Context Awareness Group Buying in D2D Networks: A Coalition Formation Game-Theoretic Approach

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***Abstract*—In this paper, we proposed a context-aware group buying mechanism to reduce users' data cost based on the content similarity. Each user's cost is formulated as the combination of the content-aware data cost and location-aware sharing cost. Data cost is the payoff of the spectrum owner's channel to download files and sharing cost is the energy and time cost in transmitting files among the coalition. Compared with downloading data alone, users would like to form different groups and download the traffic data first and then share data among the group to achieve a lower cost. The cost reducing problem through group buying mechanism is modeled as a coalition formation game (CFG). Besides the traditional Pareto order, a coalition order maximizing the coalition's benefit and a selfish order maximizing users' benefit are proposed. The CFGs with the two proposed orders are proved to be potential games, respectively, and the existence of the stable coalition partitions are also guaranteed by Nash equilibria. A cooperative exchange mechanism is designed, where users can make decisions cooperatively to achieve better performance. Simulation results show that the context awareness group buying reduces the cost and improves the benefit significantly compared with the situation without context awareness. The proposed orders both have better performance than the Pareto order.**

***Index Terms*—Group buying, coalition formation games, context awareness, spectrum market.**

I. Introduction

THE spectrum shortage problem has become much more serious since the Internet of Things (IoT) was proposed. The number of machines connecting to the Internet has exploded and aggravated the shortage. The cognitive radio technology, which allows the secondary users access the channel when authorized users are absent or silent, can be used in the IoT [1], [2], or device-to-device (D2D) networks [3]–[6] to improve the spectrum efficiency. However, it may cause spectrum disorder, spectrum security and other problems due to the openness of opportunistic spectrum access property and the lack of supervision mechanism. What's more, the cognitive radio makes little benefit for the spectrum owner. In other words, the spectrum owners have no incentives and reasons to share the spectrum with secondary users.

Recently, the spectrum market, which makes spectrum trading between users, has drawn many researchers' attention. The spectrum market provides an economical way of resource allocation and may bring a efficient situation to both spectrum owners and buyers. On one hand, the spectrum owners would like to sell the spectrum to get some rewards when they do not need. On the other hand, users may buy the spectrum to transmit data under the market mechanism protecting from disorder behavior and, the transmitting quality can be improved through paying more. Compared with traditional bargaining and auction way, the group buying mechanism can bring a win-win situation to both spectrum owners and buyers. In some situations, the spectrum price may also be too high to afford alone for single user. Besides, the cooperation between users would bring more benefits, such as user-assistant caching or cooperative communication in D2D networks. Hence, the effective cooperation mechanism in spectrum market needs be further investigated.

In some situations, such as video steam sharing [8] or content distribution [9], [10], users have some similar traffic to download. If they finish their own communication alone, it brings more cost for users and more waste for the system, especially in the heavy traffic situation. To reduce the cost, they could cooperate to afford the downloading cost through the data reuse. In the related content distribution works, many researchers focused on the mobility issue and investigated the efficient distribution problems. But the files downloading cost was not paid much attention. In the caching situations, the majority works focused on the caching hit rate for single user, and the multiple users' files downloading cost problem is not studied further, either.

In this paper, a context awareness group buying is proposed and modeled into a coalition formation game to reduce the users' downloading cost. Considering the situation where users may have same data to download, a repeated data reusing mechanism

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is designed. Users may form coalitions based on the content awareness of the similar traffic. In this mechanism, the repeated traffic data is downloaded on the paid channel only once, and then shared among the coalition. The sharing cost related to the network topology is also considered as the coalition formation cost. The existence of stable coalition partition of the proposed coalition formation games (CFGs) are also analyzed.

To summarize, the contributions in this paper are as follows:

- Based on the data reuse, the context-aware group buying mechanism is proposed to reduce the data downloading cost in spectrum market. Users would form into groups, download the group's total files once time and then distributed to other members. The cost is formulated as the sum of the content-aware data cost and location-aware sharing cost. The cost reducing problem is modeled as a coalition formation game.
- A selfish order and a coalition order are proposed in this paper. Different with the traditional Pareto order, the coalition order maximizes the new coalition benefit, and selfish order maximizes only user's own benefit. The CFGs with coalition order are proved to be potential games which have at least one pure Nash equilibrium, known as the stable coalition partition. The potential game and the existence of stable coalition partition with selfish order are also proved and guaranteed with the no sharing cost assumption.
- A cooperative exchange mechanism is proposed to improve the benefit further. Under the proposed mechanism, users can change cooperatively the action same time for higher benefits, which improve the Nash equilibriums with only one user action changed situation. The stable coalition partition of the cooperative exchange mechanism also holds.
- Simulation results show that the CAGB mechanism achieves better performance than the non-group buying situations. The two proposed orders are both better than the Pareto order. The selfish order has a close performance to the coalition order's on average cost, but worse in fairness aspect. Results also show that the cooperative exchange mechanism improves the performance of the final coalition partition.

Note that some context awareness caching problem can be found in our previous work [11]–[13]. This article is an extension of the paper [11], and the main differences are: (i) the caching cost are formulated with different caching mechanisms and parameters. Each node's caching files are regarded as entirety in this paper and [11], as independent strategy in [12], and as coupled strategies in [13]. The sharing cost is presented in this paper and while [13] has different formulations. Meanwhile, the sharing cost is even ignored in [11] and [12]. (ii) the problem is modeled as different game models. A local cooperative game is used in [13] and coalition formation games are in [11], [12] and this paper. For details, the model in [12] is overlapped while other two are not. Then two orders are proposed in this paper. (iii) The learning approaches are also different. We use the log-linear learning in [25], the best response in [23] and this paper. Also, an exchange mechanism is studied to achieve better performance.

The rest of the paper is organized as follows. In Section II, related works about group buying and coalition formulation games are reviewed. The system model of the context awareness group buying and cost reducing problem are introduced in Section III. In Section IV, the coalition formation game is modeled. The Pareto order, coalition order and selfish order are proposed and the stable coalition partition existence in three orders are also analyzed and, the best response algorithm in coalition formation games is modified. The simulation results are discussed in Section V and we provide a conclusion in the last section.

II. Related Work

A. Data Sharing in D2D Networks

D2D technology which has been regarded as a mixture of adhoc and centralized communications, has drawn a lot of attention in many fields [7], [14], [15], such as content distribution [17], [18], multi-channel transmission [19], [20].

Content distribution [8], [9], [16]–[18] is an emerging technology based on D2D communications and can improve spectrum efficiency. A novel framework for energy efficient content distribution over cellular wireless networks with mobile-to-mobile cooperation was proposed in [17]. Authors in [18] introduced a coalitional graph game model to the popular content distribution problem in vehicular ad hoc networks, considering a high speed model. Authors in [8] investigated the video sharing situation with D2D-assited cellular network from the energy efficiency view. The coalition formation game is also used in their study to find the better cooperation for users. Besides cellular networks, content distribution has also been studied in vehicular networks [9], [16] and the mobility issue is the key point.

There are also many related about works current peer-to-peer (P2P) file sharing methods in mobile ad hoc networks (MANETs). Authors in [21] an interest-oriented file searching scheme for high file searching efficiency, with deriving a node's interests from its files. Authors in [22] studied the network coding and developed an analytical framework that characterized a coding-based P2P content distribution market. Authors in [23] made some review of the P2P and internet service providers and presented a classification of the possible approaches for interaction between them. Recently, authors in [24] focused on the large-scale and designed a motive mechanism to provide quick files uploading. A guarantee-based trust model was proposed for Chord-based P2P networks in [25], to solve the shortcomings of slow convergence and high complexity.

B. Context Awareness Group Buying

Group buying is an interesting topic and has drawn much attention recently. The original group-buying concept is a kind of pricing mechanism [26] and has been widely employed in today's Internet business. On one hand, it reduces some common part for buyers. On the other, it increases the purchase with more buyers. Therefore, the group buying brings about a win-win situation both for the market and buyers. The early work [27] about group buying was studied in 2002. Authors in [27] built an incomplete information dynamic game to model the group buying mechanism and illustrated the bidding process. A weakly dominant strategy was approached. Some spectrum auction research also employed group buying mechanism [28]–[30]. Authors in [28] focused on the fairness issues with low budget buyers. They proposed a three-stage spectrum auction mechanism to improve the probability of accessing the channel for low budget users. Authors in [29] proposed a more effective algorithm compared with their former research work [30] and achieved better performance. Besides the spectrum auction, group buying has also been used in resource allocation in energy market. Authors in [31] studied the energy ahead selling model in smart grid through group buying to reduce the cost. They also proposed a Stackelberg game framework to balance loads when the traffic demands did not meet the energy supply.

The coalition formation games have been used in resource allocation widely [32]–[36]. Cooperative sensing in cognitive radio networks is a classical coalition formation game model [32]. Users form a coalition to improve the sensing accuracy and share the channel among the coalition. Authors in [36] investigated distributed long-term base station clustering in cellular networks considering the channel state information acquisition and interference alignment. A node clustering work [34] studied about ad hoc network and handled stable size-restricted clusters. A remote radio head cooperation in cloud radio access network [35] and message sharing in vehicular networks [34] were studied recently. Authors in [38] focused on the application of overlapping coalition situations in wireless communication networks. A context-aware group buying mechanism [37] is proposed in small cell networks to improve the spectrum efficiency and users' service qualities. The spectrum auction combined with overlapping coalition was proposed in [39]. A constrained coalition formation game was studied in multihop D2D networks for content uploading in [40].

Context awareness describes the users' complex relationship between environment and other users through sensing and learning, which may be useful to improve quality of experience (QoE). Authors in [41] studied the opportunistic spectrum access based on social awareness to improve the QoE. Authors in [42] focused on the interference management in D2D networks. An overview of D2D network resource allocation about social awareness was presented in [43]. Some recent advances and key requirements were respectively discussed and outlined to provide some guidelines for future research. Authors in [44] used an evolution game and modeled the relay cost reducing problem in content dissemination networks. A systematic review of the existing approaches for data dissemination over mobile wireless networks was introduced in [45]. A beyond expectation optimization problem was investigated to make full use of the time-varying channel quality in opportunistic spectrum access in [46].

