Coalition Formation Game Based Energy Efficiency Oriented Cooperative Caching Scheme in UUDN

Yu Li(✉), Heli Zhang, Hong Ji, and Xi Li

Key Laboratory of Universal Wireless Communications, Ministry of Education,
Beijing University of Posts and Telecommunications, Beijing, China
{liyu1,zhangheli,jihong,lixi}@bupt.edu.cn

Abstract. It is generally considered that Ultra-Dense Network (UDN) is a promising solution for 5G and the network is going to turn into user centric. Caching popular contents at the edge of network is an efficient way to reduce the energy consumption and data traffic of backhaul link. But most of current researches on caching in UDN fail to take into account of user centric and energy efficiency performance during caching files delivery process. In this paper, we consider an User-centric Ultra-Dense Network (UUDN) with cache-enabled Small Base Stations (SBSs) and investigate the energy efficiency of cooperative caching in UUDN. In order to achieve energy efficiency during delivery, we design a novel SBS grouping rule and a cooperative caching scheme based fragmentation with the consideration of user mobility. We formulate an energy optimization problem on caching and introduce coalition formation game to simplify and solve our optimization objective. Then we analyze the impacts of system parameters on the overall performance and compare our scheme to some other schemes. Numerical results demonstrate our scheme is energy efficient and outperforms the others.

Keywords: Energy efficiency · Cooperative cache · UUDN · Content fragmentation · Coalition game

1 Introduction

Cache popular contents at the wireless edge of network is an extensively accepted technology in 5G [6]. Cache can offload backhaul burden and improve energy efficient of the network by reducing duplicate downloads effectively [5]. UUDN aims at making every user feel like a network is always following it via very high data rate and intelligent service [3]. Thus it is imperative to deploy cache in UUDN to provide high-quality intelligent service.

X. Liu et al. (Eds.): ChinaCom 2018, LNICST 262, pp. 458–468, 2019.
https://doi.org/10.1007/978-3-030-06161-6_45

Recently, more and more researches focus on caching at SBSs, e.g. femtocell or picocell. Reference [6] demonstrates that energy efficient can benefit from caching and investigates the key parameters and locations that influence energy efficiency of caching significantly. However, considering the characters of SBSs, there are some obstacles on deploying cache in UDN [13]. First, the storage capacity of a single SBS is too limited to cache enough popular contents especially the large volume of multimedia contents. And the number of users under each SBS is too small to reflect the content aggregation effect [12]. Jointing SBSs to cache cooperatively is an effective solution to these problems and can improve network performance in multiple aspects in comparison with the non-cooperative one. In [7], the potential of energy efficiency in cache-enabled cooperative dense small cell networks is explored based on affinity propagation-based clustering. Reference [4] designs a combined cooperative caching and transmission policy in cluster-centric small cell network. Reference [2] investigate the problem of caching placement on SBS leveraging user mobility, aiming to maximize the cache hit ratio. In [3], UUDN has been defined and the authors analyze challenges and requirements of UUDN. Reference [8] investigate the problem of dynamic access point grouping in UUDN. However, most of the researches on caching fail to consider the characteristics of UUDN or ignore the delivery energy efficiency of caching files in UUDN.

In this paper, we investigate the issue of cooperative caching in UUDN in order to optimize the delivery energy efficient of caching files. We consider SBSs can form an SBS group (SBSG) to serve an User Equipment (UE) cooperatively in our UUDN. SBSG cache files according to the UE's preference. We divide the files into several fragments to cache in different SBSs. The reason of fragmentation is the burden of SBSs can be decentralized and multiple SBSs share a transmission task is more stable. In addition, we formulate an energy optimization problem on the basis of our caching scheme. Then we introduce coalition formation game to settle the optimization objective. Coalition games prove to be a very powerful tool for designing fair, practical and efficient cooperation strategies in communication networks [11]. And in this work, coalition formation game simplify and solve our problem effectively. Numerical results demonstrate that our scheme and proposed algorithm can improve the delivery energy efficiency to a great degree. The major contributions of this paper are summarized as follows:

– We study energy efficiency of cooperative caching and UUDN architecture. Then we formulate an cache-enabled UUDN model basing the previous study.
– We propose a novel SBS grouping rule and a fragmentation caching scheme with the goal of improving energy efficiency. We formulate an optimization objective on reducing energy consumption in order to improve energy efficiency.
– We introduce coalition formation game and evolve it to adapt to and solve our objective problem. Numerical results demonstrate that our work is of vital benefit and outperforms the others.

The remainder of this paper is organized as follows. Section 2 gives the system model and problem formulation. In Sect. 3, coalition formation game is introduced and evolve to solve our problem. Numerical results are given in Sect. 4. Finally, we conclude this paper in Sect. 5.

2 System Model and Problem Formulation

In this section, we introduce the system model and formulate the optimization problem.

2.1 System Model

(a) Network model: As illustrated in Fig. 1, we consider an user-centric ultra-dense wireless small cell network consisting of cache-enabled SBSs. When an UE joins the network, the SBSs around the UE would form an SBSG to serve it cooperatively. In the SBSG, SBS can communicate with the UE directly or through multi-hops. For notation ease, we denote $\mathbb{M} = \{1, 2, \cdots, M\}$ as the SBSG set and m as index for the m-th SBS in a SBSG where $m \in \mathbb{M}$. In each SBSG, an enhanced SBS (ESBS) is selected dynamically to control and manage the others.

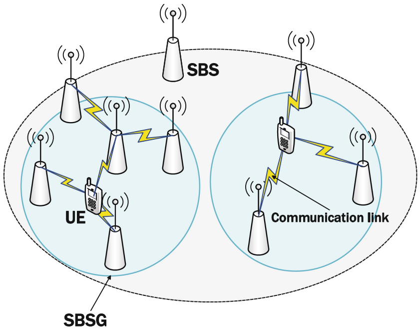


Fig. 1. Network structure

(b) Request model: We consider that all the requested files are ranked into a requesting library $\mathbb{F} = \{f_1, f_2, \ldots, f_{N_L}\}$ with all the files having same size q, where f_i is the i-th most popular file of the library and N_L is the total number of files in the library. We assume that the request probability distribution $\mathbb{P} = \{p_1, p_2, \ldots, p_{N_L}\}$ follows Zipf's distribution [1], thus the request probability of f_i is calculated as:

$$p_i = \frac{i^{-\gamma}}{\sum_{j=1}^{N_L} j^{-\gamma}} \tag{1}$$

where γ is the skewness parameter of which typical value is between 0.5 and 1.0 reflecting different levels of skewness of the distribution.

(c) Caching model: In our UUDN, each SBS is equipped with a cache which capacity is C. Files are cached according to the order of requesting library and we regard an SBSG as a cache entirety. For simplification, we assume an SBS only belong to one single SBSG. Thus the first N_C files in the requesting library are cached in the SBSG. Each caching file is divided into same-sized fragments to cache in different SBSs respectively. Denote $\mathbb{L} = \{l_1, l_2, \ldots, l_{N_C}\}$ as the fragmentation matrix in which l_i represents how many fragments f_i is divided into.We denote $f_i^{(j)}$ as the j-th fragment of file f_i, where $j \in \mathbb{Z}^+$ is between 1 and l_i. And $\mu_m^{i,j}$ is the cache coefficient denoting whether the m-th SBS in the SBSG caches $f_i^{(j)}$. ESBS has the information of $\mathbb{L}$ and each $\mu_m^{i,j}$.

