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# Energy Efficiency Optimization Algorithm Based on CNN-SPP-AM for D2D Communication

Shixia Qiao*
College of Electronic Information Engineering
Changchun University of Science and Technology
Changchun, China
* Corresponding author: 2519013881@qq.com

Kaijin Zheng
College of Electronic Information Engineering
Changchun University of Science and Technology
Changchun, China
e-mail: 462224976@qq.com

Jialu Zhou
College of Electronic Information Engineering
Changchun University of Science and Technology
Changchun, China
[c] e-mail: zhoujialu0580@163.com

Zitao Qu
College of Electronic Information Engineering
Changchun University of Science and Technology
Changchun, China
e-mail: 2863902358@qq.com

*Abstract*—**The underlying multiplexed spectrum in D2D communications has an impact on spectral efficiency and multiplexing can introduce serious interference in communication systems. Many communication devices are subject to limited power supplies. Therefore, Therefore, we need to address the issue of resource allocation in D2D communication and maximise energy efficiency. Therefore, this paper proposes a CNN-SPP-AM based optimisation method for energy efficiency of D2D communication, which firstly pools the pooling layer of the convolutional neural network with spatial pyramids and uses a zero padding strategy in the output layer to remove the input size limitation. Then, the attention mechanism is introduced into the optimised convolutional neural network to improve the learning ability of individual features.The simulation results show that the proposed CNN-SPP-AM outperforms other neural networks in terms of system energy efficiency and system sum rate.**

***Keywords—D2D communication, energy efficiency optimization , attention mechanism, resource allocation***

## I. INTRODUCTION

With the explosive growth of smart terminal devices, ultra-dense networks have become an important network form and technology application means in 5G and 6G mobile communication scenarios [1]. Device-to-device (D2D) communication, as one of the key driving technologies for 5G, eliminates the involvement of base stations and enables direct transmission of data from neighbouring terminals. It can improve network capacity, spectrum utilisation and system throughput. However, in the underlying technology, the main cause of interference is the reuse of spectrum maintained by the D2D user multiplexing CUEs, as well as limitations in the power supply of the devices themselves. Therefore, the fundamental problem that must be solved is resource allocation with the objective function of maximising the energy efficiency of the system [2].

In different D2D communication scenarios, several resource allocation schemes and improvement methods exist. In recent years, D2D communication research has focused on energy efficiency issues. In [3], a two-stage resource allocation algorithm is proposed to maximise the energy efficiency of D2D pairs. In the literature [4], the resource efficiency of CUE is maximised using the Dinkelbach method and the Lagrangian pairwise decomposition. DC programming and CCCP methods are then used in order to obtain the power allocation of D2D pairs that multiplex unallocated resource blocks.Deep learning is an effective technique that can be used in solving resource management problems in ultra-low time complexity wireless networks. In [5], the application of deep learning in wireless networks was investigated. In [6], the joint resource allocation problem for heterogeneous networks is presented. An exhaustive approach is used to generate the training dataset and a convolutional neural network based approach is proposed to obtain decisions for channel allocation and power control. In [7], the authors proposed an algorithm based on convex approximation and in order to reduce the computational complexity, a convolutional neural network is used to design the resource management framework. In[8], the CNN model consists of a convolutional layer, a pooling layer and a fully connected layer. study [9], combining CNNs with spatial pyramid pooling (SPP) overcomes the problem of CNNs in accepting arbitrary input sizes.

It is aimed at the problems of low spectrum utilization and high interference in D2D communication, we propose a convolutional neural network-based approach for improving the energy efficiency of device-to-device (D2D) communication in multicellular networks.The paper is structured as follows: a system model of a multicellular network is provided in Section II, and the proposed methodology is outlined in Section III. Simulation results are obtained in Section IV. Section V summarises the main findings of this study.

## II. SYSTEM MODEL AND PROBLEM FORMULATION

### A. System model

In this section we explore the environment and operating principles of a wireless network system that utilises D2D underlying multi-cell cellular networks with uplink resource sharing. The system model comprises multiple cells, each with a base station (BS) located at the center, as depicted in Figure 1. The cellular network is randomly distributed with M cellular



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users and N D2D pairs. B=(B1, B2,...,BB) denotes the set of BSs in each site, while the sets of CUEs and D2D pairs served by base station B1 are denoted by $CUE=\{CUE_i^{B1} / i=1,2,3,...M\}$ and $DUE=\{DUE_j^{B1} / j=1,2,3,...,N\}$ respectively.