In this paper, we combine the group buying and context awareness together, and focus on the cost reducing problem. The traffic awareness related to the data cost as well as the location awareness related to the sharing cost are considered as the coalition formation cost. Two non-Pareto orders are also proposed in coalition formation game compared with the Perto order. The coalition formation games (CFGs) are proved to be potential games and have stable coalition partition. The

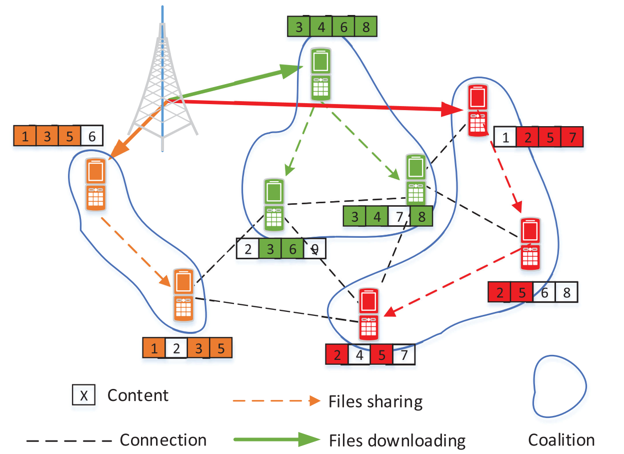

Fig. 1. The system model of the spectrum market with context awareness group buying.

exchange mechanism is another difference compared with other existing works.

III. System Model and Problem Formulation

A. System Model

We consider a spectrum market with multiple users in D2D networks, where the spectrum market employed a spectrum pool mechanism, shown in Fig. 1. When users have something to download, they need to pay for the spectrum first. When finished, the spectrum resource is released and returned to the pool for other users. We do not distinguish the users' dedicated channels or the spectrum pool channel and they are regarded as the same kind channel with same charging rules.

For the D2D communication between users, we assume that they employ the outband model. Generally, the spectrum owners, such as the mobile operators, charge the payoff based on the amount of traffic data. Denote the maximum of the data in one slot as $L_{\max}$ and the price of the unit data as α_d. User n has l_n traffic data to transmit and it needs to pay $l_n \alpha_d$ to the spectrum market for transmission.[1]

Consider that user n has l_n data to transmit in one spectrum selling round. The data vector of user n is denoted as $\bar{l}(n) = \{d_{n1}, d_{n2}, ..., d_{nl_n}\}$. In some situations, the traffic data between users may have the same part. For example, users are watching a same video/match or playing the one game [9]. Besides these popular content, some public information are also same for users [16], [18]. In these situations, if each user downloads its own data would bring many repeat downloading, which cost the users' benefits and system resource same time.

In this paper, we employed a Zip-f [47] distribution, which has been verified to be true especially in larger scale. For a total library with $D_{\max}$ files, the request probability of the k-th file is given as:

$$p_k = \left(k^{\gamma} \sum_{i=1}^{D_{\max}} i^{-\gamma} \right)^{-1}, \tag{1}$$

[1]If the traffic exceeds the maximum $L_{\max}$, users can divide the traffic into different part to satisfy the limit. And how to divide the traffic is an interesting problem and needs to be further studied.

TABLE I
PARAMETERS AND DEFINITIONS

Description	Parameter
number of users	N
user n's strategy and its coalition	a_n, CO_{a_n}
the number of user n's files	l_n
the ith data of user n	d_{ni}
the content matrix of d_{ni}	β_{ni}
unit data cost	α_d
unit sharing cost	α_s
user set in coalition a_n	$\mathcal{C}_{a_n}$
coalition total files number	$l_{coa}(\mathcal{C})$
data cost and sharing cost of user n	DC_n, SC_n
total cost of user n	r_n

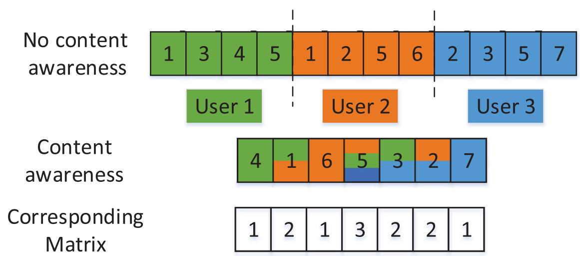

Fig. 2. A data structure example of the content awareness and no content awareness group buying situations.

where γ is the shape parameter, representing the popularity skewness [47].

To reduce the transmission cost, a repeated data reuse mechanism through group buying is proposed to make full use of the repeated data among the users. In this way, the repeated data would just need to be transmitted just once in the market channel and then it can be shared within the group via D2D communications. The users in one coalition afford the cost together. For example, when two users with demand vector $\bar{l}_1 = [d_1, d_2]$ and $\bar{l}_2 = [d_1, d_3]$, form a coalition with $\bar{l}_c = \{d_1, d_2, d_3\}$, they can almost cut down 25% data cost through reusing the repeated data d_1. Fig. 2 shows the group buying mechanism that may reduce the data cost compared with non group buying situation.

B. Problem Formulation

According to the distance limitation, two far users can not share the data without others' help. If two users are close enough to communicate with each other, we call them neighbors, i.e., $\delta(n,m) = 1$, and the neighbor set of user n is defined as

$$\mathcal{J}_n = \{m : \delta(n,m) = 1, m \in \mathcal{N} \backslash n\}. \tag{2}$$

The coalition user set of user n is as follows:

$$\mathcal{C}_{a_n} = \{m : a_m = a_n, m \in \mathcal{N}\}. \tag{3}$$

Define the total traffic data the coalition a_n is $l_{coa}(\mathcal{C}_{a_n})$. Notice that due to the repeated data, the coalition total data may be smaller than the sum of all users data, $l_{coa}(\mathcal{C}_{a_n}) \le \sum_{i \in \mathcal{C}_{a_n}} l_i$.

Considering the group buying process, the total cost in a coalition includes two parts: (i) the data cost charged by the spectrum market DC_n, and (ii) the sharing cost between the users via D2D communications SC_n. Formally, the cost $r_n(a_n, a_{-n})$ of user n is

$$r_n(a_n, a_{-n}) = DC_n(a_n, a_{-n}) + SC_n(a_n, a_{-n}). \tag{4}$$

1) Data Cost: From the above system model, users should find the coalition with most repeated traffic data to reduce cost. We can use the context awareness degree to describe the similarity between two users' traffic contents. For user n with data vector $\bar{l}(n)$, the corresponding context awareness is $\overline{\beta}_n = \{\beta_{n1}, \beta_{n2}, ..., \beta_{nl_n}\}, \beta_{ni} = 1, 2, ...,$ where β_{ni} means the number of d_{ni} in its coalition users. Denote user n's strategy is the coalition selection a_n and the corresponding coalition is CO_{a_n}. To reflect the social relationship between the user n and coalition a_n, the context awareness degree is denoted as follows,

$$s_n(a_n, a_{-n}) = \sum_{i=1}^{l_n} \beta_{ni} - l_n, \tag{5}$$

which means that the total number of the same data in the coalition CO_{a_n} except user n itself. The other users strategies is denoted as a_{-n}.

The Shapley value [48] is very suitable for the cost sharing problems in the coalition according to its fairness and optimization. Hence, it is reasonable to use the Shapley value for each user to represent coalition data cost. Generally, the Shapley value is the expectation of marginal utility. In this paper, the Shapley value of users data cost can be calculated as follows,

$$DC_n(a_n, a_{J_n}) = \begin{cases} \sum_{i=1}^{l_n} \frac{\alpha_d}{\beta_{ni}}, l_{coa}(\mathcal{C}_{a_n}) \le L_{\max} \\ l_n \alpha_d, l_{coa}(\mathcal{C}_{a_n}) > L_{\max}, \end{cases}, \tag{6}$$

which means the cost of traffic data is afforded by the number of users who need this file equally, when the sum coalition data demand $l_{coa}(\mathcal{C}_{a_n})$ is smaller than the channel capacity $L_{\max}$. If not, it indicates that group is beyond capacity and the cooperative mechanism cannot work. Therefore, users have to afford the cost alone.

An example for content-aware data cost calculating is as follows. In Fig. 2, user 1's content metric β is $\beta = [2, 2, 1, 3]$. For file 5 with $\beta = 3$, it means there are three users needing file 5 in the current coalition. Therefore, each user affords 1/3 of the cost. Then, the total cost of user 1 is as $1/2 + 1/2 + 1 + 1/3$ with assuming $\alpha_d = 1$.

2) Sharing Cost: Another consideration in group forming is the content distribution topology, including who downloads files from the base station and how to distribute them to each member. We employs a flood similar method to distribute the content in this paper with minimizing the total flood times. A min-hop flooding tree (MHFT) algorithm is used to find the head user and the optimal flooding path, details shown in algorithm section. After the path is settled down, the sharing cost is calculated in the following rule. For one flood, the sharing cost is afforded by the father node and the leaves equally. The sharing cost has a linear relationship α_s with the coalition total data $l_{coa}(\mathcal{C}_n)$. An example of the flooding tree is shown in Fig. 3. From the figure, the user 1 is selected as the head to download the group's total files and the normalized cost is $1/5$ due to four leaves users. For user 4, it needs to pay the sharing cost twice, one for user 1 and one for user 3 and 5 with the total cost $1/5 + 1/3$.

