Modified CNN to Maximize Energy Efficiency in D2D Underlying with Multi-Cell Cellular Network

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***Abstract*—The usage of Device-to-Device (D2D) underlaying to reuse spectrum has a substantial influence on spectrum efficiency. On the other side, interference issues arise as a result of frequency reused by D2D users. Furthermore, wearable devices or communication devices have limited power sources, such as batteries. As a result, the fundamental problem formulation that must be solved is power allocation, with the goal function being to maximize the energy efficiency of the system. In order to provide optimum power allocation, conventional methods such as Convex Approximation (CA)-based algorithm need to run multiple iterations to solve the non-convex problem formulation. Therefore, Convolution Neural Network (CNN) as part of Deep Learning (DL) is utilized to approach (CA)-based algorithm for generating power allocation policies to maximize the systems energy efficiency. However, the conventional method of CNN has limitations in accepting arbitrary input size. Accordingly, to the limitation of CNN, this research proposed the combination of CNN with Spatial Pyramid Pooling (SPP) to overcome the limitation on the input size of conventional CNN. Specifically, the inputs of the model are the user's channel state information, and its outputs are power control policies. The simulation results show that both CNN-SPP and CNN can achieve similar performance to the traditional method up to 95% accuracy. Furthermore, the combination of CNN and SPP can overcome the limitation on the input size of the conventional CNN method, reducing the number of models that must be trained to just one and applying it to all scenarios regardless of the number of CUEs D2D pairs.**

***Keywords*—Convolutional Neural Network, Device-to-Device underlaying, Energy efficiency, Power Allocation, Spatial Pyramid Pooling.**

I. Introduction

One of the enabler keys to the success of 5G technology is massive Machine Type Communication (mMTC), which has a tremendous development impact in terms of applications and services given in 5G technology. Such as smart houses, smart cities, smart agriculture, smart building, and smart automobile. This expansion is always associated with increases in demand for high data rates, low latency, and Quality of Service (QoS). This growth, however, is not equivalent to the availability of frequency as a resource in communication [1]. As a result, the system needs a solution that can optimize the limited available frequencies in order to provide the various services.

Device-to-Device (D2D) communication is one technology that facilitates 5G as mMTC. D2D technology enables users to send data directly without going via a base station. D2D technology is classified into two forms based on frequency: overlaying and underlying. In overlaying, D2D users utilize a distinct frequency, but in underlaying, D2D users reuse the frequency maintained by the cellular user equipment (CUE). The D2D underlying technology outperforms spectrum efficiency and network capacity due to its ability to reuse CUE frequencies. However, the use of frequencies in several devices causes interference problems. Furthermore, wearable devices or communication devices have limited power sources, such as batteries. Hence, besides interference problems, energy efficiency should be considered due to the energy limitations of each device. As a result, the fundamental problem formulation that must be solved is power allocation, with the goal function being to maximize the energy efficiency of the system [2].

In the study [3], a channel allocation technique based on weighted bipartite matching is used to solve the interference problem. The goal of the study is to raise the systems data rate. D2D users will be assigned to the channel to boost the systems data rate. The results reveal that the systems interference level may be lowered, increasing the total rate. In research [4], the objective is to solve interference concerns by integrating channel allocation and power allocation systems. Earlier, the author defined channel allocation and power allocation as Mixed-Integer non-linear programming (MIP) problems. Then divide the problem formulation into two stages: the greedy heuristic method handling channel allocation and the dual Lagrangian method handling power allocation. The total rate has increased. However, the time complexity is significanly high as the trade-off.

In the study [5], channel allocation and power allocation strategies are combined to boost the systems energy efficiency. The author began by converting the problem formulation to a MIP problem formulation. Then, the author developed a two-layer Convex Approximation Iteration Algorithm (CAIA) to give a feasible solution. The simulation findings reveal that CAIAs performance improves the systems energy efficiency while increasing its time complexity. Research [6] solves interference with channel allocation and power control schemes with the same goal in mind. The problem formulation, a non-convex problem, is first modified into a tractable convex optimization problem. The author then devises a two-stage technique for resolving the problem. The Dinkelbach method is utilized to channel allocation, and then Lagrangian is used to handle power allocation.