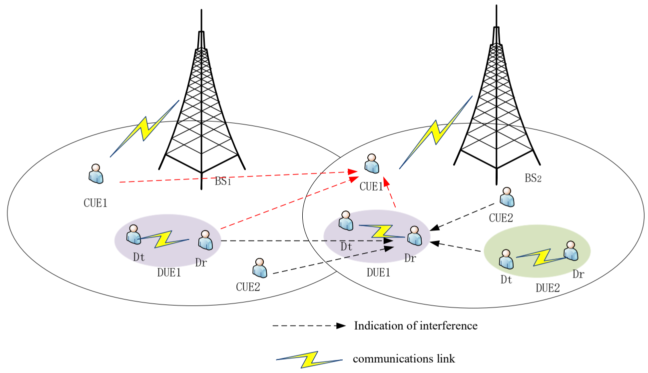


Figure 1. Model diagram of a dual base station D2D communication system (uplink)

The interference presented in the system is shown in Figure 1 .We make the assumption that uplink resource blocks have been pre-allocated orthogonally to all CUEs within each cell to avoid any intra-frame interference in the CUEs' signals. To simplify matters, we refer to the mth allocated resource block for a CUE as $C_m^b$ . A D2D pair consists of a D2D transmitter (D2D-Tx) and a D2D receiver (D2D-Rx). To achieve spectral efficiency, each of the CUE's m resource blocks can be allocated to multiple D2D pairs. In such cases, the transmit power level will be adjusted for the transmitter of the mth resource block, which includes both the CUE and the D2D transmitter.

According to the system model, the total disturbance equation for CUE is shown below

$$I_m^b = \sum_{n=1}^{N}\left(PD_{n,m}^b \cdot g_{n,B}^b\right) + \sum_{b'=1,b'\neq b}^{B}\left(PC_m^{b'} \cdot g_{m,B}^{b',b}\right) + \sum_{b'=1,b'\neq b}^{B}\left(\sum_{n=1}^{N}\left(PD_{n,m}^{b'} \cdot g_{n,B}^{b',b}\right)\right) \quad (1)$$

Similarly, The total interference for a D2D pair is given by

$$I_n^b = PC_m^b g_{m,n}^b + \sum_{n'=1,n'\neq n}^{N} PD_{n',m}^b \cdot g_{n',n}^b + \sum_{b'=1,b'\neq b}^{B} PC_m^{b'} \cdot g_{m,n}^{b',b} + \sum_{\substack{b'=1,n=1\\ b'\neq b}}^{B} \sum_{n,m}^{N} PD_{n,n}^{b'} \cdot g_{n,b}^{b',b} \quad (2)$$

According to the Shannon-Hartley (Shannon) theorem, the normalised achievable data rate equation for CUE and D2D pairs is

$$R_m^b = \log_2\left(1+\frac{PC_m^b g_{m,B}^b}{I_m^b + N_0^2}\right) \quad (3)$$

$$R_n^b = \sum_{m=1}^{M}\log_2\left(1+\frac{PD_{n,m}^b \cdot g_{m,n}^b}{I_n^b + N_o^2}\right) \quad (4)$$

where $g_{m,B}^b$ and $g_{n,n}^b$ denote the gain between the CUE to the base station and the gain between the D2D pairs, respectively.

The system and rate can be expressed as

$$R_{sum}^{system} = R_{sum}^m + R_{sum}^n \quad (5)$$

Finally, the total power consumption of the CUE and D2D pairs is calculated by the following equations, respectively

$$PC_m^b = \frac{1}{\eta} PC_m^b + P_{cir} \quad (6)$$

$$PD_n^b = \frac{1}{\eta}\sum_{m=1}^{M} PD_{n,m}^b + 2P_{cir} \quad (7)$$

where η denotes the power amplifier efficiency factor and Pcir denotes the circuit power consumption of a mobile device.

## *B. Issue formation*

The aim of this study is to maximise the overall energy efficiency of D2D communication under cellular network, the system energy efficiency EE is defined as the ratio of achievable throughput to the total power consumption in the communication network, Therefore, the objective function can be defined in the following form:

$$\max \eta_{EE} = \frac{\sum_{b=1}^{B}\left(\sum_{n=1}^{N}\left(R_n^b\right)+\sum_{m=1}^{M}\left(R_m^b\right)\right)}{\sum_{b=1}^{B}\left(\sum_{n=1}^{N} PD_n^b + \sum_{m=1}^{M} PC_m^b\right)} \quad (8)$$

Set C1: $R_m^b \geq R_{\min}^c, \forall b,m$

C2: $R_n^b \geq R_{\min}^D, \forall b,n$

C3: $0 \leq PC_m^b \leq P_{\max}, \forall b,m$

C4: $0 \leq PD_{n,m}^b \leq P_{\max}, \forall b,n,m$

C5: $0 \leq \sum_{m=1}^{M}\left(PD_{n,m}^b\right) \leq P_{\max}, \forall b,n$

Where $PD_n^b$ and $PC_m^b$ indicate the set of transmit powers of the CUE and D2D transmitters, respectively. Constraints C1 and C2 indicate that the data rates of the CUE and D2D pairs must be higher than the minimum data rates of the CUE and D2D, respectively. Constraints C3, C4 and C5 indicate the maximum power budget for each device.