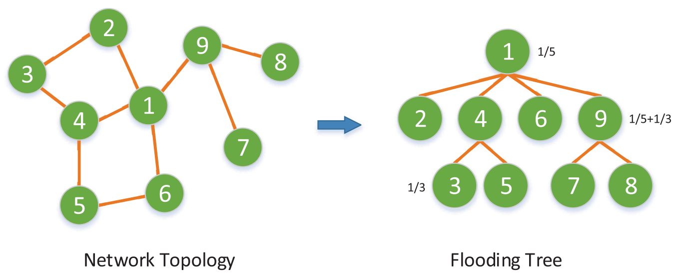

Fig. 3. An example of one network topology and the corresponding min-hop flooding tree.

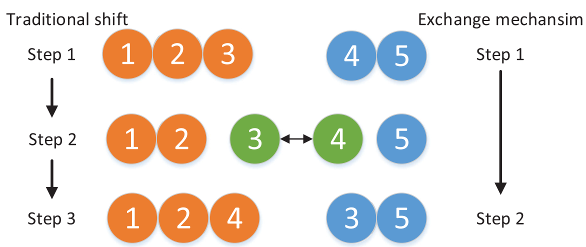

Fig. 4. Comparison of tradition shift and proposed exchange mechanism.

According to the MHFT, for user n, if it is not the head of the tree, then the number of users which have the same father node with user n is denoted as $\mathrm{MHFT}_k(n)$; if it is not the leaf node, denote its children number as $\mathrm{MHFT}_f(n)$. Then the sharing cost can be formulated as follows,

$$SC_n(a_n, a_{-n}) = \begin{cases} l_{coa}(\mathcal{C}_{a_n})\alpha_s \frac{1}{\mathrm{MHFT}_f(n)+1}, \text{user } n \text{ is head} \\ l_{coa}(\mathcal{C}_{a_n})\alpha_s \frac{1}{\mathrm{MHFT}_k(n)+1}, \text{user } n \text{ is leaf} \\ l_{coa}(\mathcal{C}_{a_n})\alpha_s (\frac{1}{\mathrm{MHFT}_f(n)+1} + \frac{1}{\mathrm{MHFT}_k(n)+1}). \text{o.w.} \end{cases} \quad (7)$$

For the head and leaves, they only afford the sharing cost once, and for the middle layer, they need to afford the sharing cost twice, i.e., others flood to them and then flood to others.[2]

The objective of this work is to reduce each user's cost through forming a better coalition structure. Formally,

$$a_{opt} = \arg\min(DC_n(a_n, a_{-n}) + SC_n(a_n, a_{-n})), \quad (8)$$

where the purpose of the former part about the content awareness, is to find the coalition with most repeated traffic data. The purpose of the second part about the location awareness, is to join the coalition with least sharing cost. The content awareness and the location awareness are the two aspects of the context awareness. A coalition formation game proposed in the next section is to solve the problem.

Remark 1: The data unit cost α_d is a constant in this paper. Sometimes, it might vary from situation to situation. For example, the operators' pricing rules may be state-phased. The more the traffic data, the cheaper the price is. In this way, users prefer to form groups to enjoy a lower average price. From view of the market, a lower price might motivate users to get more traffic data and bring about an increase total benefit, which is similar to some commercial behaviors in our daily lives. If the unit data cost α_s decreases with the increase of the total files number l_{coa}, users would have a larger fever in grouping.

[2]In the sharing cost, we just simply share the total coalition data with all users, which means the total contents are shared as an entirety for all coalition mates. Hence, according to the MHFT, users can delete some data based on the flooding sequence to reduce cost. However, the content-aware selective flooding is a little beyond the coalition formation cost in this paper and can be investigated in future.

IV. Context Awareness Coalition Formation Games (CFGs)

To achieve the objective, users need to join the close group in content awareness and in location awareness, i.e., without too much sharing cost. Forming the better group under the consideration of the traffic data and topology is the key point in this paper. This group buying mechanism is similar to the coalition formation games. Hence, we model the process into a CFG and propose three preference orders to achieve better performance.

A. Game Model

The game is modeled as $\mathcal{G} = \{\mathcal{N}, E, u, F, A, P\}$, where the $\mathcal{N}$ is the decision user set and u is the utility function. E is the network topology, i.e., each user's neighbor information. F is the decision function that determines users how to join or leave the coalition. $A = \{a_1, a_2, ..., a_N\}$ is the total users decision set. P is the coalition structure $P = \{CO_1, CO_2, ..., CO_m\}, i, j \in S, CO_{i,j} \in P, CO_i \cap CO_j = \emptyset, \sum CO_i = S$. The utility function is defined as user's data cost.

$$u_n(a_n, a_{-n}) = r_n(a_n, a_{-n}). \quad (9)$$

Definition 1 (Preference order): The preference order $\succ_n$ for any user $n, n \in \mathcal{N}$, is defined as a complete, reflexive, and transitive binary relation over the set of all feasible coalitions that user n can possibly form.

A user decides to leave or join a coalition based on the preference order. For example, for user n, if $CO \succ_n CO'$, user n prefers being a member of coalition CO rather than coalition CO'. Generally, the preference order influences the convergence and final coalition structure. In this paper, we consider three different preference orders as follows.

Definition 2 (Pareto order): For each user n and all coalition $CO, CO' \in P$, we say that:

$$CO \succ_n CO' \Leftrightarrow r_n(CO) < r_n(CO') \wedge r_i(CO) \leq r_i(CO \backslash n)$$
$$\forall i \in CO \backslash \{n\} \wedge r_i(CO') \leq r_i(CO' \backslash \{n\}) \forall i \in CO' \backslash n. \quad (10)$$

The Pareto is an ordinary preference order in CFG. In Pareto order, users will never damage other users in the original and new coalition. The property ensures that the coalition profit will not decrease and the existence of the stable coalition partition. However, the users profit is limited.

Definition 3 (Coalition order): For each user n and all coalition CO, CO' in P, we say that:

$$CO \succ_n CO' \Leftrightarrow \sum_{i \in CO \backslash n} r_i(CO) + r_n(n) - \sum_{i \in CO} r_i(CO)$$
$$> \sum_{i \in CO' \backslash n} r_i(CO') + r_n(n) - \sum_{i \in CO'} r_i(CO'), \quad (11)$$

which means user n joins the coalition where it can bring about the maximum decline in cost. This preference order cares about the coalition total social welfare.

Definition 4 (Selfish order): For each user n and all coalition $CO, CO' \in P$, we say that:

$$CO \succ_n CO' \Leftrightarrow r_n(CO) < r_n(CO') \wedge r_i(CO) \leq r_i(CO \backslash \{n\}) \quad \forall i \in CO \backslash \{n\}. \tag{12}$$

Compared with the Pareto order, the selfish order does not care about the original coalition's utility. The user simply pursues a higher benefit of itself and the new coalition.

Based on the preference order, the merge and split rules for the coalition formation game are provided as follows.

Definition 5 (Merge rule): Merge any pair of coalitions CO and CO' into a unique feasible coalition when all the users have an increased benefit, formally $\{CO \cup CO'\} \Leftrightarrow [\forall i \in CO, (CO \cup CO') \succ_i CO] \wedge [\forall i \in CO', (CO \cup CO') \succ_i CO']$.

Definition 6 (Split rule): Split any coalition in feasible coalitions when at least one user can benefit from the behavior, formally $\{CO, CO'\} \Leftrightarrow [\exists i \in CO, CO \succ_i (CO \cup CO')] \vee [\forall i \in CO', CO' \succ_i (CO \cup CO')]$.

The merge rule shows that two coalitions would form a larger coalition if at least one user reduces the cost, while all the other involved users do not experience a higher cost. The split rule implies that a coalition may split into two parts if there exists at least one player that obtains a lower cost, with other users change under the different Pareto order and selfish order constraints.

The swift action in traditional CFG is divided into two parts: leaving the coalition and joining in another one. In both processes, the preference is obeyed, which means the user's benefit is not decreasing all the time. However, for some situations, forming a feasible coalition is always better than being alone, such as a spectrum sensing in the cognitive radio networks. In these situations, once a user joins a coalition, it seldom leaves the coalition. The first choice becomes important and the performance is almost always trapped into a local optimization. The same situation is with the Pareto order. The users in Pareto order are easily trapped by their coalition mates because leaving coalition would decrease the rest utility.

To overcome the above disadvantages, a cooperative exchange mechanism is proposed in this paper.

Definition 7 (Cooperative exchange mechanism): For user subset $su_1 \subset CO_1, su_2 \subset CO_2$ and all coalition $CO_1, CO_2 \in P$, there exists an exchange if every user in the newly formed coalition CO_1', CO_2' has a better utility.

$$CO_1 \xleftarrow{su_2} \xrightarrow{su_1} CO_2$$
$$\Leftrightarrow \forall i \in CO_1, CO_2, r_i(CO_1, CO_2) \leq r_i(CO_1', CO_2'). \tag{13}$$

Under different orders, the proposed cooperative exchange mechanism has different definitions. For example, with Pareto order, coalitions will receive a reward through user exchange. But with selfish order, part of the users in the coalition CO find that they can reform a new coalition with some users in coalition CO' and in the newly formed coalition they will achieve a lower cost. Hence, they abandon their original mates, leave the coalition and form a new one. For the abandoned users in coalition CO, CO', they can just keep separated or form a coalition based on the benefit. Only part of the users achieve a higher benefit through exchange with selfish order not all in the Pareto situation.

The cooperative exchange mechanism brings about dramatical changes in coalition partition. Especially, when there are many kinds of exchange between coalitions, such as one-to-one, one-to-many, and many-to-many. In this paper, we only analyze the former two situations in the next subsection and evaluate all three in the simulation results and discuss them.

B. Analysis of the Stable Coalition Partition

Definition 8 (Stable coalition partition): We say a coalition partition is stable, if every user can not improve its utility through changing its coalition selection unilaterally with the corresponding order. That is,

$$r_i(a_n, a_{-n}) < r_i(\overline{a}_n, a_{-n}), \forall i \in \mathcal{N}, \overline{a}_n \neq a_n. \tag{14}$$

For the coalition order and the selfish order, the stability is also called Nash stability.