(d) Energy model: For wireless links, we adopt Rayleigh fading model. Hence the achievable data transmission rate among SBSs is formulated as:

$$r_{m_1,m_2} = Wlog_2(1 + \frac{pd_{m_1,m_2}^{-\alpha}}{\beta p I_{m_2} + \sigma^2}) \tag{2}$$

where $m_1, m_2 \in \mathbb{M}$ and $m_1 \neq m_2$, W and $d_{m_1 m_2}$ is the transmission bandwidth and the distance between m_1 and m_2 respectively, α is the path-loss exponent of small-scale Rayleigh fading channel, I_{m_2} is the power of ICI (inter-cell interference) at the SBS m_2 normalized by the transmit power p, σ^2 is the variance of the white Gaussian noise. Besides, $\beta \in [0, 1]$ reflects the percentage of how much of ICI can be eliminated by interference management techniques [6], i.e. $\beta = 0$ reflects the optimistic condition in which all ICIs are assumed to be removed and $\beta = 1$ represents the pessimistic case.

Similarly, the achievable throughput from SBS m to UE can be calculated by:

$$r_m = Wlog_2(1 + \frac{pd_m^{-\alpha}}{\beta p I + \sigma^2}) \tag{3}$$

where $m \in \mathbb{M}$ and d_m is the distance between the SBS m and the UE, I is the power of ICI at the UE normalized by the transmit power p.

We denote w_{m_1,m_2} as the energy consumption coefficient between SBS m_1 and m_2. They can be calculated by:

$$w_{m_1,m_2} = \frac{p}{r_{m_1,m_2}} \tag{4}$$

Similarly, for the SBS communicating with the UE directly, the energy consumption coefficient is:

$$w_m = \frac{p}{r_m} \tag{5}$$

For the SBS communicating with the UE through multi-hops, the transmission path and energy consumption coefficient with the UE can be calculated by Dijkstra algorithm and denoted as w_m as well. We set w_0 as a threshold that all the SBS with the w_m less than w_0 can join the SBSG of the UE.

2.2 Problem Formulation

We formulate the main optimization objective investigated throughout the paper in this section. In our research, we aim at maximize the average energy efficiency during the content delivery process. As q is constant, our optimization problem is to minimize the average content transmission energy consumption as below:

$$
\begin{aligned}
\min_{l_i,\mu_m^{i,j}} \; & \sum_{i=1}^{N_C} \frac{p_i}{\sum_{i=1}^{N_C} p_i} \left(\sum_{j=1}^{l_i} \sum_{m=1}^{M} \mu_m^{i,j} w_m \frac{q}{l_i} \right) \\
s.t. \quad & C1: \; 1 \leq l_i \leq M \\
& C2: \; N_C \leq \frac{MC}{q} \\
& C3: \; \mu_m^{i,j} = \{0,1\} \\
& C4: \; \sum_{m=1}^{M} \mu_m^{i,j} = 1 \\
& C5: \; \sum_{j=1}^{l_i} \sum_{m=1}^{M} \mu_m^{i,j} = l_i
\end{aligned}
\tag{6}
$$

f_1^1	f_1^2	f_1^3	f_1^4
f_2^1	f_2^2	f_2^3	f_2^4
f_3^1	f_3^2	f_3^3	f_3^4
SBS1	**SBS2**	**SBS3**	**SBS4**

(a) The coalition consists of SBS1, SBS2, SBS3 and SBS4 and file 1,2,3 need to be cached in the coalition.

Coalition 1	Coalition 2	Coalition 3
SBS1,SBS5	SBS3	SBS2,SBS4,SBS6
File1~File8	File9~File12	File13~File24

(b) Coalition 1 with two SBSs caches the first 8 files, Coalition 2 with one SBS caches 9th-12th files and Coalition 3 with three SBSs caches 13th-24th files.

Fig. 2. Allocation rule

Here $C1$ is the fragmentation constraint, $C2$ is the caching capacity constraint, $C4$ means each fragment is only cached at a single SBS and $C5$ means the SBSG cache the whole f_i.

