DUE Distribution and Pairing in D2D Communication

Weifeng Lu[1], Xiaoqiang Ren[1], Jia Xu[1], Siguang Chen[2], Lijun Yang[2], and Jian Xu[3]

[1]Jiangsu Key Laboratory of Big Data Security and Intelligent Processing, Nanjing University of Posts and Telecommunications, Nanjing, Jiangsu 210023 China
[2]College of IoT, Nanjing University of Posts and Telecommunications, Nanjing 210003, China
[3]School of Computer Science and Engineering, Nanjing University of Science and Technology, Nanjing 210094, China

***Abstract*—The D2D (Device-to-Device) communication has been very popular as it is a promising and low-cost solution to reduce the burden on the cellular network. However, there are rare concerns about the distribution and pairing of DUEs(D2D user equipments), which have a significant impact on QoS (Quality of Service) of D2D communication. In this paper, we propose a novel algorithm based on the coalitional game to optimally adjust the distribution of DUEs. The proposed algorithm aims to form the optimal coalition structure, which achieves a balance between the throughput and power consumption of each coalition, obtaining the enhanced QoS of D2D. We show that our algorithm is superior to the benchmark models in terms of the throughput and energy efficiency of the DUE coalition. To further improve the QoS, we also propose a method to predict and maximize the pairing probability of DUEs. The proposed prediction method adopts the Logistic Regression to model the global pairing probability according to the communication parameters of DUEs. Experimental results show that the proposed prediction method is significantly superior to the benchmark methods in terms of prediction accuracy. In addition, the pairing probability maximization algorithm proposed also significantly improves the pairing probability.**

***Index Terms*—D2D communication, coalition formation, DUE pairing, quality of service**

I. Introduction

One of the most engaging challenges for mobile operators today is how to manage the exponential data traffic increase. As one of the most important forms of mobile data offloading [1], D2D communication has a positive prospect thanks to the exponential data traffic increase of wireless communication in many novel applications, such as crowdsensing [2-3] and industrial IoT (Internet of Things) [4-5]. D2D communication enables DUEs to exchange data directly without the relay of the base station (BS) so as to lower the burden on the cellular network [6]. In this paper, we consider a wireless cellular network where all the DUEs colocated within a given area covered by a BS are interested in offloading the same common data in a cooperative manner. We address the cooperative data offloading among DUEs by the coalition formation game [7-8], in which the players adopt cooperative strategies to form the coalitions for improving individual payoff. Coalition formation game has recently been adopted for modeling the cooperative behaviors of communication nodes. For example, [9] formulates the cooperative content dissemination problem in D2D communication to optimize power and throughput with constraints of coalition size and density of DUEs. However, the proposed centralized approach requires global channel state information, leading to high computational complexity. For the dynamic heterogeneous network scenarios, $e.g.$, cellular networks, distributed approaches are more suitable. In [10], the cooperative DUE distribution in the context of cellular networks is investigated. It assumes that the fringe DUEs of the cell cannot download the whole data from the BS due to the limited radius of broadcasting. To tackle this problem, authors allow the central DUEs to exchange the missing chunks through a game theoretic approach without considering power consumption during the cooperative coalition formation procedure. [11] also adopts the coalitional game to investigate DUE distribution, but it focuses on mobile ad-hoc networks, where multiple DUEs compete for accessing the wireless channels.

Meanwhile, in order to get interested data from another DUEs, one DUE needs to pair with another DUE. The probability of DUE pairing can directly influence the QoS of D2D Communication such as the delay in data offloading. The prediction of pairing probability requires a lot of data, which is exactly generated by mobile networks every day. Therefore, machine learning, driven by massive data, has attracted the attention of analysts and researchers in D2D communication. [12-13] study both independent and coordinate reinforcement learning for power control in femtocell networks. [14] studies the performance on the throughput of D2D by using different types of Q-Learning based power control algorithms and different reward functions. But the above work will suffer from high time complexity and the curse of dimensions due to lack of prior data. In [15], Decision-Tree-based D2D power control algorithm is proposed. As a learning model with prior data, Decision Tree takes a relatively short time to train data. However, due to the low classification accuracy, the throughput of the algorithm proposed in [15] is not very good.

In this paper, we solve the problem of DUE distribution based on the coalitional game, Then we predict the probability of DUE pairing on the basis of the stable coalition structure.

Corresponding author: Jia Xu(xujia@njupt.edu.cn)

978-1-7281-1856-7/19/$31.00 ©2019 IEEE

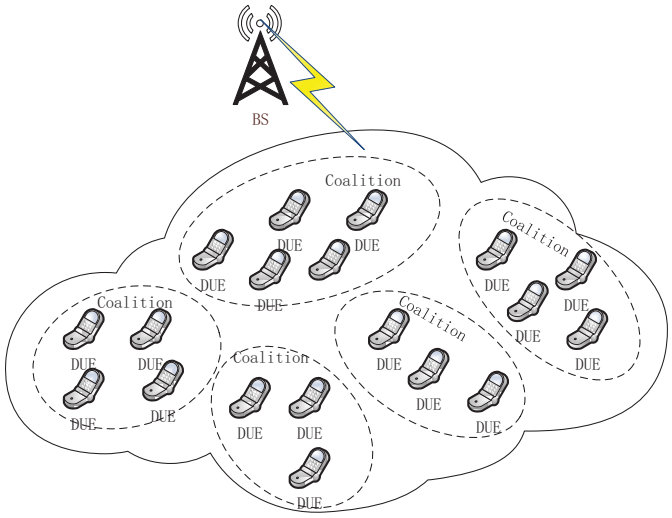

Fig. 1. Cooperative communication scenario

Finally, we optimize the DUE pairing probability. The major contributions of this paper are summarized as follows:

- A coalition formation algorithm of DUEs is proposed to maintain the balance of throughput and power consumption of DUE coalitions. Unlike most existing literature, this paper uses the water-filling power allocation [18] to each DUE in the coalition to improve the energy efficiency D2D communication.
- Unlike most existing works, which use the data-free reinforcement learning to predict the DUE pairing probability, we propose a logistic-regression-based probability prediction model to predict of DUE pairing probability with historical data.
- A DUE pairing probability maximization algorithm based on hill-climbing [16] is proposed to further improve the DUE pairing probability.