1) Pareto Order: The stable partition with Pareto order is straight forward.

Theorem 1: The coalition formation game with the Pareto order finally converges to a stable coalition partition.

Proof: In the above coalition formation game, the user set and the coalition number is finite. According to the Pareto order, the system coalition partition will shift between finite states, and finally converge to a stable one. More details can be found in [49]. ■

Based on Pareto order, the exchange mechanism may make a difference to the stability of the final coalition partition.

Theorem 2: The coalition formation game with the Pareto order and cooperative exchange mechanism also has a stable coalition partition.

Proof: Due to the exchange mechanism jumps, the single user situation within the traditional shift action, the whole process in exchange still obeys the Pareto order. For example, user n in coalition CO_1 exchanges with user k in coalition CO_2. Based on the exchange definition with Pareto order, the users n, k both realize a higher benefit and so do the rest users in the coalition CO_1, CO_2. Hence, the exchange process satisfies the Pareto order and continues the convergence process. According to the Pareto order property [49], the CFG with exchange mechanism also has a stable coalition partition with Pareto order. ■

2) Coalition Order: According to the coalition order, the utility of the proposed CFG is as

$$u_n(a_n, a_{-n}) = \sum_{i \in \mathcal{C}_n \backslash n} [r_i(\mathcal{C}_n \cup n) - r_i(\mathcal{C}_n)] + r_n(\mathcal{C}_n \cup n) - r_n(n), \tag{15}$$

which is the cost change of the user n and the coalition CO due to user n joining in the coalition a_n.

Theorem 3: The proposed coalition formation game with coalition order has at least one stable coalition partition.

Definition 9 (Exact potential game [50]): If there exists a potential function Φ, when a user changes its decision unilaterally, the difference in the potential function and in its utility function is same, the game is an exact potential game with potential function Φ. Formally,

$$\Phi(\overline{a}_n, a_{-n}) - \Phi(a_n, a_{-n}) = u_n(\overline{a}_n, a_{-n}) - u_n(a_n, a_{-n}), \quad \forall \overline{a}_n \in \mathcal{A}_n, \overline{a}_n \neq a_n^*. \tag{16}$$

Lemma 1: The potential game has at least one pure Nash equilibrium.

Proof: Denote the potential function Φ of the coalition formation game as follows:

$$\Phi(a_n, a_{-n}) = \sum_{i \in \mathcal{N}} r_i(a_n, a_{-n}), \tag{17}$$

which is the sum of the all users cost.

When user n changes the decision from a_n to $\overline{a}_n$, the change in potential function is

$$\begin{aligned} &\Phi(a_n, a_{-n}) - \Phi(\overline{a}_n, a_{-n}) \\ &= \sum_{i \in \mathcal{N}} r_i(a_n, a_{-n}) - \sum_{i \in \mathcal{N}} r_i(\overline{a}_n, a_{-n}) \\ &= \sum_{i \in \mathcal{C}_{a_n}} [r_i(a_n, a_{-n}) - r_i(\overline{a}_n, a_{-n})] \\ &\quad + \sum_{i \in \mathcal{C}_{\overline{a}_n}} [r_i(a_n, a_{-n}) - r_i(\overline{a}_n, a_{-n})] \\ &\quad + \sum_{i \in o.w.} [r_i(a_n, a_{-n}) - r_i(\overline{a}_n, a_{-n})] \\ &\quad + r_n((a_n, a_{-n})) - r_i(\overline{a}_n, a_{-n}), \end{aligned} \tag{18}$$

where the fourth part has no relationship with user n and hence is 0.

The change in utility function is as follows:

$$\begin{aligned} &u_n(a_n, a_{-n}) - u_n(\overline{a}_n, a_{-n}) \\ &= \sum_{i \in \mathcal{C}_n \backslash n} [r_i(\mathcal{C}_{a_n} \cup n) - r_i(\mathcal{C}_{a_n})] + r_n(\mathcal{C}_{a_n} \cup n) - r_n(n) \\ &\quad - \sum_{i \in \mathcal{C}_n \backslash n} [r_i(\mathcal{C}_{\overline{a}_n} \cup n) - r_i(\mathcal{C}_{\overline{a}_n})] - r_n(\mathcal{C}_{\overline{a}_n} \cup n) + r_n(n) \\ &= \sum_{i \in \mathcal{C}_{a_n}} \left[r_i(a_n, a_{-n}) - \sum_{i \in \mathcal{C}_{a_n}} r_i(\overline{a}_n, a_{-n}) \right] \\ &\quad + \sum_{i \in \mathcal{C}_{\overline{a}_n}} \left[r_i(a_n, a_{-n}) - \sum_{i \in \mathcal{C}_{\overline{a}_n}} r_i(\overline{a}_n, a_{-n}) \right] \\ &\quad + r_n((a_n, a_{-n})) - r_i(\overline{a}_n, a_{-n}) \\ &= \sum_{i \in \mathcal{N}} r_i(a_n, a_{-n}) - \sum_{i \in \mathcal{N}} r_i(\overline{a}_n, a_{-n}) \\ &= \Phi(a_n, a_{-n}) - \Phi(\overline{a}_n, a_{-n}), \end{aligned} \tag{19}$$

where the change in the potential function is just equal to the change in utility function. Hence, the game is an exact potential game, which has at least a pure Nash equilibrium. According to the definition of NE, the users can not achieve better utility from unilaterally changing action, which is also the stable coalition formation partition in the CFG.

It should be pointed out that the coalition order finally minimizes the total coalitions cost, since the potential function is the sum of total coalitions.

Theorem 4: The coalition order with cooperative exchange mechanism also has a stable coalition partition under coalition order.

Proof: Based on the above proof of the stable partition existence of the coalition order, there always exists a stable partition. When the exchange mechanism happens, it also improves the selected users' utilities, which is the same as the direction towards the Nash equilibrium. In others words, even if the exchange mechanism disturbs the convergence process, the coalition order would bring the path back to the right direction and finally to a stable coalition under coalition order. ■

Remark 2: The exchange mechanism is similar to the concept of strong Nash equilibrium, both jumping out of a user unilateral action change and considering the cooperative action in improving the utility. However, due to the complexity of the strong Nash equilibrium existence, the randomness of the network topology and users content in our model, we focus the existence of stable coalition partition only under the concept of ordinary Nash equilibrium, not the strong NE situation. The exchange mechanism is used as an approach to improve the final utilities in this paper.

3) Selfish Order: Due to the topology is generated randomly, it is hard to use a specific formulation to represent the sharing cost, which brings about lots of difficulties to prove the Nash equilibrium existence. We ignore the sharing cost in this part to prove the existence of the Nash equilibrium.

Theorem 5: Under the assumption of no sharing cost, the CFG with the selfish order finally converges to a stable coalition partition.

Proof: Define the utility function $u_n(a_n, a_{-n})$ of user n as a cost sum of its all data d_{ni}.

$$u_n(a_n, a_{-n}) = \sum_{i=1}^{l_n} u_{ni}(a_n, a_{-n}) \tag{20}$$

According to the system model, the utility of data d_{ni} is

$$u_{ni}(a_n, a_{-n}) = \frac{\alpha_d}{\beta_{ni}}, \tag{21}$$

where β_{ni} is the number of the data d_{ni} in the coalition a_n.

For data d_{ni}, assume the corresponding sequence number in $D_{\max}$ is x, the corresponding sub-potential function is defined as Φ_x,

$$\Phi_x = \sum_{n=1}^{N} \sum_{k=1}^{\beta_{ni}} \frac{\alpha_d}{k}, \tag{22}$$

which means the data x of all users in total coalitions. The potential function is the Rosenthal's potential function [52]. When the user n changes from coalition $a_n = CO$ to $\overline{a}_n = CO'$, the change in utility function is

$$u_{ni}(a_n, a_{-n}) - u_{ni}(\overline{a}_n, a_{-n}) = \frac{\alpha_d}{\beta_{ni}} - \frac{\alpha_d}{\beta_{\overline{n}i}}. \tag{23}$$

The change in potential is just as

$$\Phi_x(a_n, a_{-n}) - \Phi_x(\overline{a}_n, a_{-n}) = u_{ni}(a_n, a_{-n}) - u_{ni}(\overline{a}_n, a_{-n}). \quad (24)$$

The details is similar to the proof of Theorem 1 in [52].

Consider the final potential function as the sum of all the data potential utility, that is

$$\Phi(a_n, a_{-n}) = \sum_{x=1}^{D_{\max}} \Phi_x. \quad (25)$$

According to the potential games' additive property, the coalition formation game with potential function Φ is also a potential game, and has at least one pure Nash equilibrium. Therefore, the CFG will converge to a stable coalition partition finally. ■

The exchange mechanism does not interrupt the convergence process, either. Hence, the CFG with exchange mechanism also has a stable equilibrium under selfish order.

C. Case Discussion for Different Orders

In this subsection, the different use cases of the proposed orders are discussed. Both the coalition order and selfish order are cooperative mechanisms. Based on the definition of selfish order, to improve other coalition mates' utilities is the necessary condition when joining in the coalition. Then, it may leave the coalition to pursue its own better benefit, even this leaving behavior may damage the mates' utilities of the original coalition. This is the reason why it is called the order "selfish". For the coalition order, it pursues the current coalition's utility instead of its own utility in selfish order. With the NE analysis of the modeled games, the coalition order is achieving a total caching cost minimization, while the selfish order pursues its personal benefit. We also compare the variance of the two orders in the simulation part in Fig. 8, and the coalition order achieves a fair result compare with the selfish order.

Hence, to simply compare these two orders and to find the better one, it may not be proper. It should be considered in some specific situations. The following are three different cases, (i) all caching nodes belong to the same organization or person. (ii) caching nodes belong to different organization or people. (iii) nodes are divided into several parts with corresponding owners. For the first case, we only concerned about the total cost instead of single node's cost. On the opposite, when all nodes are personality, the selfish behavior is reasonable. Compared with the other two, the third case is complicated and the combination of coalition order and selfish order might be a more proper strategy.

