Abstract—Heterogeneous network (HetNet) has been proposed as a promising solution for handling the wireless traffic explosion in future fifth-generation (5G) system. In this paper, a joint subchannel and power allocation problem is formulated for HetNets to maximize the energy efficiency (EE). By decomposing the original problem into a classification subproblem and a regression subproblem, a convolutional neural network (CNN) based approach is developed to obtain the decisions on subchannel and power allocation with a much lower complexity than conventional iterative methods. Numerical results further demonstrate that the proposed CNN can achieve similar performance as the Exhaustive method, while needs only 6.76% of its CPU runtime.

Index Terms—Power allocation, subchannel allocation, energy-efficient, convolutional neural networks.

I. INTRODUCTION

With the development of smart phones and wearable devices in the past decades, the volume of mobile traffic in communication networks has grown exponentially. Developing effective resource allocation schemes becomes increasingly crucial. Extensive studies have been carried out to develop resource allocation schemes in various wireless networks.

In [1], the authors designed transmit beamformers to maximize the sum-utility of a MIMO broadcast channel. Energy-efficient resource allocation was investigated for the uplink of multi-user multi-channel Orthogonal Frequency Division Multiplexing (OFDM) based systems [2], and the heterogeneous networks (HetNets) [3]–[6].

Most previous works [2]–[6] derived the resource allocation strategies as the solutions of optimization problems, where iterative algorithms are applied, such as weighted minimum mean square error (WMMSE) in [1]. In iterative schemes, a large number of iterations need to be carried out before convergence is achieved. The high computational cost prevents implementing these algorithms in real-time for practical uses.

As a key technology in artificial technology, deep learning has recently been used for solving traditional problems in wireless communications, such as Polar decoding [7], [8] and Massive MIMO channel estimation [9], [10]. Deep neural networks (DNNs) can be used to solve complex nonlinear non-convex problems without constructing complicated mathematical models [11]–[13]. For example, the work in [11] showed that DNN could be used to approximate the WMMSE proposed in [1], with a much lower computational time.

In this paper, we propose a convolutional neural network (CNN) based resource allocation approach for HetNets [14], [15]. The main contributions of this work can be summarized as follows.

• Considering an OFDM-based HetNet, we formulate the resource allocation task as a joint subchannel and power allocation problem, which maximizes the energy efficiency (EE) of the network while satisfying the requirement of the spectrum efficiency (SE).

• Different from [11]–[13], which either solve a regression problem or a classification problem for resource allocation by deep learning, the proposed CNN, for the first time, decomposes the original problem into a classification subproblem and a regression subproblem, to infer the energy-efficient decisions on joint subchannel and power allocation.

• Extensive numerical experiments are conducted to demonstrate that the proposed CNN can achieve similar performance as the Exhaustive method, while substantially reduce the computational time.

The rest of the paper is organized as follows. In Section II we describe the system model and give the problem formulation. The proposed neural network architecture is developed in Section III. Simulation results are provided in Section IV followed by the conclusion in Section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

Consider the downlink transmission in an OFDM-based HetNet, where a set $\mathcal{N} := \{1, 2, \ldots, N\}$ of BSs (i.e., macrocell and microcell BSs) serve a set $\mathcal{U} := \{U_1, U_2, \ldots, U_N\}$ of users; see Fig. 1. Let $U_n := \{1, 2, \ldots, U_n\}$ denote the set of users communicating with BS $n$. Let $\mathcal{M} := \{1, 2, \ldots, M\}$ represent the set of macrocell BSs. The set of microcell BSs can be then given by $\mathcal{S} := \{\mathcal{N} - \mathcal{M}\}$.
Each BS has a set $\mathcal{K} = \{1, 2, \ldots, K\}$ of subchannels. We define $l_{u,k}^n \in \{0, 1\}$ as the subchannel allocation indicator. Let $l_{u,k}^n = 1$ if subchannel $k$ is allocated to user $u$ by BS $n$; and $l_{u,k}^n = 0$, otherwise. Assume that each subchannel of a BS can be assigned to at most one user in its cell, and each user must get at least one subchannel, as given by

$$\sum_{u \in \mathcal{U}_n} l_{u,k}^n \leq 1, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}. \quad (1a)$$
$$\sum_{k \in \mathcal{K}} l_{u,k}^n \geq 1, \quad \forall n \in \mathcal{N}, u \in \mathcal{U}. \quad (1b)$$