Deep Learning, as part of Machine Learning, has become a popular study topic in a variety of fields due to its significant advantages over traditional approaches. For example, [7], [8], and [9] are examples of Deep Learning applications in real-time face recognition, agriculture, and healthcare, respectively. Although Deep Learning has been widely used in the computer science arena, its deployment has started to overcome various problems in wireless communication systems. Such as channel estimation, data detection, and signal classification [10]. Deep Neural Network (DNN) is utilized in research [11] to solve interference problems with the power allocation scheme. The goal of the research is to maximize the system's energy efficiency. The model of DNN consists of two modules, namely total transmit power network (Tnet) and the power allocation network (Pnet). The Pnet module determines the proportion of transmit power allocated to each user. While, the Tnet module ensures that the power allocation does not exceed the maximum transmit power. DNN-based power allocation can attain near-optimal performance with a short calculation time. The research [12] employed a Convolution Neural Network (CNN) with the same goal. The CNN model consists of convolutional layers, pooling layers and fully connected layers. The CNN method outperforms the other benchmark methods and achieves similar performance to the traditional method. On the other hand, research [14] tries to overcome the problem of CNN in accepting arbitrary input size by combining CNN with Spatial Pyramid Pooling (SPP). However, the method used is for hand gesture recognition.

This research goal is to use CNN-SPP as the proposed method to approach the performance of the traditional iterative algorithm for generating power allocation policies to maximize the systems energy efficiency. The proposed method consists of convolutional layers, spatial pyramid pooling, and fully connected layers. Firstly, the CNN-SPP model is trained on a variety of datasets. Channel gain is utilized as the input model, while power allocation policies were used as the output. As a result, the proposed method achieves similar performance to the conventional method with ultra-low time consumption.

II. System Model and Problem Formulation

A. System Model

This section explained the system model and work policy in Wireless Communication System (WCS). The system is modelled with Device-to-Device (D2D) underlying with Cellular User Equipment (CUE) in uplink communication. Moreover, the system model consists of multiple cells. Each cell has one B Base Station (BS) located in the middle of the cell. Every cell consists of the number of K CUE and N D2D pairs, which are randomly distributed along with the cell. Every cell consists of the number of K CUE and N D2D pairs, which are randomly distributed along with the cell. In order to simplify the notation, set of BS in every site is symbolized with $B = (B_1,\ B_2,\ ...,\ B_B)$, and set of CUE and D2D pairs in B_b BS are symbolized with $CUE = (CUE_1^b,\ CUE_2^b,\ ...,\ CUE_K^b)$ and $D2D = (D2D_1^b,\ D2D_2^b,\ D2D_3^b, ...,\ D2D_N^b)$, respectively. Furthermore, the system model is demonstrated in Fig. 1.

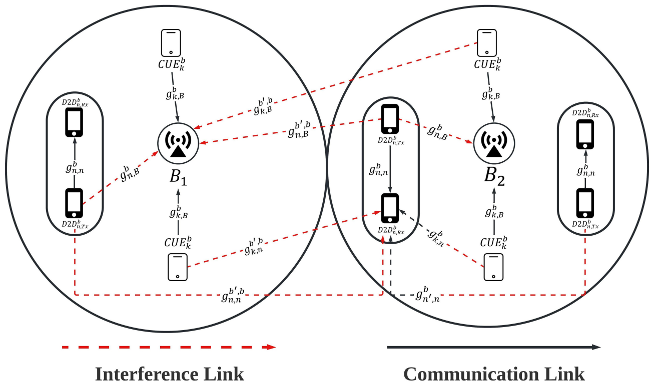

Fig. 1: System model.

The assumption of this research, every CUEs has already occupied a k resource block, so there is no intra-interference between CUE. One D2D pair consists of a D2D transmitter ($D2D_{n,Tx}^b$) and a D2D receiver ($D2D_{n,Rx}^b$). To maintain Spectral Efficiency (SE), every k^{th} resource that is owned by CUE (CUE_k^b) can be allocated to multiple D2D pairs. Level of transmit power is adjusted to the k^{th} resource used by CUE and D2D transmitter.