The rest of this paper is organized as follows. Section II describes the coalition formation of DUEs. Section III proposes the probability prediction and optimization method of DUE pairing. Section IV gives the experimental results and analysis. Section V concludes this paper.

II. System Model

The goal of coalition formation is to maximize the throughput and reduce the power consumption of DUE coalition as much as possible.

A. Communication scenario

As shown in Fig.1, we consider a single cell D2D communication scenario in the work mode of TDMA (Time Division Multiple Access). Each DUE is regarded as the transmitter, and BS is regarded as the receiver. The set of all DUEs in the cell are defined as $\mathcal{N} = \{1, ..., T\}$, where T is the number of the DUEs.

TABLE I
FREQUENTLY USED NOTATIONS

Notation	Description
$\mathcal{N}$	set of DUEs
T	number of the DUEs
S	coalition
$\boldsymbol{r}_S$	signal vector of coalition S
$\boldsymbol{G}_S$	transmitting signal vector of each slot in coalition S
$\boldsymbol{H}_S$	matrix of fast fading channel
$\boldsymbol{z}_S$	signal sent by a DUE in coalition S
Q_S	covariance matrix of transmitting signal z_S
β	channel fading index
κ	channel fading coefficient
ϕ_i	signal phase from DUE i to the BS
$\bar{P}_S$	average transmitting power limitation of coalition S
$I_{\|S\|}$	information amount of all DUEs in coalition
C_S	channel capacity of coalition S in a time slot
T_S	system throughput of coalition S
B	bandwidth
P_i	power limitation of any DUE i
λ_i	eigenvalue of transmitting signal matrix of DUE i
σ^2	noise of the transmitting signal
v_0	average signal-to-noise ratio (SNR) of the target
$\mathcal{A}$	coalition structure
$\mathfrak{N}$	set of all the structures of $\mathcal{N}$
CR	set of coalitions want to combine S_i
SR	set of coalitions within search radius d
T_{w_i}	waiting time
$\bar{p}_i$	probability of each pairing attempts
p_{SR}	average probability of all pairing attempts
$e_{\mathcal{N}}$	average energy efficiency of DUE coalition structure
p_{cir}^i	circuit power consumption of the DUE
e	energy efficiency of a single D2D
p_{BS}	BS transmitting power
H_{DB}	channel gain
p_{DUE}	transmitting power of DUE

In the TDMA transmitting network, time is divided into a number of equal slots. Each time slot is exclusively owned by one user at the same time, and all users use the same frequency in different time slots. In the non-cooperative scenario of TDMA, a DUE takes up a time slot to transmit information separately. While in the cooperative scenario studied in this paper, the DUEs compose different disjoint coalitions. Each coalition can be considered as a MIMO (multiple-input and multiple-output) device [17]. In this case, all the DUEs of a coalition take up a time slot to carry out one transmitting.

B. Throughput of the coalition

The communication system formed by any coalition $S \subseteq \mathcal{N}$ with size $|S|$ in the work mode of TDMA can be modeled as:

$$\boldsymbol{r}_S = \boldsymbol{G}_S + \boldsymbol{H}_S \boldsymbol{z}_S \tag{1}$$

where $\boldsymbol{H}_S$ is the matrix of fast fading channel and $\boldsymbol{z}_S = [z_1, \cdots, z_{|S|}]^T$ is the transmitting signal vector of each slot in coalition S. Each element in $\boldsymbol{z}_S$ represents the signal sent by a DUE in the coalition S. The signal vector received by the BS in each slot is defined as $\boldsymbol{r}_S = [r_1, \cdots, r_{|S|}]^T$. $\boldsymbol{G}_S = [G_1, \cdots, G_{|S|}]^T$ is the independent and identically distributed additive complex Gauss white noise vector of the BS.

According to information theory, the best distribution of the transmitting signal is also the Gauss signal for Gauss channel. It is reasonable to make the elements of $\boldsymbol{z}_S$ independent and identically distributed Gauss variable with zero mean value. The covariance matrix of the transmitting signal z_S is:

$$Q_S = E\left[\boldsymbol{z}_S \cdot {\boldsymbol{z}_S}^{\dagger}\right] \tag{2}$$

where ${\boldsymbol{z}_S}^{\dagger}$ is the conjugate transposed matrix of $\boldsymbol{z}_S$. For a coalition S, we consider the path loss model between the DUE and the BS. Each element of the fast fading channel matrix $\boldsymbol{H}_S$ represents the channel fading coefficient h_i from any DUE i to the BS:

$$h_i = e^{i\phi_i}\sqrt{\kappa/{d_i}^{\beta}} \tag{3}$$

where e is the value of the base of natural logarithms, β is a channel fading index, and κ is the channel fading coefficient. ϕ_i and d_i are the signal phase and distance from DUE i to the BS, respectively.

For the TDMA system, a fixed transmitting power limitation is defined for each time slot, $i.e.$, regardless of the number of DUEs in any coalitions, the average transmitting power limitation is :

$$\bar{P}_S = tr(Q_S) = tr(E[\boldsymbol{z}_S \cdot {\boldsymbol{z}_S}^{\dagger}]) \tag{4}$$

where $tr(\cdot)$ is the trace of a matrix, which can be obtained by summing the diagonal elements of the matrix.