V. Best Response in Coalition Formation Games

A. Min-Hop Flooding Tree Algorithm

According to the system model, the sharing cost is calculated based on the topology. For a small scale network, the performance of the greedy algorithm is close to the exhaustive searching but takes less computational effort. Hence, a greedy algorithm is modified to search the min-hop flooding tree among the coalition's topology in this subsection. The greedy algorithm is to find the node with most neighbors to color by steps. The detail of the greedy searching is as follows.

Algorithm 1: A Greedy Approach of Min-Hop Flood Tree (MHFT).

Initialization: Denote the total node set of the topology is $\mathcal{N}_t$ and a empty set $\mathcal{N}'$. Find the node with most neighbors, and color them. If there are more than one nodes with the maximum neighbors, select one node randomly. Denote the selected node is $x_{\max}$ and the corresponding neighbor set is $\mathcal{J}_{x_{\max}}$. Then, each of them affords the cost with $SC([x_{\max} \cup \mathcal{J}_{x_{\max}}]) = \frac{\alpha_{x_{\max}}}{1+|\mathcal{J}_{x_{\max}}|}$. Set $\mathcal{N}' = \mathcal{N}' \cup \mathcal{J}_{x_{\max}} \cup x_{\max}$.

Loop: while $\mathcal{N}' \neq \mathcal{N}_t$

Find the node $x_{\max}$ with most uncolored neighbors $\mathcal{J}_{x_{\max}}$, color them. Repeat the cost calculating process, and update the new metrics:

$$\mathcal{N}' = \mathcal{N}' \cup \mathcal{J}_{x_{\max}} \cup x_{\max} \quad (26)$$

$$SC([x_{\max} \cup \mathcal{J}_{x_{\max}}]) = SC([x_{\max} \cup \mathcal{J}_{x_{\max}}]) + \frac{\alpha_{x_{\max}}}{1+|\mathcal{J}_{x_{\max}}|} \quad (27)$$

End loop Record the node coloring sequence and the final cost of the MHFL SC_n.

B. Best Response Coalition Formation Algorithm

We modify the best response algorithm into the coalition formation game with the selfish order. The proposed algorithm is also suitable for the coalition order, by changing the utility function from user to coalition.

Theorem 6: Under the selfish order and coalition order, the proposed best response algorithm in coalition formation games finally converges to a stable coalition partition.

Proof: The corresponding games of the two orders are proved to be potential games, which has the finite improvement property [51]. According to the property, the best algorithm mechanism converges to the Nash equilibrium, which is the stable partition in the CFG. ■

C. Introduction of Coalition Formation Mechanism

The system mechanism of coalition formation mainly contains following steps, especially for a new comer to join the coalitions.

- Find neighbors and search coalitions from neighbors. Based on the network topology, users can only join in the nearby coalitions. Therefore, find neighbors is the first step to join the coalition. Users can broadcast a Hello similar message and then the neighbors receiving this message would response. Through the neighbor finding mechanism, the user could know the neighbors around. Also, the around coalition set can be get from the neighbors with further information exchange.
- Try to join in the coalition. Through communicating with neighbors, the user could try to join one coalition through the neighbor. The bridge neighbor has been the coalition

Algorithm 2: Best Response Approach in Coalition Formation.

Initialization: Each user forms a non-cooperative and independent coalition itself.
Loop:
Step 1: Users exchange information including data content and coalition information.
Step 2: Assume the coalition partition is $P_{coa} = \{\{CO_1\}, \{CO_2\}, ..., \{CO_k\}\}$. Select one user at one time randomly, such as user n, calculate the utility when it joins all the coalitions, respectively:

$$\overline{u}_n(P_{coa}) = \{r_n(CO_1), r_n(CO_1), ..., r_n(CO_k)\}. \quad (28)$$

Step 3: Find the best utility and join the corresponding coalition.

$$a_n^{opt} = \arg\min \overline{u}_n(P_{coa}). \quad (29)$$

Update coalition partition and users' utility.
Step 4: Exchange mechanism. For two coalitions CO_1, CO_2, randomly select two user subsets of each coalition, $su_i \subset CO_i, i = 1, 2$. Denote the rest of the coalition is $\overline{su}_i$. Complete the new benefit of the temporary formed coalition $su_{1,2} \cup \overline{su}_{2,1}$ and compare the utility. If all users of at least one new formed coalition achieves a better performance, the exchange mechanism works. Check and update the coalition partition and utility.
End loop Until the coalition partition does not change with a round of user.

member and know the coalition information. For the new formed coalition, the flooding structure would be reconstructed. For the new comer and other members, the demands information of the coalition can be updated with through the neighbor. Then, the members' cost utilities can be calculated.

- Make decision. Based on the utilities, the user and the original coalition members can make the decision whether to join and accept the new user. If joining successfully, the topology of the new formed coalition should be updated. So are the coalition information and utilities. In some situations, if the user is jumping from one coalition to another coalition, the leaving user might break and divide the original coalition into different parts. Hence, the topology should be checked and updated to tackle with the user's leaving.

VI. Simulation Results and Discussion

In this section, we compare the coalition order, selfish order and Pareto order with different situations. Assume that there are 10 users randomly located in the system. Each user is generated randomly $l_n = 100$ traffic data from $D_{\max} = 500$ different data, respectively. The channel capacity $L_{\max}$ is set as 300. The unit price of one data is $\alpha_d = 1$ and the sharing cost unit is $\alpha_s = 0.05$. We regenerate the demand vector and the network topology

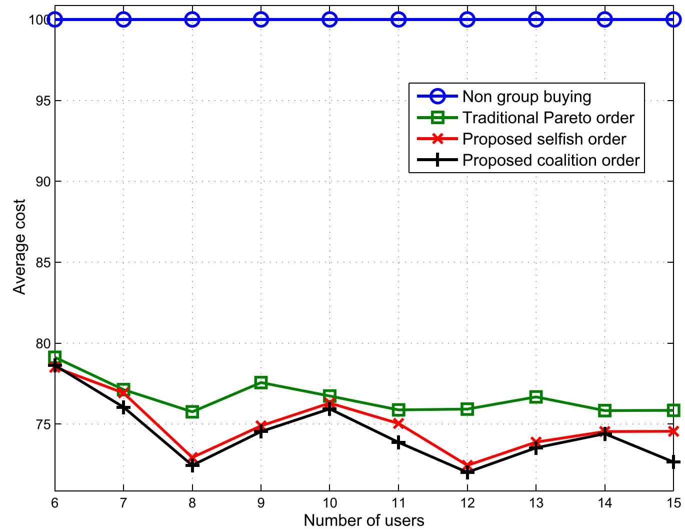

Fig. 5. The average cost of different user numbers with Pareto order, selfish order, and coalition order.

for each trial and we did 500 repeated trials to achieve the average value.

A. Basic Performance

The users average cost with different number of users is shown in Fig. 5. From the figure, we can find that the context awareness relationship dramatically reduces the users' costs compared with non context awareness group buying situation. The proposed coalition order and selfish order are both better than the Pareto order. The reason for this result is that, sometimes the users with selfish order and coalition order have a larger probability and stronger desire to leave the current coalition to pursue a better benefit. However, in the Pareto order situation, users are trapped by the coalition members because leaving the coalition may increase in cost of the rest in the coalition. Also, due to that the potential function of coalition order is the total utility, the coalition order achieves a little better performance than the selfish order. The result provides us with two interesting facts: (i) being totally public is not good, because the selfish behavior of the two orders finally realizes a better performance than the totally public behavior. (ii) suitable cooperation is better than total selfish actions due to the coalition order and selfish order.

Note that the average cost line fluctuates in the figure. The main reason is that there is an upper bound in the coalition structure. For example, if there are at most 4 users in one coalition, when the total user number is increasing from 5 to 10, the performance of the average cost might decrease first until users' number is 8, then increase. When the users' number increases from 4 to 5, the original coalition cannot afford 5 users at the same time, so the coalition structure becomes one coalition with 4 users and one coalition with only one user. Since the group mechanism contributes a lot in decreasing the cost, it is important to be in a full filled coalition instead of to be alone. Then, the separated user has a bad performance, which also increases the total users average cost performance. Then with the number increasing, the new formed coalition has more users, which has

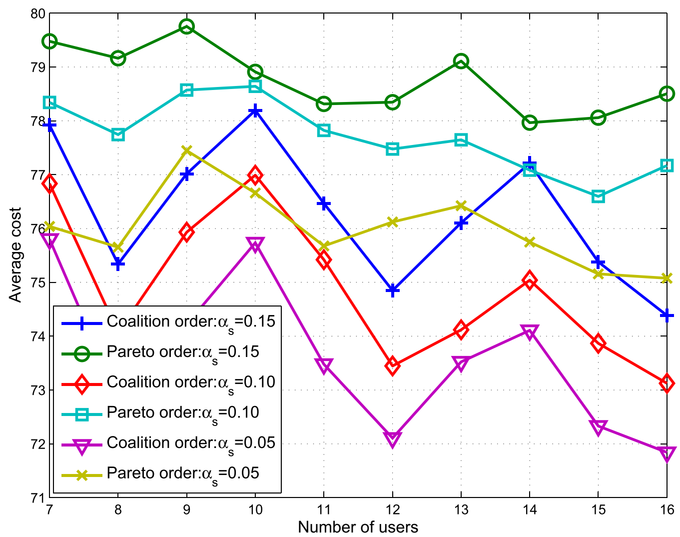

Fig. 6. The comparison of different cost situations.

