# DUE Distribution and Pairing in D2D Communication

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Part 1

# System Model

# System Model

We consider a single cell D2D communication scenario in the mode of TDMA.

Each DUE is regarded as the transmitter, and BS is receiver.

In cooperative case, the DUEs compose different disjoint coalitions, and all the DUEs in a coalition take up a time slot to carry out one transmitting.

We aim to structure the coalitions of DUEs to improve both the throughput and power consumption

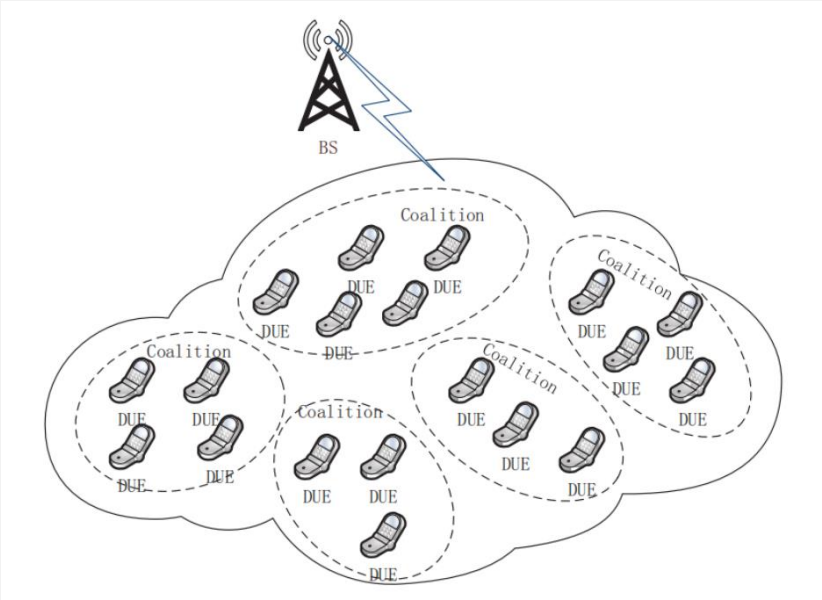


Fig.1 Cooperative communication scenario

# Throughput of the coalition

For the TDMA system, a fixed transmitting power limitation is defined for each time slot.

Then, the average transmitting power limitation for any coalition is

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

where $z_S$ is the transmitting signal vector of each time slot in coalition $S$.

$Q_S$ is the covariance matrix of the transmitting signal

*tr*( ) is the trace of a matrix

# Throughput of the coalition

According to the water-filling power allocation of each DUE in the coalition, the system throughput of the coalition *S* can be defined as:

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

$\lambda_i$ is the eigenvalue of the transmitting signal matrix of DUE *i*,
$\sigma^2$ is the noise of the transmitting signal.
$P_i$ is the power limitation of any DUE *i*

$$s.t. \quad \sum_{i=1}^{|S|} P_i = \overline{P_S}$$

# Power Consumption of the Coalition

the power required by each DUE to propagate its information to the farthest DUE in the coalition S

$$P_{i,i'} = v_0 \cdot \sigma^2 / {g_{i,i'}}^2 \qquad g_{i,i'} = \sqrt{\kappa / {d_{i,i'}}^\beta}$$

*v* is the target average signal-to-noise ratio (SNR)

$g_{i,i}$ is the path fading

$d_{i,i'}$ is the distance

The power consumption of coalition *S* is: $P_c^S = \sum_{i,i' \in S} P_{i,i'}$

We need to maximize the throughput , and minimize the power consumption.

Part 2

# Coalition Formation Algorithm

# Coalition Formation Algorithm for DUEs(CFAD)

We transform the problem into a single objective payoff function for each coalition $S_k$

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

For the coalition structure $A = \bigcup_{k=1,\dots K} \{S_k\}$

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

Objective: $\max_{\mathcal{A} \in \mathfrak{N}} v(\mathcal{A})$

# Coalition Formation Algorithm

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.*, $\{\bigcup_{k=1}^{K'} S_k\} \rightarrow \{\{S_1\}, ..., \{S_{K'}\}\}$.