The objective function is a non-linear non-convex optimization function, and it is difficult to obtain the optimal solution directly. Therefore, In [10], a convex approximation-based algorithm for joint channel assignment and power control is proposed,and a convolutional neural network-based algorithm is designed for the sub-optimal assignment results to reduce the complexity of the algorithm and improve the energy efficiency of the system.

# III. ENERGY EFFICIENCY OPTIMIZATION ALGORITHM BASED ON CNN-SPP-AM FOR D2D COMMUNICATION

The CNN presents a challenge due to the requirement of fixed input and output data sizes during both the training and testing phases. Additionally, since the number of CUEs and D2Ds can differ between scenes, the input and output sizes may vary as well. To overcome this issue, we introduce a spatial pyramid pooling layer between the convolutional and fully connected layers, which allows us to remove the fixed input size



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constraint. Moreover, we use a zero-padding strategy on the output layer to eliminate the fixed output size limitation.

### *A. Proposed CNN architecture*

The CNN-SPP architecture proposed in this paper adds the SPP module before the convolutional or fully connected layers to overcome the limitations of the model in terms of accepting various input sizes.

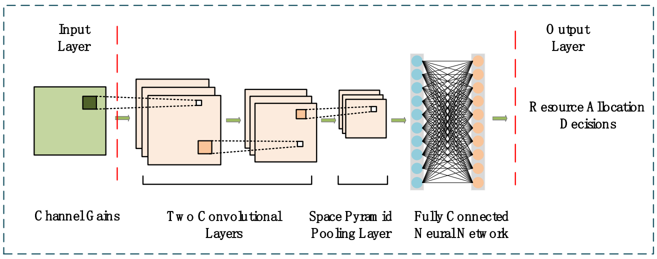


Figure 2 CNN architecture

#### *1) Convolutional layers*

The convolution layer is the process used to extract the features of the data. In the proposed CNN architecture, there are two interconnected convolutional layers, each with a filter set to 16, a shape of (2, 2) and a step size of 1. No fill strategy is used. After each convolutional layer, Leaky ReLU is used as the activation function.

#### *2) Space Pyramid Pool Level*

The function of the pooling layer is to gradually reduce the size of the representation space, known as downsampling or compression. The SPP layer includes one, four, and sixteen pooled regions, allowing it to preserve spatial information by combining the convolution-generated feature map with multiple spatial bins. The SPP idea is to maintain spatial information mainly by merging the feature maps generated by convolution with multiple spatial boxes. In each spatial box, the neural network is downsampled using the maximum pool. The results are eventually aggregated into a fixed-size representation and passed to the fully connected layer.

#### *3) Fully connected layer*

The main purpose of the fully connected layer is to combine the previously extracted features and produce an output value. The neurons in this layer make full connections to all neurons in the previous layer, which determines the weights and biases. In the CNN architecture, 512 neurons are used in the fully connected layer, with ReLU as the activation function.

### *B. Attention mechanism*

In recent years, attention mechanisms have been continuously applied in deep learning, which is essentially similar to the attention mechanism in human selective vision, selecting the more critical information from all the information [11].

When using linear mapping to compute attention weights, we first assume that we have an input feature vector x with dimension d. The weight matrix and bias vector are initialised: a fully connected layer is introduced to initialise the weight matrix W and the bias vector b. A linear mapping is then performed: the input features x are matrix multiplied with the weight matrix W and the bias vector b is added to obtain a scalar value z. The scalar value z is non-linearly transformed using ReLU as the activation function to increase the expressiveness of the model. Next, for the resource allocation attention weights, the scalar z can be normalised to ensure that the sum of the attention weights is 1. The final output attention weights represent the importance or weight of each resource in the allocation and can be used to guide the resource allocation decision.It is important to note that the weight matrix W and the bias vector b are parameters of the model and need to be learned during the training process by a back propagation algorithm. During the training process, the attention weights are automatically adjusted and optimised based on the data and objectives to maximise the energy efficiency of the resource allocation.

### *C. Data training process*

The dataset of this paper consists of two parts of data. The first part consists of channel gains for all link communications as input; the second part consists of power allocation policies as output. By varying the number of 2 to 4 cellular users as well as the number of D2D users, we created multiple scenarios in the dataset, each consisting of 20,000 randomly generated channel realities. After completing the above process, we obtained an internal dataset and divided it into a training set and a test set according to the 80/20 rule. We then implemented a convolutional neural network-based algorithm using the Keras deep learning toolkit and a TensorFlow backend.