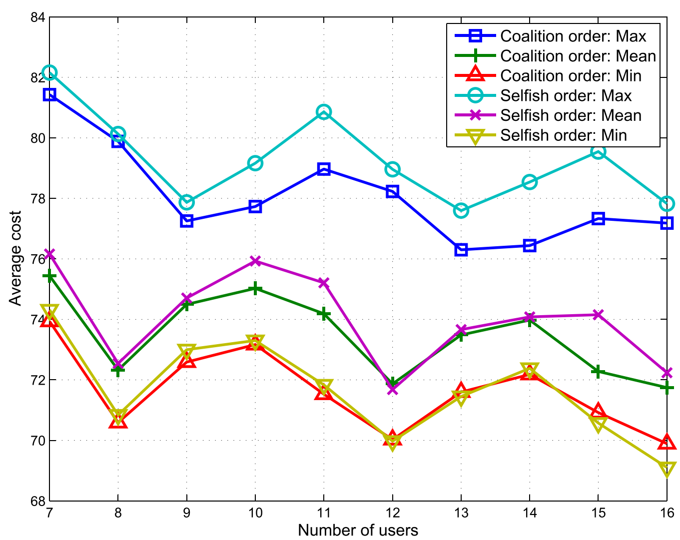

Fig. 7. The comparison of best equilibrium, worst equilibrium, and mean value.

a positive effect on total users' average cost. Therefore, the cost performance is decreasing until the coalition is full filled. This situation lasts until the new formed coalition reaches the upper bound, i.e., the users' number reaches 8. The situation is the same when the number increases from 4 to 5. The difference is that the influence of increasing from 8 to 9 is smaller than that of 4 to 5, because there are more users to afford the increasing cost. Therefore, the performance shows such a fluctuant shape.

The average cost with different sharing cost has been shown in Fig. 6. From the figure, we can find that the average cost increases with the sharing cost α_s, from 0.05 to 0.15.

B. Different Orders

In this subsection, we mainly discuss about the different aspects of the two proposed orders, i.e., the performance of NE and the variance. The performance of NE is first compared in Fig. 7. For every time demand and network topology generated,

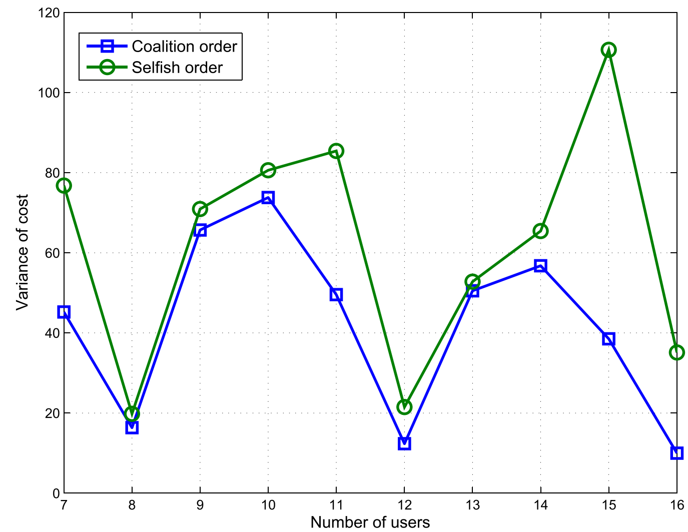

Fig. 8. The variance of selfish order and coalition order.

we do 100 trials using selfish order and coalition order. Then the maximum value, minimum value and the mean value are recorded. We generate 500 times demand and topology for each user number and get the expectation of the corresponding values. From the figure, we can find that the average costs of two proposed orders are very close. For the minimum, which can be regarded as the optimal values, are almost close. However, for the worst situations, the gap between two orders are increasing, and the coalition order is still the better one.

Fig. 8 shows the variance of the two orders. Similar to the above figure, we calculate the variance of the two proposed orders under the same simulation environment. From the results, we can find that the variance of coalition order is smaller than that of selfish order. The difference is caused by the different definitions of the two orders. For selfish order, users care more about their own benefits, which may reduce others' benefits sometime. On the opposite, the coalition order pursues coalition's total benefits, which brings about a more fair result. In this way, the variance of the coalition order is better.

C. Context Awareness

Fig. 9 shows the average cost with different $D_{\max}$. With the total data increasing, the content awareness between users is decreasing. Therefore, the cost takes on upward trend. The proposed orders are also better than the Pareto order. Fig. 10 shows the average cost of different users with heterogeneous location awareness. In the simulations, a user is set to be connected with all other users, which are located randomly Hence, the average utility of the special one and others are shown in the figure. The special user's cost is lower than others in all three orders. Because it can play a role as a bridge to connect two coalitions, turning location advantage into benefit. Furthermore, we compare another location awareness in Fig. 11, where the topology is designed to be all connected and another is partially connected. The average cost of coalition order is still the best of the three orders. The figure shows that a well connective network topology can reduce the cost and improve benefits.

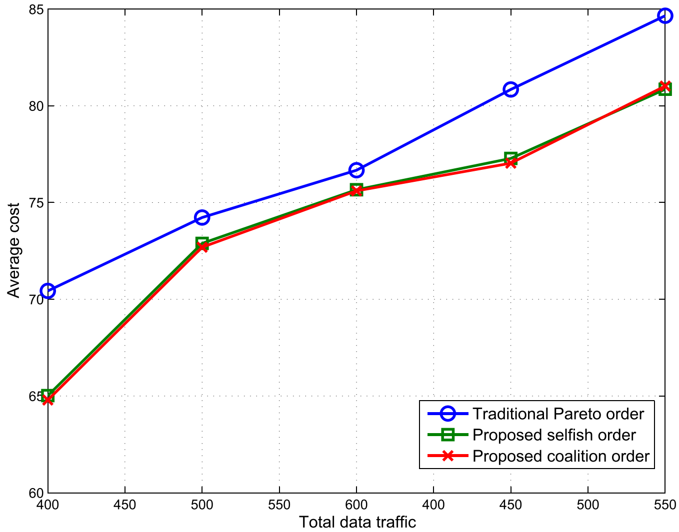

Fig. 9. The comparison of different number of total data.

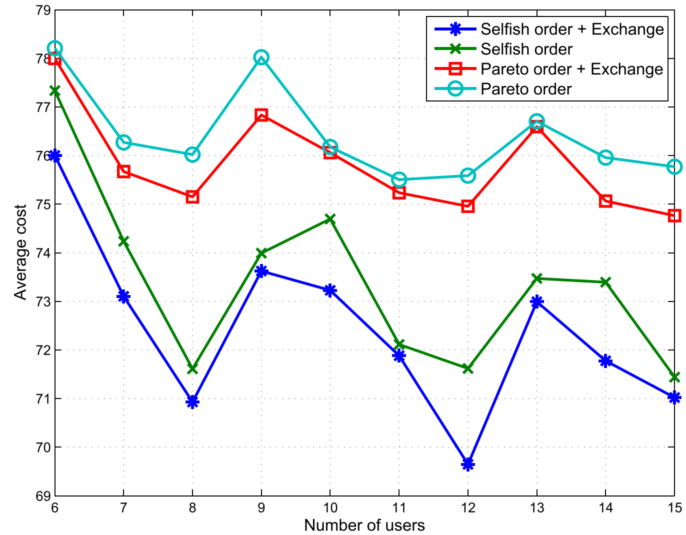

Fig. 12. The comparison of exchange mechanism and no exchange situation in Pareto and selfish order.

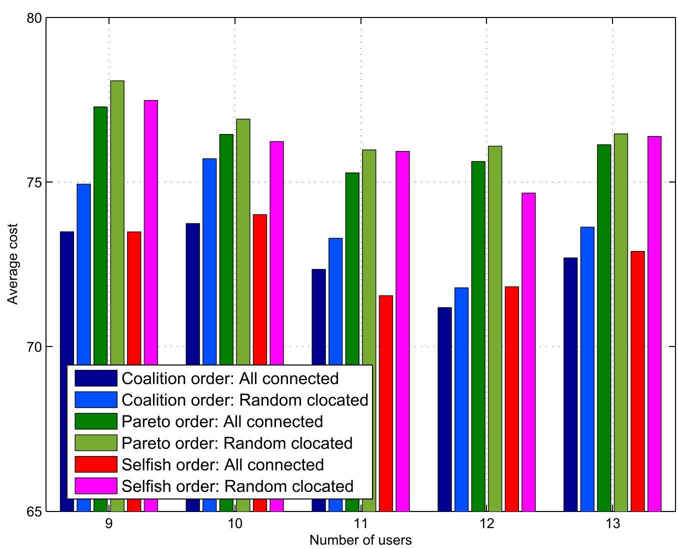

Fig. 10. The comparison of different connection of one user.

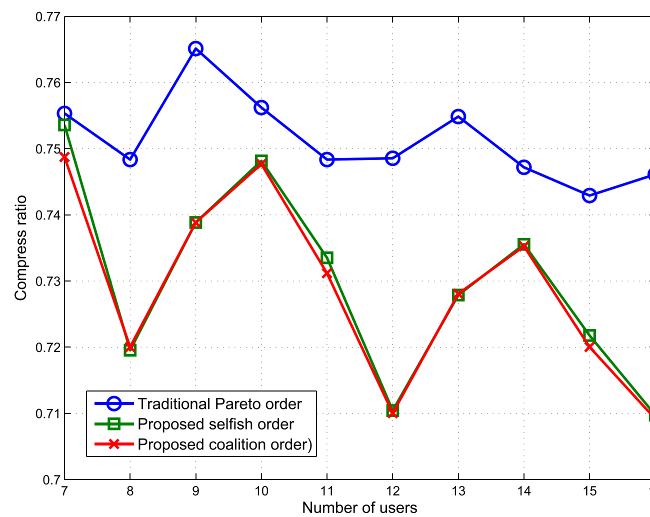

Fig. 13. The compression ratio of three orders.