**Algorithm 1** CFAD

**Input:** $\mathcal{A}' = \{S_1, \cdots, S_T\}$

1: **for** each $S_i \in \mathcal{A}'$ **do**
2:  **repeat**
3:  Combine($S_i$);
4:  Separate($S_i$);
5:  **until** Converged;
6: **end for**
7: **return** $\mathcal{A}$;

# Distributed Coalition Formation Algorithm

**Function of Combine( )**

1. Broadcast information to other coalitions to state its existent
2. Wait the requirement from other coalition until $T_{w_{\max}}$
3. Combine the coalition such that maximize utility of the combined coalition
4. Send the requirement to the coalition that can maximize utility of the combined coalition
5. if accepted then

   Combine, and goto 1

   else

   Goto 4

# Distributed Coalition Formation Algorithm

## Function of Separate( )

**Algorithm 3** Function Separate() of CFAD

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

# Analysis of Coalition Formation Algorithm

**Theorem 2.** *CFAD is convergent.*

## Complexity analysis

(1) Combination stage

For each DUE, there are at most T−1 equipments can be combine, and the computational complexity is O(T).

(2) Separation stage

In each round, the number of all possible partitions of the coalition structure is Bell number, we can control the complexity of the algorithm by limiting the size of the coalition.

Part 3

# Probability Prediction and Optimization of DUE Pairing

# Probability Prediction of DUE Pairing

We learn the behavior of one DUE trying to pair with another DUE. Binary variable y represent the result for each pairing attempt. Given the eigenvector xi, we choose Logistic Regression as the prediction model. where θ is the regression coefficient.

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

The logit function of xi is

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

The likelihood function of the data set containing n independent paired samples

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

where $h_\theta(\mathbf{x}_i) = p(y = 1|\mathbf{x}_i; \theta)$

# Probability Prediction of DUE Pairing

The parameter of the prediction model is $\theta^T$, which maximizes the likelihood function.

The iteration equation based on the gradient descent is:

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

where η is the learning rate of the gradient descent.

Then the probability after training is:

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

# Optimization of DUE Pairing

There are X pairing attempts and Y pairing DUEs. Then the pairing result can be represented as the following matrix c.

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

Define $p_{SR}$ as the average probability of pairing attempts

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

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

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

Part 4

# Performance Evaluation

# Performance of CFAD

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

$w1 = w2 = 0.5$

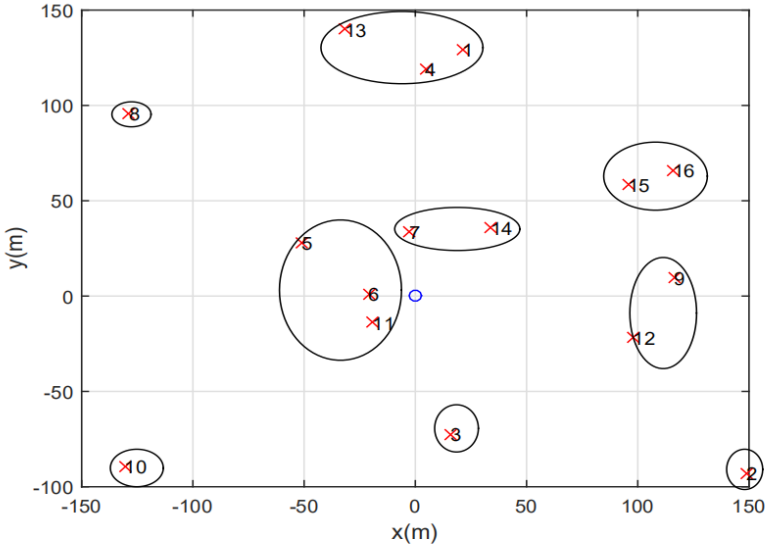


Fig. 2. Experimental results of the coalition structure.

A coalition structure of DUEs of CFAD algorithm

The DUEs can self-organize into a stable coalition structure with maximum payoff.

# Performance of CFAD

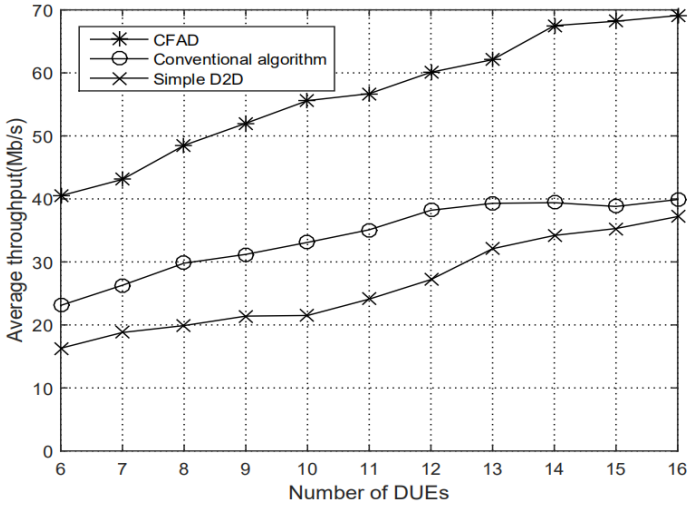


Fig. 3. Average Throughput Versus The Number of DUEs.