Let $p_{m,k}^n$ denote the transmit power of BS $n$ on subchannel $k$. We have

$$0 \leq \sum_{k \in \mathcal{K}} p_{m,k}^n \leq P_{\text{max}}^M, \quad \forall m \in \mathcal{M}, \quad (2a)$$
$$0 \leq \sum_{k \in \mathcal{K}} p_{s,k}^n \leq P_{\text{max}}^S, \quad \forall s \in \mathcal{S}, \quad (2b)$$
$$P_{\text{max}}^M > P_{\text{max}}^S, \quad \forall m \in \mathcal{M}, s \in \mathcal{S}, \quad (2c)$$

where $P_{\text{max}}^M$ is the maximum transmit power of a macrocell BS and $P_{\text{max}}^S$ is the maximum transmit power of a microcell BS. \((2c)\) indicates that the maximum transmit power of a macrocell BS is larger than that of a microcell one.

Let $h_{u,k}^n$ denote the channel gain from BS $n$ to user $u$ on subchannel $k$. We assume that the BSs and users have perfect channel state information (CSI). Then the achieved transmit rate of user $u \in \mathcal{U}_n$ on subchannel $k$ is

$$r_{u,k}^n = B \log_2 (\frac{h_{u,k}^n p_{k}^n}{I_{u,k}^n + \sigma^2}) \quad (3)$$

where $B$ is the subchannel bandwidth, $I_{u,k}^n = \sum_{j \in \mathcal{K}, j \neq n} h_{u,k}^j p_{k}^j$ is the inter-cell interference, and $\sigma^2$ is the power of the Additive White Gaussian Noise (AWGN). The overall throughput of the network is therefore given by

$$R(l, p) = \sum_{n \in \mathcal{N}} \sum_{u \in \mathcal{U}_n} \sum_{k \in \mathcal{K}} l_{u,k}^n r_{u,k}^n \quad (4)$$

where $l := \{l_{u,k}^n, \forall n, u, k\}$ and $p := \{p_k^n, \forall n, k\}$. The total power consumption of the network can be described as

$$p_{\text{tot}}(p) = \frac{1}{\rho} \sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} p_{k}^n + (M p_{c}^m + S p_{c}^s), \quad (5)$$

where $\rho$ is the power-amplifier inefficiency factor of BSs, and $p_{c}^m$ and $p_{c}^s$ are constant values denoting the circuit power consumption of macrocell BSs and microcell BSs, respectively. The system EE is defined as the ratio of achievable throughput to total power consumption in the HetNet, and the system SE is defined as the ratio of achievable throughput to system bandwidth, as given by

$$\eta_{\text{EE}}(l, p) = \frac{R(l, p)}{p_{\text{tot}}(l)}, \quad (6)$$
$$\eta_{\text{SE}}(l, p) = \frac{R(l, p)}{K B}. \quad (7)$$

With $\varepsilon$ denoting the target value of the system SE, it is required that

$$\eta_{\text{SE}}(l, p) \geq \varepsilon. \quad (8)$$

\[B. Problem Formulation\]

Our objective is to maximize the EE of the HetNet by making optimal decisions on the subchannel assignment $l$ and power allocation $p$, while guaranteeing the target SE. The problem of interest is to solve

$$\max_{\{l, p\}} \eta_{\text{EE}}(l, p) \quad (9)$$

s.t. \(1)\), \(2\), and \(3\).

Note that problem \(9\) is a mixed-integer nonlinear non-convex optimization problem, which is in general difficult to solve. In this paper, we propose a CNN-based approach to solve this problem.

\[III. Machine Learning for Resource Allocation\]

In this section, we introduce our data generation process and give details on the CNN structure we propose.

\[A. Data Generation\]

In order to generate our data set, we set a HetNet in urban area scenario, which consists of one macrocell and several microcells. The specific setting of the HetNet will be given in Section IV. The channel gains $\{h_{u,k}^n, \forall u, k, n\}$ are first generated following a standard normal distribution, i.e., Rayleigh fading distribution with zero mean and unit variance. With fixed $P_{\text{Max}}^M$, $P_{\text{Max}}^S$ and $\sigma$, we generate the corresponding subchannel allocation indicator $l$ and the allocated power $p$ for each channel realization by running an exhaustive method. The Exhaustive method iteratively calculates and compares the EE for all possible schemes and chooses one of the scheme that maximizes the EE as the optimal solution. By doing so, the Exhaustive method sets a benchmark for the proposed CNN-based approach with a high complexity. By repeating the above process for a large number of times, we generate the entire training data set $\{h_{u,k}^n, l, p\}$. Let a matrix $H_{N \times U \times K}$ collect the channel gains from BS $n$ to user $u$ on subchannel $k$, i.e., \{h_{u,k}^n, \forall u, k, n\}. \]
B. Proposed Convolutional Neural Network