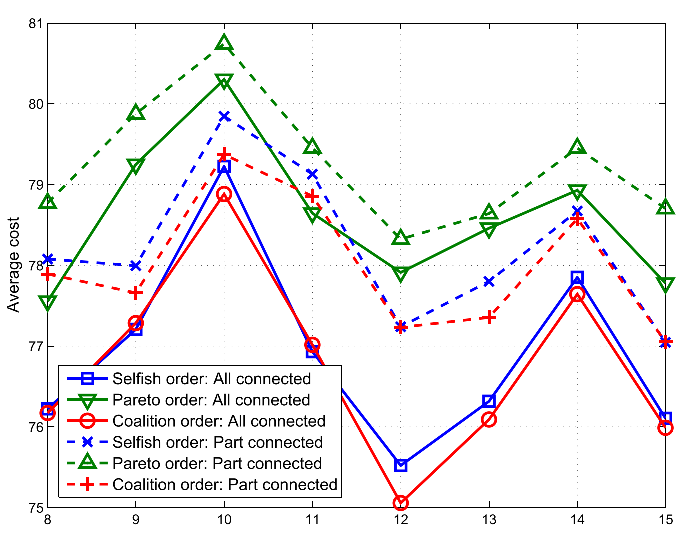

Fig. 11. The comparison of all connected and partially connected topology.

D. Exchange Mechanism

The exchange mechanism with Pareto order and selfish order is shown in Fig. 12. We assume that all users can connect to each other to enhance the probabilities of an exchange happening. From the figure, the exchange mechanism has both improvement in the two orders, which indicates the effectiveness of the mechanism. It also can be found that the improvement of selfish order is larger than the Pareto order. The reason is similar to the above. The successful probability of an exchange happening in Pareto order is smaller than in selfish order, due to the fact that the Pareto order protects all users.

E. Other Issue

In this subsection, we consider some other metrics of the context awareness group buying situations. The compression ratio of different orders are compared in Fig. 13. The compression ratio is defined as the ratio between total used spectrum resources

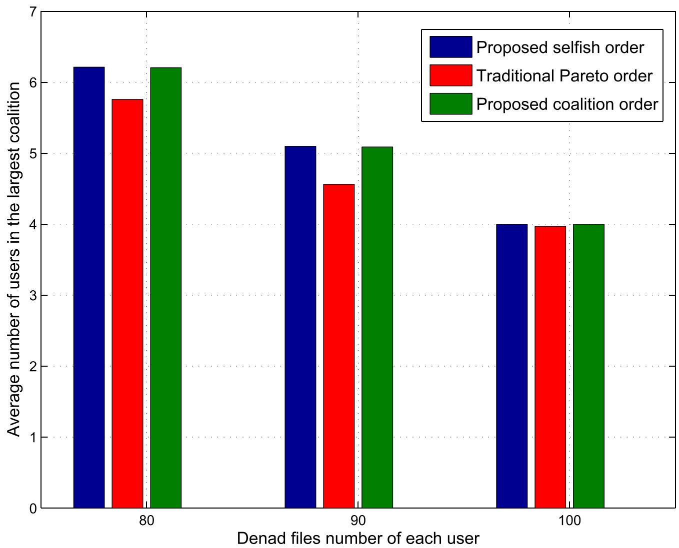

Fig. 14. The average number of users per channel with different demand lengths.

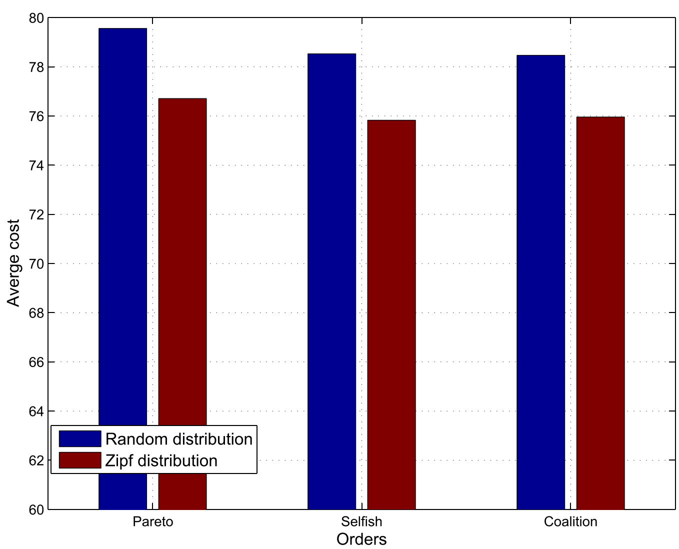

Fig. 15. The average cost comparison of Zipf and random distributions. ($N = 10$).

and all users' demands. A lower ratio indicates that the coalition mates have more same data, which will bring a lower cost. From the figure, the coalition order and the selfish order also achieve close performance and better than the Pareto order.

Furthermore, we also compare the maximum number of users per channel in Fig. 14. The metrics reflects the coalition formation in another way. The more users in one coalition, the lower cost will be. With the increasing demand lengths, the channel capacity of users is decreasing rapidly. Due to the increasing demand length, the cooperation space for users is reducing. It is hard to supply more users with the limit channel capacity. Hence, the number of users in one coalition decrease.

Besides the Zipf distribution, we also compared with the random distributions of users data. The comparison of two distributions are shown in Fig. 15. From the figure, we can find that the Zipf distribution has a better performance than the random situation. Because users would have more similar files in the Zipf distribution, especially in the most popular part. Therefore, it would bring more benefits from cooperation.

VII. Conclusion

In this paper, the context awareness group buying was studied to reduce the users' cost in D2D network with spectrum market. The users' group buying cost was formulated as a mixture of content-aware data cost and location-aware sharing cost in this paper. To reduce the cost, users formed different groups based on content and location awareness and downloaded the traffic in the role of groups, instead of downloading the same traffic from the base station repeatedly. The cost reducing problem was modeled into a coalition formation game, and the content awareness related to data cost and location awareness related to sharing cost were both considered in coalition forming. Besides the Pareto order, a coalition order and a selfish order were proposed to minimize the cost of coalition and user itself, respectively. The existence of stable coalition partition was guaranteed through proving the proposed CFG with two proposed orders were also potential games. A further benefit improvement mechanism was designed, where users could cooperate and make decision to achieve better performance. Simulation results showed that the group buying with context awareness significantly improved the benefit compared to non-context awareness group buying situation, and the proposed coalition order and selfish order had better performance than the Pareto order.

There are still some interesting works to study in future, such as, the influence of users' mobility. To adapt the user mobility, there are some measures can be taken as follow: (i) We can reduce users' data length in one coalition formation process, to short the sharing process, (ii) The coalition formation algorithm can be set with a fixed iteration as upper bound, with sacrificing part performance but achieving faster convergence,(iii) Furthermore, based on the prediction of users' mobility, a stable time weighted coalition formation mechanism might contribute to solving the mobility problem in future.

References

[1] Q. Wu *et al.*, "Cognitive Internet of things: A new paradigm beyond connection," *IEEE Internet Things J.*, vol. 1, no. 2, pp. 129–143, Apr. 2014.

[2] Z. Feng, C. Qiu, Z. Feng, Z. Wei, W. Li, and P. Zhang, "An effective approach to 5G: Wireless network virtualization," *IEEE Commun. Mag.*, vol. 53, no. 12, pp. 53–59, Dec. 2015.

[3] K. Doppler, M. Rinne, C. Wijting, C. B. Ribeiro, and K. Hugl, "Device-to-device communication as an underlay to LTE-advanced networks," *IEEE Commun. Mag.*, vol. 47, no. 12, pp. 42–49, Dec. 2009.

[4] J. Liu, N. Kato, J. Ma, and N. Kadowaki, "Device-to-device communication in LTE-advanced networks: A survey," *IEEE Commun. Surv. Tut.*, vol. 17, no. 4, pp. 1923–1940, Oct.–Dec. 2015.

[5] Y. Chen, G. Yu, Z. Zhang, H.-H. Chen, and P. Qiu, "On cognitive radio networks with opportunistic power control strategies in fading channels," *IEEE Trans. Wireless Commun.*, vol. 7, no. 7, pp. 2752–2761, Jul. 2008.

[6] A. Asadi, Q. Wang, and V. Mancuso, "A survey on device-to-device communication in cellular networks," *IEEE Commun. Surv. Tut.*, vol. 16, no. 4, pp. 1801–1819, Oct.–Dec. 2014.

[7] J. Liu, H. Nishiyama, N. Kato, and J. Guo, "On the outage probability of device-to-device-communication-enabled multichannel cellular networks: An RSS-threshold-based perspective," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 1, pp. 163–175, Jan. 2016.

[8] Y. Shen, C. Jiang, T. Q. S. Quek, and Y. Ren, "Device-to-device-assisted communications in cellular networks: An energy efficient approach in downlink video sharing scenario," *IEEE Trans. Wireless Commun.*, vol. 15, no. 2, pp. 1575–1587, Feb. 2016.

[9] H. Zhou *et al.*, "ChainCluster: Engineering a cooperative content distribution framework for highway vehicular communications," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 6, pp. 2644–2657, Dec. 2014.

[10] T. Wang, L. Song, Z. Han, and B. Jiao, "Dynamic popular content distribution in vehicular networks using coalition formation games," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 9, pp. 538–547, Sep. 2013.

[11] Y. Zhang, Y. Xu, and Q. Wu, "Group buying based on social aware in D2D networks: A game theoretic approach," in *Proc. IEEE Int. Conf. Commun. China*, Qingdao, Sep. 2017, pp. 1–6.

[12] L. Ruan *et al.*, "Context-aware group buying in D2D networks: An overlapping coalition formation game approach," in *Proc. IEEE Int. Conf. Commun. Technol.*, Chengdu, Oct. 2017, pp. 867–872.

[13] Y. Zhang, Y. Xu, Q. Wu, K. Yao, and A. Anpalagan, "A game-theoretic approach for optimal distributed cooperative hybrid caching in D2D networks," *IEEE Wireless Commun. Lett.*, vol. 7, no. 3, pp. 324–327, Jun. 2018.