3 Proposed Solution

From the above description, we can know that several SBSs cache different parts of a file cooperatively in an SBSG. Thus we use coalition formation game to divide the SBSG into several small coalitions. SBSs in the same coalition cache different fragments of same files cooperatively. Coalition formation game usually aim to seek cooperative group where network structure and cost for cooperation play a major role. The following of this section will introduce the algorithm based coalition formation game in detail.

In order to solve the objective properly, we make some adaptive settings on the optimal objective. As previously mentioned, several SBSs composing a coalition cache different part of same files. In the coalition, each SBS is numbered according to their w_* in the order of small to large. The number of fragments the caching files divided into is the same with the size of their caching coalition and the sequence numbers of the SBSs and fragments are corresponding. As is described in Fig. 2(a), the blocks in four colors represent the caching space of the four SBSs and they are signed by the fragments cached inside them. In addition, the files are cached in the order of coalition. As illustrated in Fig. 2(b), Coalition 1 caches File 1- File 8, Coalition 2 caches File 9- File 12 and so forth. The ranking rule of coalitions will be described in the following part.

We denote $\mathbb{S} = \{S_1, S_2, \cdots, S_J\}$ as the coalition set, in which S_j is the j-th coalition in the SBSG, $\bigcup_{j=1}^{j=J} S_j = \mathbb{M}$ and $S_i \bigcap S_j = 0$ for any $i \neq j$. A coalition set is usually regarded as a partition. We define the utility function to evaluate the energy efficiency capacity of coalition $\mathbb{S}$ as following:

$$v(\mathbb{S}) = \sum_j P_j \overline{w_j} \tag{7}$$

where P_j and $\overline{w_j}$ are the total file request probability and the average of energy consumption coefficient in the coalition S_j respectively. They can be calculated by:

$$P_j = \sum_{\sum_{i=1}^{j-1} \alpha_i + 1}^{\sum_{i=1}^{j} \alpha_i} P_i \tag{8}$$

$$\overline{w_j} = \frac{\sum_k w_k}{\alpha_j} \tag{9}$$

in which SBS k belong to the coalition S_j. α_j represents the total cache capacity of S_j i.e. how many files can be cached in S_j in all calculated by:

$$\alpha_j = \lfloor \frac{|S_j| C}{q} \rfloor \tag{10}$$

where $|S_j|$ is the number of SBSs in coalition S_j.

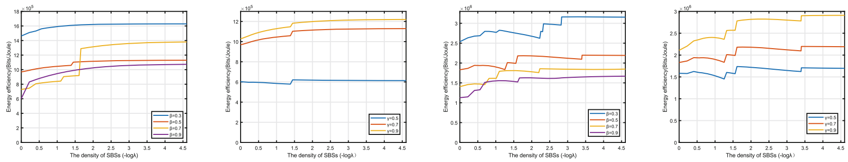
Algorithm 1 Coalition formation game based algorithm

```
Initialization:
Set each SBS form a coalition itself in the SBSG and this partition is the initial 𝕊.
Calculate the initial 𝕊 according to (8).
repeat
    Arbitrary merging and splitting in 𝕊 to form a temporary 𝕊'.
    Calculate the utility value v(𝕊') according to (8).
    if v(𝕊') < v(𝕊) then
        𝕊 = 𝕊'
    end if
until 𝕊 converge to a 𝔻_hp-stable partition
```

In our coalition formation game based algorithm, there are several key operations described as follows:

1. Ranking: Calculate all the $\overline{w_j}$s in $\mathbb{S}$ and rerank the coalitions in the order of small to large.
2. File allocation: Assign files to each coalition. The coalitions with smaller numbers cache the top files in the requesting library, as described in Fig. 2b. Thus the files with high requesting probability can be transmitted in a low energy consumption.
3. Merging: Merge any set of coalitions $\{S_1, \cdots, S_k\}$ to form a new coalition S_j thereby composing a new partition $\mathbb{S}'$.
4. Splitting: Split any coalition S_j into several coalitions $\{S_1, \cdots, S_k\}$ to compose a new partition $\mathbb{S}'$ where $\bigcup_{i=1}^{i=k} S_i = S_j$.