Fig. 2: The CNN structure used in this work, which consists of one input layer, multiple hidden layers, and one output layer. The hidden layers are composed of four convolutional layers and three fully connected (FC) layers.

Different from existing works which either solve a regression problem [11], [12], or a classification problem [13] for resource allocation by deep learning, our proposed CNN architecture decomposes the original problem into a classification subproblem and a regression subproblem, and then outputs the energy-efficient decisions on joint subchannel and power allocation. It consists of three part: input layer, hidden layers and output layer.

- **Input Layer**: The input data is a three-dimensional matrix $H_{N \times U \times K}$ collecting the channel gains from BS $n$ to user $u$ on subchannel $k$.

- **Hidden Layers**: The hidden layers are composed of four convolutional layers and three fully connected (FC) layers with the activation function, Rectified Linear Unit (ReLU). The reason a CNN is chosen as our neural network is that the sliding window of CNN can extract the features between the elements of the input matrix, which leads to better performance of classification and regression than other neural networks (e.g., a FC DNN). The parameters of the hidden layers will be given in Section IV.

- **Output Layer**: Two sets $\hat{l}$ and $\hat{p}$ are output from this layer. Here, $\hat{l}$ is the subchannel allocation indicator that determines the allocation of subchannels to users; $\hat{p}$ collects the power allocation decisions that maximize the system EE. For the output $\hat{l}$ applying to a classification subproblem, we choose linear as the activation function; while for the output $\hat{p}$ applying to a regression subproblem, softmax is selected as the activation function.

We use the training data set to optimize the weights of the CNN. The CNN is trained to regenerate the subchannel and power allocation derived from the Exhaustive method, given channel gains $H_{N \times U \times K}$. Since the proposed CNN aims to solve different subproblems (i.e., classification and regression), different loss functions are chosen adapting to different features of the subproblems.

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$$L_{\text{reg}}(l, \hat{l}) = \sum_i l_i \log(\hat{l}_i)$$

where $\hat{l}$ is the predicted subchannel allocation indicator output by the CNN, and $l$ is the subchannel allocation indicator in the training set. In (10), $\hat{l}_i$ and $l_i$ are the elements in $\hat{l}$ and $l$, respectively.

$$L_{\text{cls}}(p, \hat{p}) = \sum_i (p_i - \hat{p}_i)^2$$

where $\hat{p}$ is the predicted power vector output by the CNN, and $p$ is the allocated power in the training set. Also, $\hat{p}_i$ and $p_i$ are the elements in $\hat{p}$ and $p$, respectively.

Therefore, the CNN is trained to minimize the following total loss function:

$$L_{\text{total}} = L_{\text{reg}}(l, \hat{l}) + L_{\text{cls}}(p, \hat{p})$$

At last, CNN would be convergence by training process. The network parameters are shown in Section IV.

IV. Simulation Results

A. Simulation Configuration

In this section, we evaluate the performance of the proposed CNN approach. We consider a scenario where there is one macrocell and two microcells, each with a BS communicating with $U_n = 2$ users; $K = 2$ subchannels are allocated to each BS. The users are located uniformly in the entire cells; see Fig. 3. Table I summarizes the parameters of the HetNet scenario.

According to the data generation process in section III, we generate 20,000 training data sets and 2000 testing data sets.
To better extract the characteristics of the CNN, we transpose the channel matrix $H_{3 \times 6 \times 2}$ to $H_{6 \times 6 \times 1}$ as the input of the neural network. We compare the performance of the CNN-based approach with four other schemes: 1) DNN by using a FC DNN, as specified in Table II; 2) Benchmark by using the Exhaustive method; 3) RandomPower by randomly generating the power allocation following a uniform distribution; and 4) MaxPower by allocating the maximum transit power of BSs. The latter two schemes serve as heuristic baselines.