The process of data training involves training for different scenarios and different input-output sizes. Zero padding is added to the outputs of the dataset to form fixed-length output vectors for the fully connected layer. Once the CNN-SPP-AM model is trained, a testing model is formed, and the channel gains of all link communications are inputted into the trained model to obtain resource allocation strategies.

## IV. SIMULATION AND ANALYSIS OF RESULT

TABLE 1 Parameter Settings

| Parameters | Value |
|---|---|
| Cell radius | 500 metres |
| Number of base stations | 2 |
| Number of cellular users | 2-4 |
| Number of D2D pairs | 2-4 |
| D2D to distance | 15 metres |
| Path loss between the base station and other equipment | 128.1 + 37.6 log10(d(km)) |
| Path loss between CUE and D2D | 128.1 + 37.6 log10(d(km)) |
| Path loss between D2D pairs | 148 + 40 log10(d(km)) |
| Noise | -121.45 (dBm) |
| Power budget | 23 (dBm) |

The experimental simulation parameters are shown in Table 1. We compare the performance metrics of each algorithm by using the traditional fully connected algorithm (FCN), the convolutional neural network algorithm (CNN), the CNN-SPP algorithm, the convex approximation (CA) based algorithm and the proposed CNN-SPP-AM algorithm, where the convex approximation algorithm is used as the highest benchmark.



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### A. System energy efficiency

As shown in Fig. 3, the system energy efficiency varies with the number of CUEs when determining the number of D2D pairs. The reason for this is that when the number of CUEs increases the block of resources reused by the D2D can be steadily expanded. Therefore, it can be observed that CNN-SPP-AM can achieve a performance of CA of about 96% in terms of system energy efficiency.

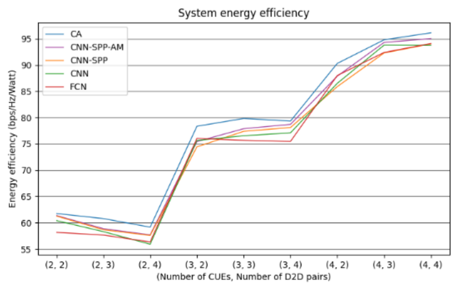


Figure 3 Comparison of system energy efficiency for different algorithms

### B. Systems sum rate

The comparison of system sum rate is shown in Figure 4. Since D2D communication has the property of increasing network capacity, spectrum utilization, and system throughput through spatial multiplexing, the system and rate increase with the number of D2D pairs. The D2D pairs can achieve significantly higher achievable data rates with a small amount of transmission power, which results in a larger system sum rate.

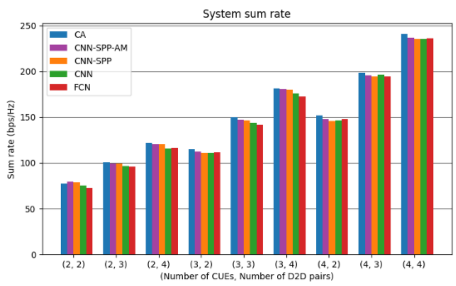


Figure 4 System and rate comparison for different algorithms

### C. System power consumption

From the comparison of system energy consumption in Fig. 5, it can be seen that CA consumes the least system energy, but the system sum rate are at their maximum. Moreover, the power consumption of other algorithms is not much different. According to the energy efficiency formula, the higher the system sum rate, the higher the system energy efficiency.

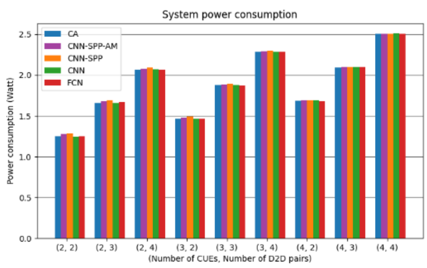


Figure 5 Comparison of system power consumption for different algorithms

## V. CONCLUSION

In this paper, an energy efficiency optimization scheme based on d2d is proposed for multi-cell network systems. The scheme uses CNN networks as the base network and adds spatial pyramid pooling and attention mechanisms to achieve the goals of eliminating input-output size limitations and improving information attention. The process of data training involves training for different scenarios and different input-output sizes. Zero padding is added to the outputs of the dataset to form fixed-length output vectors for the fully connected layer. Once the CNN-SPP-AM model is trained, a testing model is formed, and the channel gains of all link communications are inputted into the trained model to obtain resource allocation strategies.

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