Then, we apply the average power limitation to all the DUEs in the coalition. According to information theory, the channel capacity of a coalition in a time slot with power limitation is:

$$\begin{aligned} &C_S = \max_{Q_S} I(\boldsymbol{z}_S; \boldsymbol{r}_S) = \max \log\left(\det\left(I_{|S|} + \boldsymbol{H}_S \cdot Q_S \cdot {\boldsymbol{H}_S}^{\dagger}\right)\right) \\ &s.t. \quad tr[Q_S] \le \bar{P}_S. \end{aligned} \tag{5}$$

where $I(\boldsymbol{z}_S; \boldsymbol{r}_S)$ is the mutual information between $\boldsymbol{z}_S$ and $\boldsymbol{z}_S$; $\det$ represents the value of the determinant of matrix; $I_{|S|}$ is the information amount of all DUEs in the coalition; ${H_S}^{\dagger}$ is the conjugate transposed matrix of H_S. According to Hadamard Inequality, the optimal solution $\boldsymbol{X}$ of the problem in Eq.(5) must be a diagonal matrix. Thus, the problem in Eq.(5) can be simplified as follows:

$$\begin{aligned} &C_S = \max_{x_i \ge 0} \sum_{i=1}^{r} \log(1 + \frac{x_i}{a_i}) \\ &s.t. \quad \sum_{i=1}^{r} x_i \le \bar{P}_S. \end{aligned} \tag{6}$$

where r denotes the rank of $\boldsymbol{H}_S$, x_i and a_i denote the diagonal elements of $\boldsymbol{X}$ and $\boldsymbol{H}_S$, respectively. Finally, according to the water-filling power allocation of each DUE in the coalition, the system throughput of the coalition S can be defined as:

$$T_S = B\sum_{i=1}^{|S|} \log\left(1 + \frac{P_i \lambda_i}{\sigma^2}\right) \tag{7}$$

where B is the bandwidth, P_i is the power limitation of any DUE i, λ_i is the eigenvalue of the transmitting signal matrix of DUE i, and σ^2 is the noise of the transmitting signal.

C. Power consumption of the Coalition

The power consumption of the coalition is mainly caused by the information exchange among the DUEs in the coalition. In the TDMA system, the block fading channel has a long correlation time. The channel state changes slowly, and the exchange of channel state information (CSI) takes place periodically. Thus, compared with the cost of data exchange between DUEs, the cost of information exchange between DUEs and BS is negligible. On the other hand, the power consumption of the coalition is equal to the sum of the power required by each DUE i to propagate its information to the farthest DUE i'in the coalition S. This is because that when any DUE transmits its information to the farthest DUE, other DUEs in the coalition will receive such information at the same time. The power consumption for DUE i to propagate its information to the farthest DUE i' is:

$$P_{i,i'} = v_0 \cdot \sigma^2 / {g_{i,i'}}^2 \tag{8}$$

where v_0 is the target average signal-to-noise ratio (SNR) for information exchange between DUEs, σ^2 is noise power, and $g_{i,i'}$ is the path fading between DUE i and the farthest DUE i' in the coalition:

$$g_{i,i'} = \sqrt{\kappa/{d_{i,i'}}^{\beta}} \tag{9}$$

where $d_{i,i'}$ is the distance between DUEs i and i'. Thus, the power consumption of coalition S is:

$$P_c^S = \sum_{i,i' \in S} P_{i,i'} \tag{10}$$

Then, the actual power limitation of the coalition S is:

$$P_S = \max(0, (\bar{P}_S - P_c^S)) \tag{11}$$

That is to say, the available power of the coalition S will not be greater than the difference between the average power limitation of the coalition and the power consumption used to form the coalition.

D. Coalition Formation Algorithm

The payoff functions of DUEs in the coalition are different because they are independent of each other. So we consider the Non Transferable Utility game where each player can decide its payoff independently.The frequently used notations of this paper is shown in Table 1.

In this paper, we define Non Transferable Utility game as $(\mathcal{N}, \mathcal{A}, v)$, in which $\mathcal{N}$ is the set of DUEs. $\mathcal{A} = \{S_1, S_2, ..., S_K\}$ is called a coalition structure, where each element $S_k (1 \le k \le K)$ is a coalition that satisfies $\bigcup_{k=1}^{K} S_k = \mathcal{N}$. For any k and $k' \in \{1, 2, \cdots, K\}$, $k' \ne k$, $S_{k'} \bigcap S_k = \varnothing$. $v(S_k)$ is the payoff function of the coalitional game. We define the payoff function for each coalition S_k as:

$$v(S_k) = T_{S_k} - P_c^{S_k} \tag{12}$$

The payoff is positively correlated with the throughput of the coalition and negatively correlated with the power

consumption of the coalition. We use the linear method to transform it into a single objective payoff function:

$$v(\mathcal{A}) = w_1 \frac{\sum_{S_k \in \mathcal{A}} T_{S_k}}{|\mathcal{A}|} - w_2 \frac{\sum_{S_k \in \mathcal{A}} P_c^{S_k}}{|\mathcal{A}|} \tag{13}$$

Suppose that the set of all the structures of $\mathcal{N}$ is $\mathfrak{N}$, then the optimal formation of a coalition $\mathcal{N}$ can be formalized as the following optimization problem:

$$\begin{aligned} &\max_{\mathcal{A} \in \mathfrak{N}} v(\mathcal{A}) \\ &s.t. \quad P_{S_k} > 0, \forall S_k \in \mathcal{A} \end{aligned} \tag{14}$$

where w_1 and w_2 are not negative and satisfy $w_1 + w_2 = 1$. They used to adjust the expectation of higher throughput and lower power consumption. $|\mathcal{A}|$ is the number of coalitions in coalition structure $\mathcal{A}$.