Table III lists the CPU runtime of Benchmark, CNN (with 10k or 20k training data), and DNN (with 10k or 20k training data). We can see that the CPU runtime of CNN and DNN with 10k training data is only 6.76% and 3.94% of the CPU runtime of Benchmark, respectively. With more parameters in the neural network, the runtime of CNN is slightly bigger than that of DNN. It is also obvious that more training data results

$TABLE I$: Parameters

| Parameter                | Value                        |
|--------------------------|------------------------------|
| System bandwidth         | 2 MHz                        |
| Carrier frequency        | 2 GHz                        |
| Number of total users    | 6                            |
| Number of macrocell BSs  | 1                            |
| Number of microcell BSs  | 2                            |
| Number of subchannels    | 2                            |
| Antenna height           | 15 m                         |
| Macrocell pathloss       | $128.1 + 37.6 \log_{10}(R_{\text{macro}})$ |
| Microcell pathloss       | $140.7 + 36.7 \log_{10}(R_{\text{micro}})$ |
| Inter-cell distance      | 0.2 km                       |
| User-BS distance         | Uniform Distribution (0, 0.12 km) |
| $\rho$                   | 0.3                          |
| Noise                    | -128.1 dBm                   |
| Max transmit power of macrocell BS | 12 W |
| Max transmit power of microcell BS | 1.2 W |

$TABLE II$: An Overview of Network Configurations and Parameters.

| Input Layer | DNN | CNN |
|-------------|-----|-----|
| Layer1      | Dense 256-ReLU | Conv2D 6x6x16-ReLU |
| Layer2      | Dense 256-ReLU | Conv2D 6x6x16-ReLU |
| Layer3      | Dense 128-ReLU | Conv2D 6x6x32-ReLU |
| Layer4      | Dense 128-ReLU | Conv2D 6x6x32-ReLU |
| Layer5      | -               | Dense 256-ReLU |
| Layer6      | -               | Dense 256-ReLU |
| Layer7      | -               | Dense 128-ReLU |
| Output Layer| 8-way softmax and 6-way linear | 8-way softmax and 6-way linear |

Total Parameters: 126478

$TABLE III$: An Overview of CPU Runtime.

| Approach        | 10k Training Data | 20k Training Data |
|-----------------|-------------------|-------------------|
| Benchmark       |                   |                   |
| CNN             | 126478            | 401182            |

$B. \text{Simulation Results}$

Fig. 4 plots the cumulative distribution function (CDF) that describes the EE (in bps/J) achieved by different approaches. As shown in the figure, CNN and DNN can achieve EE very close to Benchmark, while substantially improving the performance of RandomPower and MaxPower.

Fig. 5 shows the error rates of different approaches compared to Benchmark, defined as

$$\xi = \frac{|EE_{NN} - EE_o|}{EE_o}$$  \hspace{1cm} (13)

where $EE_{NN}$ is the EE of different approaches, and $EE_o$ is the EE of Benchmark. It is observed that CNN incurs the minimum error rate among all approaches, followed by DNN, RandomPower and MaxPower. The error rates of around 90% testing data using CNN are lower than 8% compared to Benchmark.

We also evaluate CNN and DNN with different size of training data. Fig. 6 and Fig. 7 show the CDFs that describe the EE and error rate of CNN and DNN using different size of training data. We can observe that a network trained with more training data has the performance closer to Benchmark. We can also see that the proposed CNN has better performance than DNN because CNN can extract more detailed data characteristics through sliding windows.

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|-----------------|-------------------|-------------------|
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| CNN             | 126478            | 401182            |
in a larger runtime.

TABLE III: CPU Runtime Comparison

| Method      | Benchmark | CNN-20k | CNN-10k | DNN-20k | DNN-10k |
|-------------|-----------|---------|---------|---------|---------|
| Time (s)    | 2.41      | 0.165   | 0.163   | 0.106   | 0.095   |
| CNN (DNN)   | -         | 6.85%   | 6.76%   | 4.4%    | 3.94%   |

V. CONCLUSION

By introducing deep learning technology to resource allocation problem in wireless communications, we proposed a CNN-based approach to maximize the EE for HetNets. The proposed approach decomposed the original problem into a classification subproblem and a regression subproblem, and output the energy-efficient decisions on joint subchannel and power allocation with a low computational complexity. Extensive numerical experiments demonstrated that the proposed CNN achieved similar performance as the Exhaustive method, while needed only 6.76% of its CPU runtime.

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