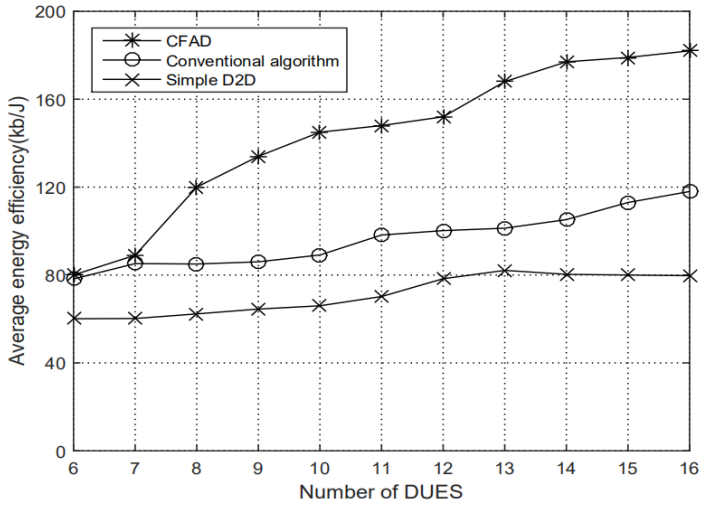


Fig. 4. Average energy efficiency versus the number of DUEs.

We use water-filling power allocation to allocate higher power to the channels with higher SNR.

The coalitions in CFAD are always made up of DUEs close to each other in order to reduce path loss.

# Performance of Probability Prediction and Optimization

We consider the influence factors of probability pi as search radius, throughput, power consumption, power limitation, and energy efficiency.

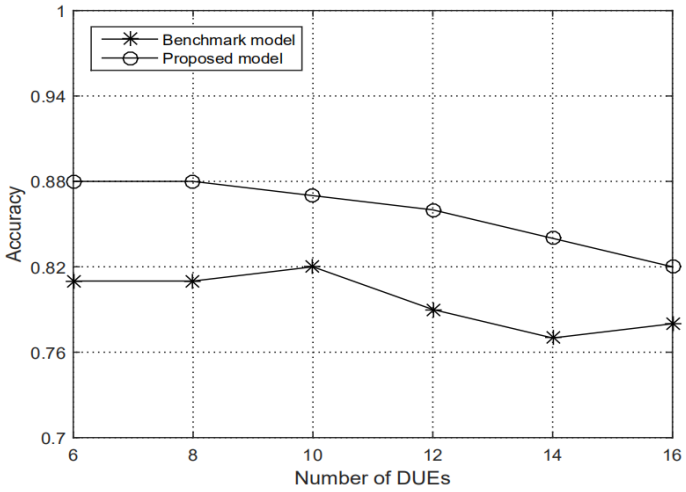


Fig. 5. Accuracy versus the number of DUEs

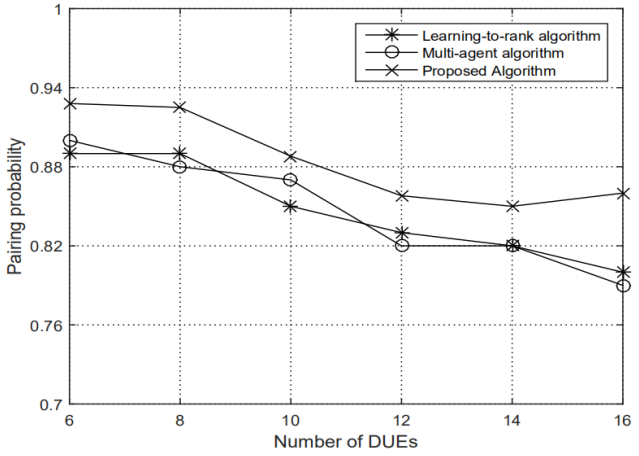


Fig. 6. Pairing probability versus the number of DUEs.

Our pairing algorithm achieves a high pairing success rate up to 93%, which is 7% higher than benchmark algorithms.

# Thank you!

## Q & A

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