The method proposed in this paper follows the Combination-Separation (C-S) principle:

a) Combination principle: For any coalition set $\{S_1, \cdots, S_{K'}\}$, iff $v(\{\bigcup_{k=1}^{K'} S_k\}) > \sum_{k=1}^{K'} v(S_k)$, we combine all coalitions in this set, *i.e.*, $\{\{S_1\}, ..., \{S_{K'}\}\} \rightarrow \{\bigcup_{k=1}^{K'} S_k\}$.

b) Separation principle: For any coalition set $\{S_1, \cdots, S_{K'}\}$, iff $\sum_{k=1}^{K'} v(S_k) > v(\{\bigcup_{k=1}^{K'} S_k\})$, we separate all coalitions in this set, *i.e.*, $\{\bigcup_{k=1}^{K'} S_k\} \rightarrow \{\{S_1\}, ..., \{S_{K'}\}\}$.

In short, if a combination (or separation) can bring extra payoff based on Pareto Criterion, the coalitions will combine or separate. With Pareto Criterion, each combination (or separation) will be conducted when it makes at least one DUE increase payoff itself, and all related DUEs guarantee their payoff.

We propose a Coalition Formation Algorithm of DUEs (CFAD) based on Combination-Separation principle. In the initial state, each DUE forms a coalition independently:

$$\mathcal{A}' = \{S_1, \cdots, S_T\} \tag{15}$$

where $S_i = \{i\}$ and $i \in \mathcal{N}$.

Then, CFAD performs the combination and separation stage iteratively in distribution. In the combination stage, each coalition tries to combine itself with the neighbor, and verifies whether it can form a better coalition. In the separation stage, if there is a coalition that satisfies the separation principle, the coalition separates. When the algorithm terminates, the optimal coalition structure $\mathcal{A}$ is returned. The algorithm is illuminated in Algorithm 1.

In the combination stage, the function $Combine()$ is illuminated in Algorithm 2, where CR is the set of coalitions which want to combine S_i, SR is the set of coalitions within the search radius d, T_{w_i} is the current waiting time and $T_{w_{\max}}$ is the maximum waiting time of DUEs in their affiliated coalition. First, the coalition broadcasts its information to other nodes within the search radius. Then the coalition waits for the combination request of other coalition in the waiting time and store the request in CR. In CR, the coalition seeks another coalition for combination that can maximize the payoff. If there is no combination request from the neighbor coalition, the coalition will send combination request to the coalitions in SR that can maximize the payoff. If the request is refused, the coalition will continue to try other coalitions in SR until the SR is empty.

Algorithm 1 CFAD

Input: $\mathcal{A}' = \{S_1, \cdots, S_T\}$
for each $S_i \in \mathcal{A}'$ **do**
  repeat
    Combine(S_i);
    Separate(S_i);
  until Converged;
end for
return $\mathcal{A}$;

Algorithm 2 Function Combine() of CFAD

Input: d, $T_{w_{\max}}$;
$CR \leftarrow \varnothing$;
$SR \leftarrow$ Set of coalitions within d of S_i;
S_i broadcast the information of to the coalitions in SR;
while $T_{w_i} < T_{w_{\max}}$ **do**
  if any $S_k \in SR$ requests Combination **then**
    $CR \leftarrow CR \bigcup \{S_k\}$;
  end if
end while
if $CR \neq \varnothing$ **then**
  $S'_x \leftarrow \arg\max_{S_x \in CR} v(S_i \bigcup S_x)$;
  $S_i \leftarrow S_i \bigcup S'_x$;
else
  $SR \leftarrow SR - CR$;
  if $SR = \varnothing$ **then**
    return ;
  else
    $S'_x \leftarrow \arg\max_{S_x \in SR} v(S_i \bigcup S_x)$;
    Send combination request to S'_x;
    if request accepted **then**
      $S_i \leftarrow S_i \bigcup S'_x$;
      Goto Step 4;
    else
      $SR \leftarrow SR - \{ S'_x\}$;
      Goto Step 14;
    end if
  end if
end if

In the separation stage, each coalition seeks the coalition partition with the maximum payoff after separation in all possible partitions. If the partition exists, the coalition separates. The function $Separate()$ is illustrated in Algorithm 3.

E. Analysis of CFAD

We demonstrate the stability of the coalition structure obtained from CFAD algorithm, and then prove the convergence of the algorithm.

Algorithm 3 Function Separate() of CFAD

$P \leftarrow$ set of all partition of S_i;
$P'_x \leftarrow \varnothing$;
$P'_x \leftarrow \arg\max_{P_x \in P} v(P_x)$;
if $P_{x'} \neq \varnothing$ **then**
    Broadcast separation request to $S_i, \forall S_i \in P_{x'}$;
end if

We define the stability of the coalition structure as $\mathbb{D}_{hp}$-stable. That is, no coalition will leave the current coalition structure by both of the combination and/or separation operations.

Theorem 1. *The final coalition structure obtained from CFAD is $\mathbb{D}_{hp}$-stable.*

Proof. Assuming that the final structure $\mathcal{A}$ obtained after the termination of CFAD is not $\mathbb{D}_{hp} - stable$, there must exist a structure $\mathcal{A}'$, through the combination and/or separation operations. This means that the C-S principle is satisfied, and the CFAD algorithm will not terminate. A contradiction arises.

Theorem 2. *CFAD is convergent.*

Proof. Consider the optimal payoff of the coalition structure is $v^*(\mathcal{A})$. According to the C-S principle, each round of combination or separation can improve the payoff of the coalition structure. This improvement is bounded by $v^*(\mathcal{A})$, thus CFAD can terminate.