[14] J. Liu, Y. Kawamoto, H. Nishiyama, N. Kato, and N. Kadowaki, "Device-to-device communications achieve efficient load balancing in LTE-advanced networks," *IEEE Wireless Commun.*, vol. 21, no. 2, pp. 57–65, Apr. 2014.

[15] J. Liu, S. Zhang, N. Kato, H. Ujikawa, and K. Suzuki, "Device-to-device communications for enhancing quality of experience in software defined multi-tier LTE-A networks," *IEEE Netw.*, vol. 29, no. 4, pp. 46–52, Jul./Aug. 2015.

[16] Z. Zhou, H. Yu, C. Xu, Y. Zhang, S. Mumtaz, and J. Rodriguez, "Dependable content distribution in D2D-based cooperative vehicular networks: A big data-integrated coalition game approach," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 3, pp. 953–964, Mar. 2018.

[17] L. Al-Kanj, Z. Dawy, W. Saad, and E. Kutanoglu, "Energy-aware cooperative content distribution over wireless networks: Optimized and distributed approaches," *IEEE Trans. Veh. Technol.*, vol. 62, no. 8, pp. 3828–3847, Oct. 2013.

[18] T. Wang, L. Song, and Z. Han, "Coalitional graph games for popular content distribution in cognitive radio VANETs," *IEEE Trans. Veh. Technol.*, vol. 62, no. 8, pp. 4010–4019, Oct. 2013.

[19] J. Dai, J. Liu, Y. Shi, S. Zhang, and J. Ma, "Analytical modeling of resource allocation in D2D overlaying multihop multichannel uplink cellular networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 8, pp. 6633–6644, Aug. 2017.

[20] J. Liu, S. Zhang, H. Nishiyama, N. Kato, and J. Guo, "A stochastic geometry analysis of D2D overlaying multi-channel downlink cellular networks," in *Proc. IEEE Conf. Comput. Commun.*, 2015, pp. 46–54.

[21] K. Chen, H. Shen, and H. Zhang, "Leveraging social networks for P2P content-based file sharing in disconnected MANETs," *IEEE Trans. Mobile Comput.*, vol. 13, no. 2, pp. 235–249, Feb. 2014.

[22] X. Zhang and B. Li, "On the market power of network coding in P2P content distribution systems," *IEEE Trans. Parallel Distrib. Syst.*, vol. 22, no. 12, pp. 2063–2070, Dec. 2011.

[23] G. Dan *et al.*, "Interaction patterns between P2P content distribution systems and ISPs," *IEEE Commun. Mag.*, vol. 49, no. 5, pp. 222–230, May 2011.

[24] Y. Zheng, D. Huang, Y. Yang, Y. Huang, and C. Chen, "A motivate mechanism for large-scale P2P content delivery system," *China Commun.*, vol. 11, no. 14, pp. 118–127, 2014.

[25] X. Meng and D. Liu, "GeTrust: A guarantee-based trust model in chord-based P2P networks," *IEEE Trans. Dependable Secure Comput.*, vol. 15, no. 1, pp. 54–68, Jan./Feb. 2018.

[26] Z. Zhang, J. Shi, H.-H. Chen, M. Guizani, and P. Qiu, "A cooperation strategy based on Nash bargaining solution in cooperative relay networks," *IEEE Trans. Veh. Technol.*, vol. 57, no. 4, pp. 2570–2577, Jul. 2008.

[27] J. Chen, X. Chen, and X. Song, "Bidder's strategy under group-buying auction on the Internet," *IEEE Trans. Syst., Man, Cybern.*, vol. 32, no. 6, pp. 680–690, Nov. 2002.

[28] P. Lin, X. Feng, Q. Zhang, and M. Hamdi, "Groupon in the air: A three-stage auction framework for spectrum group-buying," in *Proc. IEEE Conf. Comput. Commun.*, 2013, pp. 2013–2021.

[29] D. Yang, G. Xue, and X. Zhang, "Group buying spectrum auctions in cognitive radio networks," *IEEE Trans. Veh. Technol.*, vol. 66, no. 1, pp. 810–817, Jan. 2017.

[30] D. Yang, G. Xue, and X. Zhang, "Truthful group buying-based spectrum auction design for cognitive radio networks," in *Proc. IEEE Conf. Comput. Commun.*, 2014, pp. 2295–2300.

[31] J. Xu, L. Duan, and R. Zhang, "Energy group buying with loading sharing for green cellular networks," *IEEE J. Sel. Area Commun.*, vol. 34, no. 4, pp. 786–799, Apr. 2016.

[32] Z. Jiang, W. Yuan, H. Leung, X. You, and Q. Zheng, "Coalition formation and spectrum sharing of cooperative spectrum sensing participants," *IEEE Trans. Cybern.*, vol. 47, no. 5, pp. 1133–1146, May 2017.

[33] R. Brandt, R. Mochaourab, and M. Bengtsson, "Distributed long-term base station clustering in cellular networks using coalition formation," *IEEE Trans. Signal Inf. Process. Over Netw.*, vol. 2, no. 3, pp. 362–375, Sep. 2016.

[34] R. Massin, C. J. Le Martret, and P. Ciblat, "A coalition formation game for distributed node clustering in mobile ad hoc networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 6, pp. 3940–3952, Jun. 2017.

[35] S.-C. Zhan and D. Niyato, "A coalition formation game for remote radio head cooperation in cloud radio access network," *IEEE Trans. Veh. Technol.*, vol. 66, no. 2, pp. 1723–1738, Feb. 2017.

[36] B. Das, S. Misra, and U. Roy, "Coalition formation for cooperative service-based message sharing in vehicular ad hoc networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 27, no. 1, pp. 144–156, Jan. 2016.

[37] Y. Zhang *et al.*, "Context-aware group buying in ultra-dense small cell networks: Utility is strength," *IEEE Wireless Commun.*, 2018. [Online]. Available: https://arvix.org/abs/1807.08426

[38] Z. Zhang, L. Song, Z. Han, and W. Saad, "Coalitional games with overlapping coalitions for interference management in small cell networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 5, pp. 2659–2569, May 2014.

[39] Y. Sun, Q. Wu, J. Wang, Y. Xu, and A. Anpalagan, "VERACITY: Overlapping coalition formation-based double auction for heterogeneous demand and spectrum reusability," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 10, pp. 2690–2705, Oct. 2016.

[40] L. Militano, A. Orsino, G. Araniti, A. Molinaro, and A. Iera, "A constrained coalition formation game for multihop D2D content uploading," *IEEE Trans. Wireless Commun.*, vol. 15, no. 3, pp. 2012–2024, Mar. 2016.

[41] D. Wu, Q. Wu, Y. Xu, and Y.-C. Liang, "QoE and energy aware resource allocation in small cell networks with power selection, load management and channel allocation," *IEEE Trans. Veh. Technol.*, vol. 66, no. 8, pp. 7461–7473, Aug. 2017.

[42] Y. Li, Z. Zhang, and H. Wang, "Transmission mode selection and interference mitigation for social aware D2D communication," in *Proc. IEEE Global Commun. Conf.*, 2016, pp. 1–6.

[43] E. Ahmed, I. Yaqoob, A. Gani, M. Imran, and M. Guizani, "Social-aware resource allocation and optimization for D2D communication," *IEEE Wireless Commun.*, vol. 24, no. 3, pp. 122–129, Jun. 2017.

[44] Z. Huang, H. Tian, S. Fan, Z. Xing, and X. Zhang, "Social-aware resource allocation for content dissemination networks: An evolutionary game approach," *IEEE Access*, vol. 5, pp. 9568–9579, 2017.

[45] Y. Zhao and W. Song, "Survey on social-aware data dissemination over mobile wireless networks," *IEEE Access*, vol. 5, pp. 6049–6059, 2017.

[46] Y. Xu, J. Wang, Q. Wu, J. Zheng, L. Shen, and A. Anpalagan, "Dynamic spectrum access in time-varying environment: Distributed learning beyond expectation optimization," *IEEE Trans. Commun.*, vol. 65, no. 12, pp. 5305–5318, Dec. 2017.

[47] Z. Chen, J. Lee, T. Q. S. Quek, and M. Kountouris, "Cooperative caching and transmission design in cluster-centric small cell networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 5, pp. 3401–3415, May 2017.

[48] W. Saad, Z. Han, M. Debbah, A. Hjorungnes, and T. Basar, "Coalitional game theory for communication networks," *IEEE Signal Process. Mag.*, vol. 26, no. 5, pp. 77–97, Sep. 2009.

[49] K. R. Apt and A. Witzel, "A generic approach to coalition formation," *Int. Game Theory Rev.*, vol. 11, no. 3, pp. 347–367, 2009.

[50] D. Monderer and L. S. Shapley, "Potential games," *Game Econ. Behav.*, vol. 14, pp. 124–143, 1996.

[51] A. Mukherjee, S. A. A. Fakoorian, J. Huang, and A. L. Swindlehurst, "A comprehensive survey of potential game approaches to wireless networks: A survey," *IEEE Commun. Surv. Tut.*, vol. 16, no. 3, pp. 1550–1573, Sep. 2014.

[52] Y. Xu, J. Wang, Q. Wu, A. Anpalagan, and Y. Yao, "Opportunistic spectrum access in unknown dynamic environment: A game-theoretic stochastic learning solution," *IEEE Trans. Wireless Commun.*, vol. 11, no. 4, pp. 1380–1391, Apr. 2012.

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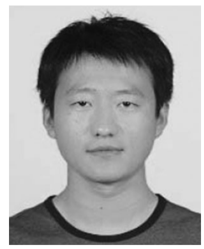

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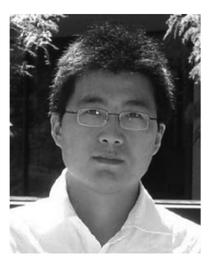

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