The signal between CUE and BS will be hampered by: interference generated by the D2D in the same cell interference induced by CUE and D2D from the different cells. The total interference occur in CUE ($CUE\,_k^b$) shown in equations 1.

$$I_k^b = \sum_{n=1}^{N} \left(PD_{n,k}^b \cdot g_{n,B}^b\right) + \sum_{\substack{b'=1,\\ b'\neq b}}^{B} \left(PC_k^{b'} \cdot g_{k,B}^{b',b}\right) + \sum_{\substack{b'=1,\\ b'\neq b}}^{B} \left(\sum_{n=1}^{N} \left(PD_{n,k}^{b'} \cdot g_{n,B}^{b',b}\right)\right) \tag{1}$$

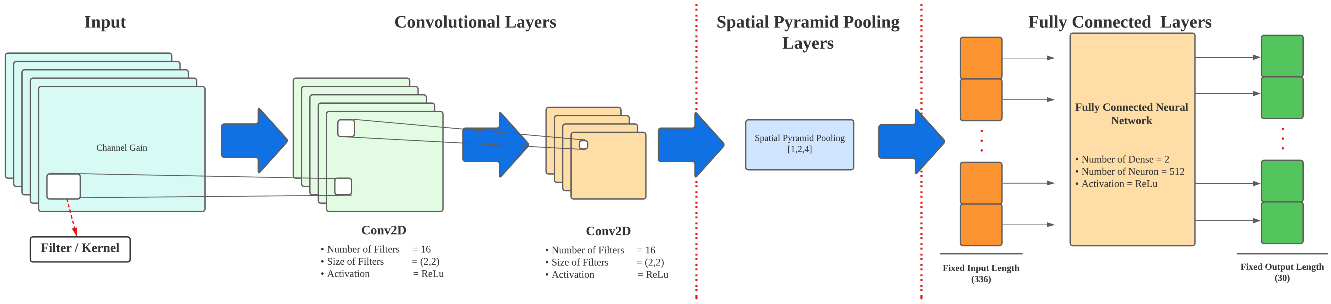

Fig. 2: Proposed CNN-SPP model for power allocation.

On the other hand, the signal between the D2D pairs will be hampered by: interference induced by CUE and another D2D in the same cell and the interference induced by CUE and D2D from a different cell. The total interference occur in D2D pairs ($D2D\,_k^b$) shown in equations 2.

$$\begin{gathered} I_n^b \; = \; PC_k^b \, g_{k,n}^b + \sum_{\substack{n'=1, \\ n' \neq n}}^{N} PD_{n',k}^b \cdot g_{n',n}^b + \\ \sum_{\substack{b'=1, \\ b' \neq b}}^{B} PC_k^{b'} \cdot g_{k,n}^{b',b} + \sum_{\substack{b'=1, \\ b' \neq b}}^{B} \sum_{n=1}^{N} PD_{n,k}^{b'} \cdot g_{n,n}^{b',b} \end{gathered} \tag{2}$$

with $g_{k,B}^{b',b}$, $g_{n,B}^{b',b}$, $g_{k,n}^{b',b}$, $g_{n,n}^{b',b}$ denote, gain from CUE to D2D, gain from D2D to another D2D, gain from CUE to D2D, gain from D2D to another D2D, in the different cell respectively. $g_{n,B}^b$, $g_{k,n}^b$, $g_{n',n}^b$, denote, gain from D2D to BS, gain from CUE to D2D, gain from D2D to another D2D, in the same cell respectively. Furthermore, PC_k^b, $PD_{n,k}^b$, $PC_k^{b'}$ and $PD_{n,k}^{b'}$ denote, respectively, power transmit of CUE with k^{th} resource, power transmit of D2D pair with k^{th} resource, power transmit of CUE with k^{th} resource in neighbour cell and power transmit of D2D pair with k^{th} resource in neighbour cell.

Based on Shannon-Hartley theorema, data rate τ_k^b that is obtained from CUE (CUE_k^b) and data rate τ_n^b that is obtained from D2D pairs ($D2D_n^b$) is show in equations 3 and 4, respectively.

$$\tau_k^b = \log_2 \left(1 + \frac{PC_k^b \cdot g_{k,B}^b}{I_k^b + \phi^2} \right) \tag{3}$$

$$\tau_n^b = \sum_{k=1}^{K} \log_2 \left(1 + \frac{PD_{n,k}^b \cdot g_{n,n}^b}{I_n^b + \phi^2} \right) \tag{4}$$

with $g_{k,B}^b$ and $g_{n,n}^b$ denote, respectively, gain between CUE to BS and gain between D2D pairs.

