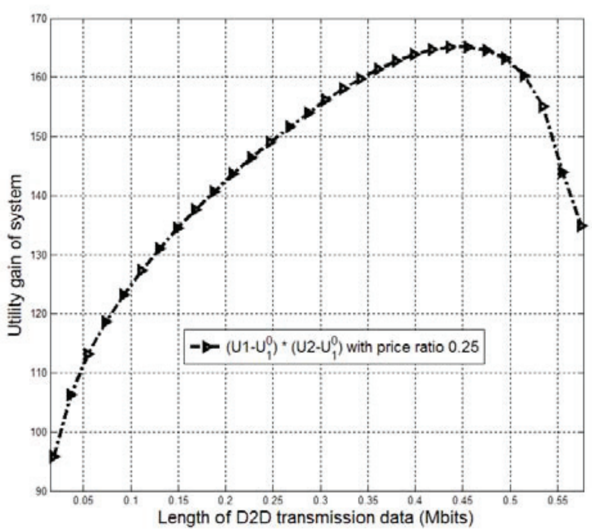

Fig. 8. Value of $(u_1 - u_1^0) * (u_2 - u_2^0)$ versus varying reselling strategies.

concept, the proposed scheme achieves close to globally optimum performance. First an unequal weight proportion method is presented for efficiency resource allocation based on media quality. Then a cooperative game model is formulated between two EDs. Under the help of Nash bargaining game, the cooperative data reselling strategy based on NBS is presented in this paper. The simulation results demonstrate that the proposed proportion method addressed the complex frames dependency problem and satisfied the quality-driven data service requests. Results also show that both players in the bargaining game benefit from the proposed strategy and get the best utilities at the NBS.

VI. Future Work

It is worth noting that possible extensions of this work include: grouping more EDs in the cooperation game to maximize their individual utility. The objective function could be redesigned if there are more EDs. The existence and uniqueness of NBS for multiple EDs should also be proved through the six axioms. Furthermore, based on the unequal weight proportion method, gradually increasing the reselling price of cached data from less important level to high level is another way to improve profit. More complex system modeling and utility functions are needed for the future work extension.

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