F. Complexity analysis of Combine() and Separate()

CFAD algorithm is an iterative distributed algorithm. The computation of coalition structure in each round of the algorithm is mainly divided into two parts: (1) Combination stage: In the initial case of the algorithm, each DUE forms a coalition separately. For each DUE, there are at most $T-1$ equipments in its CR or SR within time $T_{w_{\max}}$, Thus there are at most T-1 combination for each DUE. Therefore, the computational complexity of Combination stage is $O(T)$. (2) Separation stage: In each round, all possible partitions of the coalition are Bell numbers. Obviously, when the size of the coalition increases gradually, the complexity of the algorithm will be quite high, so we can control the complexity of the algorithm by limiting the size of the coalition.

III. Probability Prediction and Optimization of DUE Pairing

In this section, we aim to predict the probability of DUE pairing and optimize it to improve the QoS in D2D communication.

A. Probability prediction of DUE pairing

In order to get data from other DUEs, a DUE always has the tendency to try to pair with other DUEs. We record the behavior of one DUE trying to pair with another as a pairing attempt. Let the binary variable y represent the result for each pairing attempt: $y = 0$ if the attempt fails, $y = 1$ otherwise. The probability p_i of pairing attempt i is affected by many factors of QoS, which constitute the eigenvector $\mathbf{x}_i$.

We choose Logistic Regression as the prediction model. According to Sigmoid function, p_i is equal to:

$$p_i = p(y = 1|\mathbf{x}_i) = \frac{1}{1 + e^{-\theta^T \mathbf{x}_i}} \tag{16}$$

where θ is the regression coefficient.

The logit function of $\mathbf{x}_i$ is:

$$logit(\mathbf{x}_i) = \ln(\frac{p(y=1|\mathbf{x}_i)}{p(y=0|\mathbf{x}_i)}) = \ln(\frac{p(y=1|\mathbf{x}_i)}{1-p(y=1|\mathbf{x}_i)}) \tag{17}$$

According to Eq.(16), it can be simplified to:

$$logit(\mathbf{x}_i) = \theta^T \mathbf{x}_i \tag{18}$$

So far, we have transformed Logical Regression into linear regression. In this paper, the gradient descent method is used to train data and determine the regression coefficients, $i.e.$, θ^T. We use Maximum Likelihood as the learning method in Logistic Regression. The probability of each sample $(\mathbf{x}_i, y_i)$ in the training data is:

$$p(\mathbf{x}_i, y_i) = p(y = 1|\mathbf{x}_i; \theta)^{y_i} p(y = 0|\mathbf{x}_i; \theta)^{1-y_i} \tag{19}$$

Then we can get the likelihood function of the data set containing n independent paired samples:

$$L(\theta) = \prod_{i=1}^{n} h_\theta(\mathbf{x}_i)^{y_i}(1 - h_\theta(\mathbf{x}_i))^{1-y_i} \tag{20}$$

where $h_\theta(\mathbf{x}_i) = p(y = 1|\mathbf{x}_i; \theta)$. Then the log-likelihood function can be obtained by taking logarithms on both sides of the equation:

$$l(\theta) = \log L(\theta) = \sum_{i=1}^{n} y_i \log h_\theta(\mathbf{x}_i) + \sum_{i=1}^{n} (1-y_i) \log(1-h_\theta(\mathbf{x}_i)) \tag{21}$$

According to Eq.(20), it can be reduced to:

$$l(\theta) = \sum_{i=1}^{n} y_i(\theta^T \mathbf{x}_i) - \sum_{i=1}^{n} \log(1 + e^{\theta^T \mathbf{x}_i}) \tag{22}$$

The parameter of the prediction model is θ^T, which maximizes the likelihood function. The iteration equation based on the gradient descent is:

$$\theta^{t+1} = \theta^t - \eta \frac{\partial l(\theta)}{\partial \theta} = \theta^t - \eta \frac{1}{n} \sum_{i=1}^{n} (h_\theta(\mathbf{x}_i) - y_i)\mathbf{x}_i \tag{23}$$

where η is the learning rate of the gradient descent, $i.e.$, the step length of each descent. The probability prediction model obtained after training is:

$$p_i = \frac{e^{\theta^T \mathbf{x}_i}}{1 + e^{\theta^T \mathbf{x}_i}} \tag{24}$$

B. Probability optimization of DUE pairing

If there are X pairing attempts and Y pairing DUEs in a complete pairing process, the pairing result can be represented as the following matrix $\boldsymbol{c}$:

$$\begin{pmatrix} c_{11} & \cdots & c_{1Y} \\ \cdots & c_{ij} & \cdots \\ c_{X1} & \cdots & c_{XY} \end{pmatrix}, 1 \leq i \leq X, 1 \leq j \leq Y \tag{25}$$

where $c_{ij} = 1$ when DUE j is one of the two DUEs of pairing attempt i, $c_{ij} = 0$ otherwise. Since any DUE can send pairing attempts to multiple DUEs but can only accept one pairing attempt, the following constraints are satisfied:

$$\forall j, \sum_{i=1}^{X} c_{ij} \leq 1 \tag{26}$$

Thus, the probability of each pairing attempts is:

$$\bar{p}_i = 1 - \prod_{j=1}^{Y} (1 - p_{ij})^{c_{ij}} \tag{27}$$

where $p_{ij} = p_i / Y$. And the average probability p_{SR} of all pairing attempts is:

$$p_{SR} = \frac{\sum_{i=1}^{X} (1 - \prod_{j=1}^{Y} (1 - p_{ij})^{c_{ij}})}{X} \tag{28}$$

Then the problem of probability maximization of DUE pairing can be formalized as:

$$\begin{aligned} &\max p_{SR} \\ &s.t. \quad \forall j, \sum_{i=1}^{X} c_{ij} \leq 1, c_{ij} \in \{0, 1\} \end{aligned} \tag{29}$$

Considering the discreteness of pairing data, this is a typical combinatorial optimization problem. We present the DUE pairing algorithm based on hill-climbing to solve the problem. The process of DUE pairing is illustrated in Algorithm 4. Let $E[i]$ be the pairing DUE of pairing attempt i. For each unassigned DUE, if the pairing to attempt i can obtain higher probability, we assign the DUE to the attempt i.