B. Problem Formulation

Based on research background, this research aims to maximize overall energy efficiency in Device-to-Device communication that underlays with the cellular network system in multiple cells. Power allocation policies are the critical goal functions that must be solved to improve the system's energy efficiency. This study's problem formulation is presented in equations 5.

maximize

$$\frac{\sum\limits_{b=1}^{B} \left(\sum\limits_{n=1}^{N} \left(\tau_n^b\right) + \sum\limits_{k=1}^{K} \left(\tau_k^b\right) \right)}{\sum\limits_{b=1}^{B} \left(\sum\limits_{n=1}^{N} \left(PD_n^b\right) + \sum\limits_{k=1}^{K} \left(PC_k^b\right) \right)} \tag{5}$$

subject to:

$$\tau_k^b \;\geq\; \tau_{min}^{CUE} \;, \forall b, k \tag{6}$$

$$\tau_n^b \;\geq\; \tau_{min}^{D2D} \;, \forall b, n \tag{7}$$

$$0 \leq PC_k^b \leq P\_max \;, \forall\, b, k \tag{8}$$

$$0 \leq PD_{n,k}^b \leq P\_max \;, \forall\, b, n \tag{9}$$

$$0 \leq \sum_{k=1}^{K} \left(PD_{n,k}^b\right) \leq P\_max \;, \forall\, b, n \tag{10}$$

while 6 and 7 are the constraints and indicate, the data rate of CUE and D2D pairs must be above the minimum data rate of CUE (τ_{min}^{CUE}) and D2D (τ_{min}^{D2D}), respectively. As well as with 8, 9 dan 10 indicate the maximum power budget (P_max) for every device.

III. Convolution Neural Network with Spatial Pyramid Pooling

This section explains the CNN-SPP structure, the dataset generation, and the model training process. Based on the previous explanation, this study presents a modification of the conventional CNN method by using CNN-SPP in delivering power allocation policies. The proposed CNN-SPP structure generally consists of convolutional layers, a Spatial Pyramid Pooling (SPP) layer, and fully connected layers. In this study, CNN-SPP is trained by supervised learning. The dataset is generated by utilizing the Convex Approximation (CA)-based algorithm.

A. CNN Architecture

In general, the CNN architecture consists of convolutional layers and a fully connected layer. On the other hand, the model has the limitation of accepting various input sizes [13]. As a result, adding the SPP module at the last convolution layer or before the fully connected layer can overcome the models limitation in accepting various input sizes [14]. The architecture of porposed CNN-SPP model for this research is shown in Fig. 2.

1) Convolutinal layer: The Convolutional Layers' main goal is to extract the features present in the input data. Convolutional Layers are made up of a series of filters. Each filter performs convolution on the input data to generate a feature map as an output. There are two convolution layers utilized in this research, and the filter is set to 16 with the shape to 2 (2,2), the stride size to 1, and no padding is used. At the end of the convolutional layer process, the Rectified Linear Unit (ReLU) is employed as the activator.

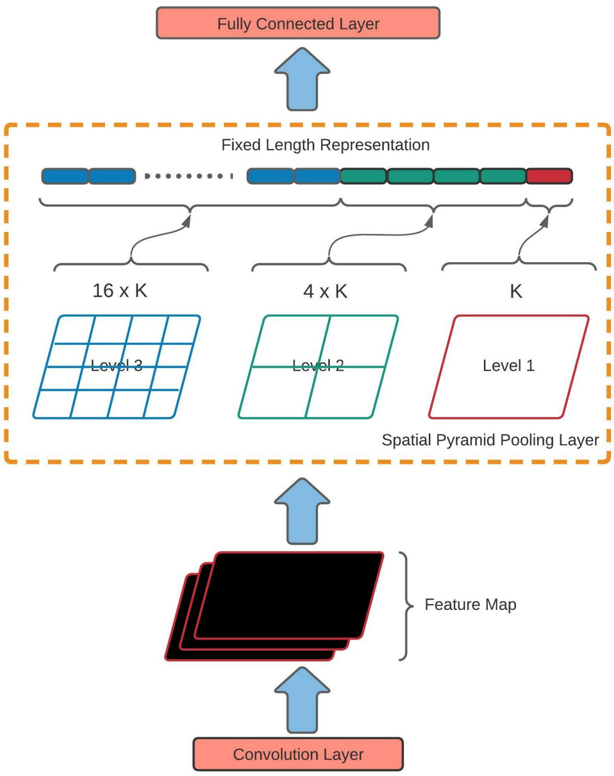

Fig. 3: The process of SPP to generate fixed-length vector.