The ultimate propose of our algorithm is to converge to a final stable partition by any arbitrary sequence of merging and splitting. According to [10], every partition resulting from our proposed merging and splitting way is $\mathbb{D}_{hp}$-stable. In a $\mathbb{D}_{hp}$-stable partition $\mathbb{S}$, no players in $\mathbb{S}$ are interested in leaving their coalitions through merging and splitting to form other partitions. The specific process of our proposed algorithm is summarized in Algorithm 1.



(a) UE1: Energy efficiency versus SBS density with different β

(b) UE1: Energy efficiency versus SBS density with different γ

(c) UE2: Energy efficiency versus SBS density with different β

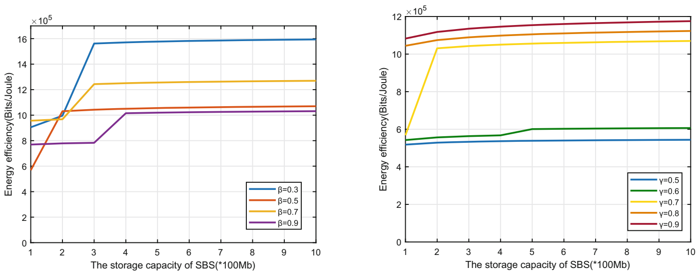
(d) UE2: Energy efficiency versus SBS density with different γ

Fig. 3. Impact of SBS density λ

4 Numerical Results

In this section, simulation results of the proposed coalition formation game based algorithm are presented to discuss the energy efficiency performance and the impacts of different parameters in our UUDN. In this work, we consider the SBSs in the network are uniform distribution and the density of SBSs is λ. But we must emphasize that our caching scheme and proposed algorithm can be further generalized to any network topology. The simulation parameters are described as follows. The transmission power of SBS is 0.1 W. The background noise is -95 dBm. The path-loss exponent α of small-scale Rayleigh fading channel is 3. The transmission bandwidth of SBSs is 200 kHz. There are 1000 files in the requesting library and the size q of each file is 50 Mb. The impacts of SBS density λ, threshold of SBSG w_0, SBS's storage capacity C, interference elimination coefficient β and skewness parameter of Zipf's distribution γ are investigated in the next part of this section.

(a) *Impact of SBS density*: In Fig. 3, we first investigate the impact of SBS density λ with $C = 500$ Mb and $w_0 = 10^{-5}$ Joule/bit. After extensive simulation, we find that the energy efficiency is related to the UEs' location with different SBS density. So we pick two represented UEs to investigate the impact of SBS density. Figure 3(a) and (b) is about UE1 and Fig. 3(c) and (b) is about UE2. In order to decentralize the observation point, we set the x axis as $-log^{\lambda}$ and λ's unit is m^{-2}. All of the four figures has similar tendency that is rising a little. As $-log^{\lambda}$ is a monotone decreasing function, the λ is smaller, the $-log^{\lambda}$ is larger. Thus the curves on the rise mean that the energy efficiency is descending lightly with the density increasing. And when the distribution of SBSs is relatively dense, the energy efficiency is fluctuant a little with λ change. The fluctuation is result from the member of SBSG change frequently when the λ is larger. In addition, the interference elimination coefficient β and skewness parameter γ have obvious influence on the energy efficiency. Lower β or higher γ can generate higher energy efficiency. And β can influence the overall trend to varying degrees while γ can not. This is because β changes the $SINR$ which influences the SBSG while γ change the requesting probability distribution which influence the caching files assignment.