IV. Performance Evaluation

In this section, we evaluate the proposed coalition formation algorithm, the probability prediction model, and the pairing probability maximization algorithm. For the coalition formation algorithm, we compare CFAD with other two methods in terms of throughput and energy efficiency of DUEs. For the probability prediction model, we compared the prediction accuracy with another method based on ten test samples. For the DUE pairing probability maximization algorithm, we compare the pairing probability with the other benchmark algorithms. We consider a single-cell scenario with simplified interference. The cell radius is 300 meters, the maximum D2D communication distance is 50 meters; the base station transmitting power is 46dBm; the circuit power consumption of DUEs is 23dBm. In addition, we consider that higher throughput and lower power consumption are equally important, *i.e.*, $w_1 = w_2 = 0.5$.

Algorithm 4 DUE Pairing

Input: X, Y, $\boldsymbol{c} \leftarrow \mathbf{0}$
for $i \leftarrow 1$ to X **do**
  $E[i] \leftarrow 0$;
end for
for $i \leftarrow 1$ to X **do**
  $N_i \leftarrow$ set of DUEs unassigned to pairing attempt i;
  for each $j \in N_i$ **do**
    if $p_{i,j} > p_{i,Ei}$ **then**
      replace j with $E[i]$;
      $c_{i,j} = 0; c_{i,E[i]} = 1$;
    end if
  end for
end for
return $\boldsymbol{c}$;

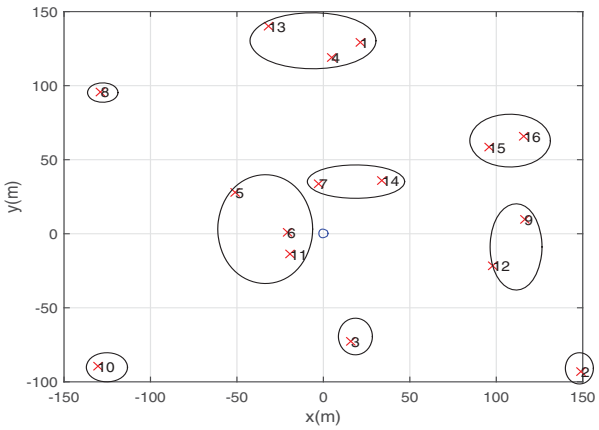

Fig. 2. Experimental results of the coalition structure.

A. Performance of coalition formation algorithm of DUEs

Fig. 2 plots a snapshot of a coalition structure of DUEs of CFAD algorithm. The BS is located at position (0,0), and the DUEs are distributed in a 300*300 square area. By applying CFAD algorithm, the DUEs can self-organize into a stable coalitional structure with the maximum payoff.

Fig. 3 shows the variation of average throughput versus the number of DUEs. We choose two methods for comparison. One is simple D2D, where DUEs don't form coalitions. The other one is the algorithm mentioned in [11], where the power limitation is not taken into account. As can be seen from Fig. 3, the average throughput of all the methods increases when the number of DUEs increases. Specifically, we can also see that the CFAD outperforms the other two methods in all cases because we use water-filling power allocation to allocate higher power to the channels with higher signal-to-noise ratio (SNR).

Fig. 4 shows the variation of average energy efficiency versus the number of DUEs. Here, the average energy efficiency

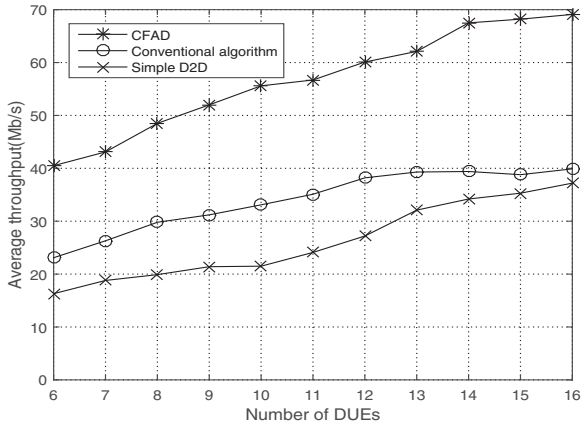

Fig. 3. Average Throughput Versus The Number of DUEs.