2) Spatial Pyramid Pooling Layer: SPP is used after the last convolutional process and to replace the last pooling layer in order to build model with an arbitrary input size. The feature map, which is the result of the final convolutional phase, is separated depending on the spatial bins level. Then, at each spatial bins level, maximum pooling is utilized. SPP's output size is $\Sigma_i^I (K \cdot M_i)$, where K is the convolutional filter's size and M_i is the number of spatial bins at level bins i^{th}. Fig. 3 show the process of SPP [14].

3) Fully Connected Layer: In general, this portion serves as a predictor, with the primary function of predicting input based on labels. The fully connected layer comprises three layers: the input layer, the hidden layer, and the output layer, each of which contains multiple neurons. Neurons in each layer are entirely linked to neurons in the following layer, and this connection results in weight and bias. In this research, the number of dense used is 2 with 512 numbers neurons and for the activation is ReLU

B. Dataset Generation

Dataset is needed to train the convolutional neural network. The dataset is consists of two main parts. The first part is channel gain of all the link communication as input and power allocation policies as the output obtained from the Convex Approximation (CA)-based algorithm [15]. Several scenarios are created in the dataset by altering the number of users from 4 to 7. Each scenario includes 20.000 data points. As a result, the datasets maximum size is set to 80.000.

C. Training and Testing Section

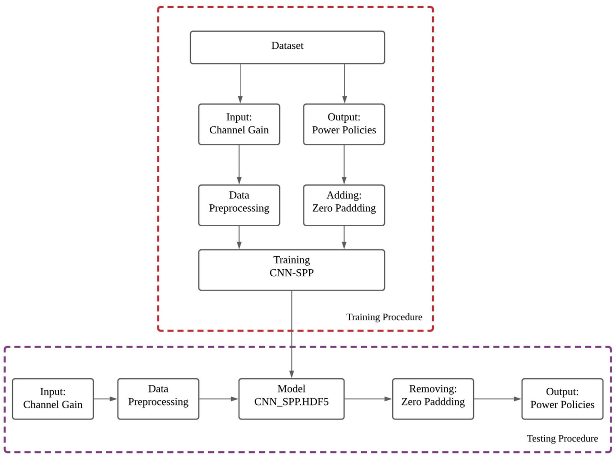

Fig. 4: Training and testing procedure.

The output of the training phase is to produce the model. The model is utilized in the testing section to produce power allocation policies. According to the preceding explanation, the model is trained with several scenarios, each with different input and output size of the dataset. Zero padding is added to the output of the dataset to make a fixed-length output vector of the fully connected layer. Furthermore, when CNN-SPP has been trained, the output of the training process of CNN-SPP is the CNN-SPP model with hdf5 file extension. In order to test the model, the channel gain of all link communication is fed into the well-trained model. In the last process of testing phase, preprocessing is performed by eliminating zero padding from the output to obtain actual power allocation policies. The overal training and testing model is defined in Fig. 4.

IV. Simulation Result

In this section, the simulation is done repeatedly to see how well the proposed method conducts optimal power allocation policies. The simulation is conducted by evaluating the tendency of data rate and energy efficiency to the number of users. The simulation set-up details are shown in Table I.