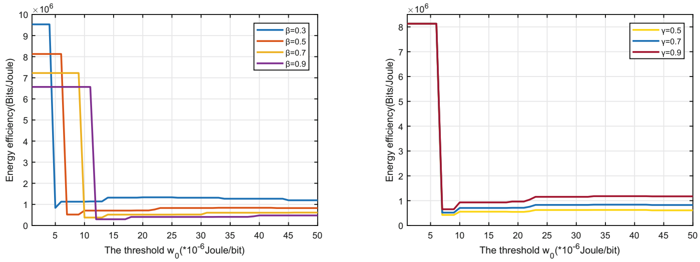


(a) Energy efficiency versus storage capacity with different β

(b) Energy efficiency versus storage capacity with different γ

Fig. 4. Impact of SBS storage capacity C

(b) *Impact of storage capacity*: In Fig. 4, we plot the energy efficiency with respect to the SBS storage capacity C with $\lambda = 0.04\,\mathrm{m}^{-2}$. β and γ are serving as the other parameters in (a) and (b) respectively as well. In Fig. 4(a), all of the four tracks are increasing rapidly first and then turn the rapidly increasing into gently increasing. Smaller β has bigger slope and more increase. However, when the β is large, there is a slow rising before the rapidly increasing. In Fig. 4(b), the tracks of $\gamma = 0.5$, $\gamma = 0.6$, $\gamma = 0.8$ and $\gamma = 0.9$ have similar tendency that is the energy efficiency rises gently with the storage capacity getting larger. However, there is a sharp rise on the track of $\gamma = 0.7$ reaping from the low energy efficiency group to the high energy efficiency group. Thus $\gamma = 0.7$ can be seen as a watershed.



(a) Energy efficiency versus SBSG's threshold with different β

(b) Energy efficiency versus SBSG's threshold with different γ

Fig. 5. Impact of SBSG's threshold w_0

(c) *Impact of SBSG's threshold*: Fig. 5 depicts the energy efficiency with different SBSG's threshold w_0 under different β and γ respectively in (a) and (b). Their overall trends are similar that are the energy efficiency keeps a stable status first, then declines dramatically and enters a slight fluctuant status. All the decline slopes are the same. And the sharp decline result from SBSs with higher w_* join in the SBSG then the average of energy costs coefficient is improved. The interference elimination coefficient β can affect the first status's value and length. Smaller β has higher energy efficiency first but declines earlier. However, when they are all in the slight fluctuant status, the line with smallest β still exceeds the others. The skewness parameter γ has nothing to do with the first status's value and length, but higher γ is still better.

In Fig. 6, we show the energy efficiency generated by different caching schemes. They are proposed coalition formation game algorithm, sequence caching scheme and random caching scheme. As there is no work solving our proposed problem, we only use two simple caching scheme to deploy in our UUDN to compare with our proposed algorithm. Sequence caching scheme is sorting the SBSs from small to large in the SBSG. And the sorted SBSs cache files after the previous one filled up with files. Random caching scheme is the files in the requesting library are cached in random SBS in order. We notice

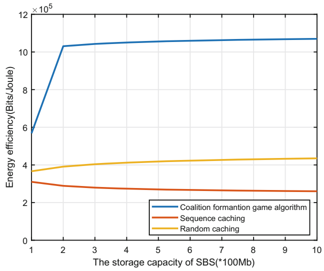


Fig. 6. Energy efficient performance comparison

that the energy efficiency of our proposed algorithm is higher than the other two schemes obviously. So our fragmentation scheme and coalition formation game are benefit.

5 Conclusion

In this paper, we concentrate on the issue of energy efficient cooperative caching in UUDN. We define a novel but simple SBS grouping rule basing the energy consumption coefficient to form SBSG. Considering the situation that multiple SBSs serve one UE cooperatively in UUDN, we divide each file into several fragments to cache in different SBSs. For solving the optimizing problem effectively, coalition formation game is introduced and promoted. Simulation results demonstrate that our proposed scheme and algorithm is energy efficient and outperforms the others. For future work, we could investigate the tradeoff between service quality and energy costs or deployment costs. Or we could turn our focus into investigating the dynamic contents by online caching.