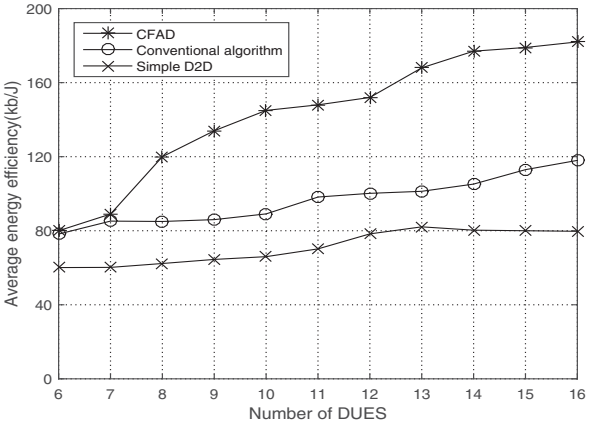

Fig. 4. Average energy efficiency versus the number of DUEs.

of DUE coalition structure is defined as:

$$e_{\mathcal{N}} = \frac{\sum_{S\in\mathcal{A}} T_S}{\sum_{S\in\mathcal{A}} P_c^S + \sum_{S\in\mathcal{A}} \sum_{i\in S} p_{cir}^i} \tag{30}$$

where T_S is the throughput of the DUE, which can be calculated by Eq.(7); P_c^S is the transmitting power of the DUE, which can be calculated by Eq.(9); p_{cir}^i is the circuit power consumption of the DUE. In simple D2D, the energy efficiency of a single D2D is:

$$e = \frac{\log(1 + \frac{p_{BS}H_{DB}}{\sigma^2})}{p_{DUE} + p_{cir}} \tag{31}$$

where p_{BS} is the BS transmitting power, H_{DB} is the channel gain and p_{DUE} is the transmitting power of DUE. It can be seen from Fig. 4 that the average energy efficiency of all the methods increases when the number of DUEs goes up. Specifically, we can see that the performance of CFAD outperforms the other two methods because the coalitions in CFAD are always made up of DUEs close to each other in order to reduce path loss.

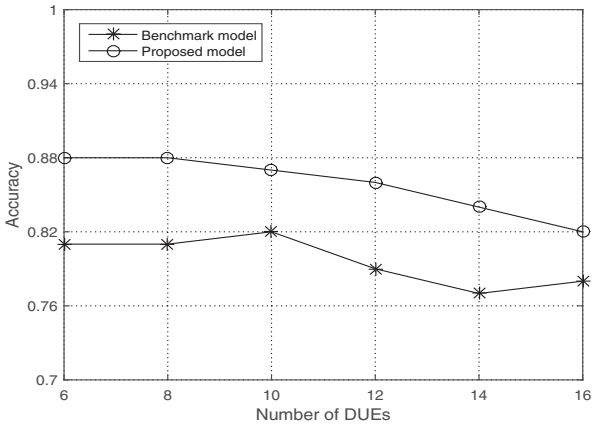

Fig. 5. Accuracy versus the number of DUEs

B. Performance of probability prediction and optimization of DUE pairing

1) Probability prediction: Test samples are used to evaluate the accuracy of the proposed prediction model. We input the coalition structure obtained by CFAD proposed in section 2. into the Network Simulator WINTERsim [19] to simulate the DUE pairing and count pairing results as training data. In this paper, we consider the influence factors of probability p_i as search radius, throughput, power consumption, power limitation, and energy efficiency as they have a high correlation with coalition formation, which affects the results of DUE pairing. Thus, the eigenvector $\mathbf{x}_i$ can be defined as:

$$\mathbf{x}_i = (x_1, x_2, x_3, x_4, x_5)^T \tag{32}$$

The elements of $\mathbf{x}_i$ represent the factors mentioned above in turn. After training, θ^T in Eq.(24) is:

$$\theta^T = (0.2253, -0.00556, 0.00202, -0.00247, 0.00986, 0.00274)^T \tag{33}$$

We use the regression functions in Eq.(24) to predict pairing probability. The accuracy on the test samples versus the number of DUEs is shown in Fig. 5. We observe that our model outperforms the benchmark model mentioned in [20]. Specifically, our prediction model achieves a high accuracy up to 93%, which is 7% higher than that of the benchmark model. This is because that the model proposed in this paper is based on prior data while the benchmark model based on Q-learning is not.

2) Probability optimization: First, we introduce two benchmark algorithms:

Learning-to-rank algorithm: [21] propose a machine learning ranking method. This method obtains the matching score of each DUE from the historical data of the base station for the pairing attempt, and sends a message to the DUE with the highest score.

Multi-agent algorithm: [22] uses a multi-agent DUE distribution system that is superior to known systems for optimizing the pairing probability.

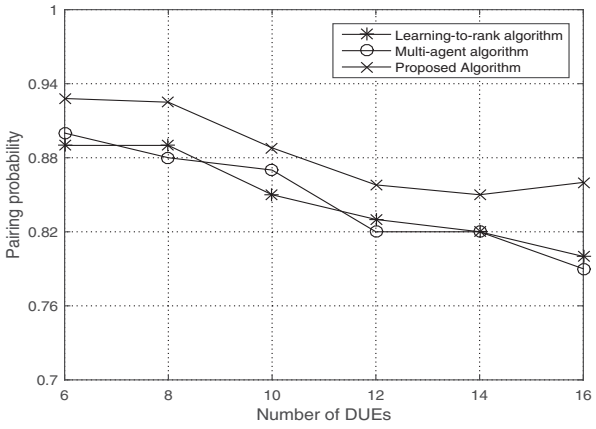

Fig. 6. Pairing probability versus the number of DUEs.

Fig.6 plots the pairing probability of the three algorithms versus the number of DUEs. The results show that Learning-to-rank algorithm and Multi-agent algorithm have almost the same probability of pairing that gradually reduces with the increasing number of DUEs. It is because that each DUE of Learning-to-rank algorithm and Multi-agent algorithm can only handle one pairing attempt at the same time. So when the number of pairing attempts is greater than the number of DUEs, the pairing probability of pairing will decrease.

V. Conclusion

In this paper, we have proposed a novel DUE distribution method based on the coalitional game to form several disjoint coalitions, which achieves the balance of the throughput and the power consumption of the coalition structure. To further enhance QoS of D2D communication, we have also proposed a method to predict and optimize the pairing probability of DUEs. The performance of the two methods proposed has been evaluated by experiments. In the future, we will further investigate some interesting problems in the distributed pairing management method.