TABLE I: PARAMETERS SETTING

Parameter	Value
Cell Radius	500 meters
Number of Cell	2
Number of CUE	2 - 5
Number of D2D	2
D2D pair distance	15 meters
Pathloss between BS to other device	$128.1 + 37.6 \log_{10}(d(km))$
Pathloss between CUE and D2D	$128.1 + 37.6 \log_{10}(d(km))$
Pathloss between D2D pair	$148 + 40 \log_{10}(d(km))$
Noise	-121.45 (dBm)
Power budget	23 (dBm)
Deep Learning API	Keras
Backend	Tensorflow

A. Average System Datarate

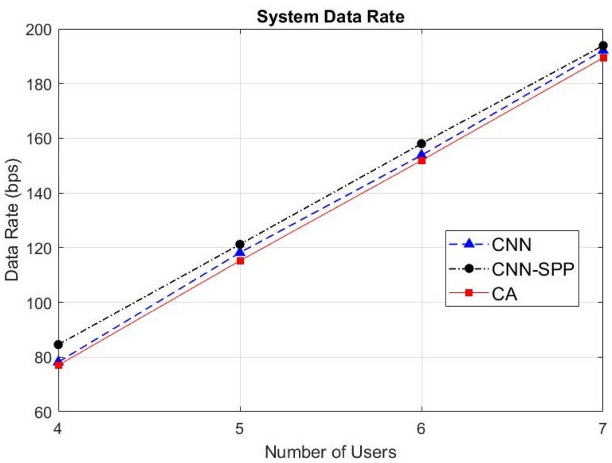

Fig. 5: System data rate with fixed number of D2D = 2

Fig. 5 shows the simulations result in terms of system data rate. The system data rate increases as the number of users in the system grow. This is because the number of resources available to D2D pairs is steadily expanding. As a result, D2D pairs have more flexibility in modifying the level of power by considering resource availability.

B. Average System Energy Efficiency

The performance of the proposed method in terms of energy efficiency is shown in Fig. 6. According to equations 5, the value of energy efficiency increases as the data rate of the system increases. As a result, the higher the data rate value, the greater the value of energy efficiency.

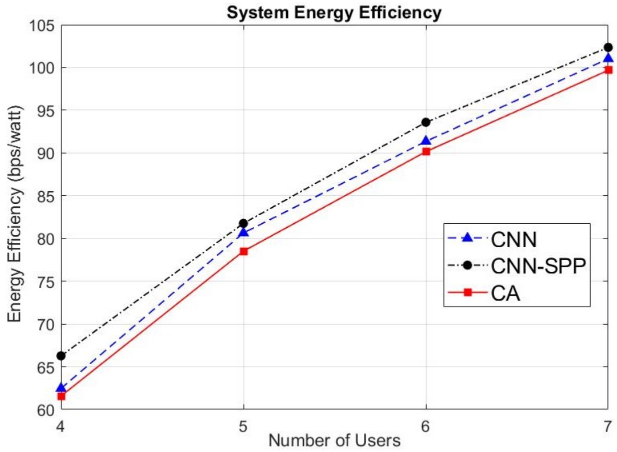

Fig. 6: System energy efficiency with fixed number of D2D= 2

C. Performance Comparison

Through Table II, both CNN and CNN-SPP can approximate CA-based algorithms in terms of average system energy efficiency and average system data rate with an accuracy of performance above 95%. Therefore, CNN and CNN-SPP deep learning can replace CA-based algorithm which in iterative method. However, since CNN-SPP provides a fixed input size to the fully connected layer, the data in the feature map is probably discarded. As a result, the conventional CNN method still outperforms CNN-SPP.

TABLE II. PERFORMANCE COMPARISON

Method	CA	CNN	CNN-SPP
Data Rate (bps)	133.3	135.5	137.4
Energy Efficiency (bps/watt)	82.4	83.8	85.9

Even though the conventional CNN method outperforms the CNN-SPP in terms of system data rate and energy efficiency, there is a significant difference in training cost that this paper cannot demonstrate. The combination of CNN and SPP can overcome the CNN method's limitations in accepting various input sizes. In other words, one CNN-SPP model can be trained and used to a variety of sample scenarios, regardless of the number of users. As a result, the number of models that must be trained for all scenarios can be reduced to just one.

V. Conclusion

In this paper, a power control scheme based on machine learning is observed to approximate traditional iterative method on the D2D underlying with the multi-cell cellular network system. By combining CNN with SPP, CNN-SPP can overcome conventional CNN's input size constraints, resulting in reducing the number of models that must be trained to just one and applying to all scenarios. Through simulation, both CNN and CNN-SPP can approximate the performance of the traditional method (CA-based algorithm) above 95% accuracy. Therefore, the proposed method of CNN-SPP is better than conventional CNN in terms of the training process due to reducing the number of trained models

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