Acknowledgement. This paper is sponsored by the National Science and Technology Major Project of China (Grant No.2017ZX03001014).

References

1. Breslau, L., Cao, P., Fan, L., Phillips, G., Shenker, S.: Web caching and Zipf-like distributions: evidence and implications. In: INFOCOM '99, Eighteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings, vol. 1, pp. 126–134. IEEE (1999). https://doi.org/10.1109/INFCOM.1999.749260
2. Chen, M., Hao, Y., Hu, L., Huang, K., Lau, V.K.N.: Green and mobility-aware caching in 5G networks. IEEE Trans. Wirel. Commun. **16**(12), 8347–8361 (2017). https://doi.org/10.1109/TWC.2017.2760830
3. Chen, S., Qin, F., Hu, B., Li, X., Chen, Z.: User-centric ultra-dense networks for 5G: challenges, methodologies, and directions. IEEE Wirel. Commun. **23**(2), 78–85 (2016). https://doi.org/10.1109/MWC.2016.7462488

4. Chen, Z., Lee, J., Quek, T.Q.S., Kountouris, M.: Cooperative caching and transmission design in cluster-centric small cell networks. IEEE Trans. Wirel. Commun. **16**(5), 3401–3415 (2017). https://doi.org/10.1109/TWC.2017.2682240
5. Kamel, M., Hamouda, W., Youssef, A.: Ultra-dense networks: a survey. IEEE Commun. Surv. Tutor. **18**(4), 2522–2545 (Fourthquarter 2016). https://doi.org/10.1109/COMST.2016.2571730
6. Liu, D., Yang, C.: Energy efficiency of downlink networks with caching at base stations. IEEE J. Sel. Areas Commun. **34**(4), 907–922 (2016). https://doi.org/10.1109/JSAC.2016.2549398
7. Liu, J., Sun, S.: Energy efficiency analysis of cache-enabled cooperative dense small cell networks. IET Commun. **11**(4), 477–482 (2017). https://doi.org/10.1049/iet-com.2016.0680
8. Liu, Y., Li, X., Yu, F.R., Ji, H., Zhang, H., Leung, V.C.M.: Grouping and cooperating among access points in user-centric ultra-dense networks with non-orthogonal multiple access. IEEE J. Sel. Areas Commun. **35**(10), 2295–2311 (2017). https://doi.org/10.1109/JSAC.2017.2724680
9. Ozfatura, E., Gndz, D.: Mobility and popularity-aware coded small-cell caching. IEEE Commun. Lett. **22**(2), 288–291 (2018). https://doi.org/10.1109/LCOMM.2017.2774799
10. Saad, W., Han, Z., Debbah, M., Hjorungnes, A.: A distributed merge and split algorithm for fair cooperation in wireless networks. In: ICC Workshops - 2008 IEEE International Conference on Communications Workshops, pp. 311–315 (May 2008). https://doi.org/10.1109/ICCW.2008.65
11. Saad, W., Han, Z., Debbah, M., Hjorungnes, A., Basar, T.: Coalitional game theory for communication networks. IEEE Signal Process. Mag. **26**(5), 77–97 (2009). https://doi.org/10.1109/MSP.2009.000000
12. Wang, X., Chen, M., Taleb, T., Ksentini, A., Leung, V.C.M.: Cache in the air: exploiting content caching and delivery techniques for 5g systems. IEEE Commun. Mag. **52**(2), 131–139 (2014). https://doi.org/10.1109/MCOM.2014.6736753
13. Zhou, Y., Zhao, Z., Li, R., Zhang, H., Louet, Y.: Cooperation-based probabilistic caching strategy in clustered cellular networks. IEEE Commun. Lett. **21**(9), 2029–2032 (2017). https://doi.org/10.1109/LCOMM.2017.2717398