Acknowledgement

This work has been supported in part by NSFC grant (No.61872193, 61872186, 61602263), NSF of Jiangsu province (No. BK20160916), and China Postdoctoral Science Foundation (No. 2018M630590).

References

[1] F. Rebecchi, M. D. de Amorim, V. Conan, A. Passarella, R. Bruno, and M. Conti, "Data offloading techniques in cellular networks: A survey," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 2, pp. 580-603, 2015.

[2] J. Xu, Z. Rao, L. Xu, D. Yang and T. Li, "Incentive Mechanism for Multiple Cooperative Tasks with Compatible Users in Mobile Crowd Sensing via Online Communities," in *IEEE Transactions on Mobile Computing*. doi: 10.1109/TMC.2019.2911512.

[3] J. Xu, J. Xiang, and D. Yang, "Incentive Mechanisms for Time Window Dependent Tasks in Mobile Crowdsensing," *IEEE Transactions on Wireless Communications*, vol. 14, no. 11, pp. 6353-6364, 2015.

[4] S. Chen, K. Wang, C. Zhao, H. Zhang, and Y. Sun, "Accelerated distributed optimization design for reconstruction of big sensory data," *IEEE Internet of Things Journal*, vol. 4, no. 5, pp. 1716-1725, 2017.

[5] S. Chen, Z. Wang, H. Zhang, G. Yang, and K. Wang, "Fog-based optimized Kronecker-supported compression design for industrial IoT," *IEEE Transactions on Sustainable Computing*, 2019.

[6] P. Mach, Z. Becvar, and T. Vanek, "In-band device-to-device communication in OFDMA cellular networks: A survey and challenges," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 4, pp. 1885-1922, 2015.

[7] W. Lu, X. Zheng, J. Xu, S. Chen, and L. Yang, "Improving physical layer security and efficiency in D2D underlay communication," *Wireless Networks*, vol. 4, pp. 1-16, 2018.

[8] H. Chen, D. Wu, and Y. Cai, "Coalition formation game for green resource management in D2D communications," *Communications Letters IEEE*, vol. 18, no. 8, pp. 1395-1398, 2014.

[9] Y. Zhang, F. Li, X. Ma, K. Wang, and X. Liu, "Cooperative energy-efficient content dissemination using coalition formation game over device-to-device communications," *Canadian Journal of Electrical and Computer Engineering*, vol. 39, no. 1, pp. 2-10, 2016.

[10] J. Hu, W. Heng, Y. Zhu, G. Wang, X. Li, and J. Wu, "Overlapping coalition formation games for joint interference management and resource allocation in D2D communications," *IEEE Access*, vol. 6, pp. 6341-6349, 2018.

[11] Y. Zeng, H. Hu, T. Xu, and B. Jia, "User pairing stability in D2D-relay networks," *IEEE Communications Letters*, vol. 21, no. 10, pp. 2278-2281, 2017.

[12] S. Nie, Z. Fan, M. Zhao, X. Gu, and L. Zhang, "Q-Learning Based Power Control Algorithm for D2D Communication," *in Proc. 2016 IEEE 27th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, 2016.

[13] Z. Gao, B. Wen, L. Huang, C. Chen, and Z. Su, "Q-Learning-Based Power Control for LTE Enterprise Femtocell Networks," *IEEE Systems Journal*, vol. 11, no. 4, pp. 2699-2707, 2017.

[14] O. Van Den Biggelaar, J. M. Dricot, P. De Doncker, and F. Horlin, "Sensing time and power allocation for cognitive radios using distributed Q-learning," *Eurasip Journal on Wireless Communications & Networking*, vol. 2012, no. 138, pp. 1-12, 2012.

[15] H. Saad, A. Mohamed, and T. ElBatt, "A cooperative Q-learning approach for online power allocation in Femtocell networks," *in Proc. 2013 IEEE 78th Vehicular Technology Conference (VTC Fall)*, 2013, pp. 1-6.

[16] I. Tsamardinos, L. E. Brown, and C. F. Aliferis. "The max-min hill-climbing Bayesian network structure learning algorithm," *Machine Learning*, vol. 65, no. 1, pp. 31-78, 2006.

[17] A. Goldsmith, S. A. Jafar, N. Jomdal, and S. Vishwanath, "Capacity Limits of MIMO Channels," *IEEE Journal on Selected Areas in Communications*, vol. 21, no. 5, pp. 684-702, 2003.

[18] W. Yu, W. Rhee, S. Boyd, and J. Cioffi, "Iterative Water-filling for Gaussian Vector Multiple Access Channels," *IEEE Transactions on Information Theory*, vol. 50, no. 1, pp. 145-151, 2004.

[19] S. Andreev, O. Galinina, A. Pyattaev, K. Johnsson, and Y. Koucheryavy, "Analyzing assisted offloading of cellular user sessions onto D2D links in unlicensed bands," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 1, pp. 67-80, 2015.

[20] R. Moein, B. Malmir, and M. Mousavi. "Evaluating and ranking the learning components of entrepreneurial skills based on a hybrid approach of the M-learning technology and TOPSIS method," *in Proc. International Conference on Industrial Engineering & Operations Management*, 2015.

[21] N. Kumar, S.N. Swain, and C.S.R. Murthy, "A Novel Distributed Q-Learning Based Resource Reservation Framework for Facilitating D2D Content Access Requests in LTE-A Networks," *IEEE Transactions on Network & Service Management*, vol. 15, no. 2, pp. 718-731, 2018.

[22] A. Asheralieva and Y. Miyanaga, "Multi-agent Q-Iearning for autonomous D2D communication," *in Proc. International Symposium on Intelligent Signal Processing & Communication Systems*, 2016, pp. 1-6.