Sub-Band Assignment and Power Control for IoT Cellular Networks via Deep Learning

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ABSTRACT As various Internet of things (IoT) communication services have recently received great attention, the development of resource allocation schemes that can support the connection of a number of IoT devices becomes an important task for next-generation communication systems. Motivated by this challenge, we propose deep learning-based optimization algorithms for a joint resource allocation problem in uplink IoT cellular networks, in which the base station uses multiple sub-bands to serve IoT users and inter-sub-band interference exists due to spectral leakage. Specifically, to maximize the achievable sum rate of IoT users with low complexity, we develop a two-stage optimization method built on convolutional neural networks (CNNs) that sequentially optimizes sub-band assignment and transmit power control. Moreover, in order to examine the performance according to the neural network structure, the proposed scheme is also implemented through fully-connected neural networks (FNNs) and compared with the CNN-based scheme. Simulation results show that our proposed CNN-based algorithm significantly improves the sum rate and reduces the required computation time compared to previous schemes without deep learning.

INDEX TERMS Convolutional neural network, deep learning, fully-connected neural network, Internet of Things, resource allocation, sum rate maximization.

I. INTRODUCTION

The Internet of things (IoT), which connects various physical things to the Internet, is expected to become one of the important usage scenarios in the fifth generation (5G) communication systems [1]. To be specific, IoT can support a wide range of services such as smart city, smart home, transportation, surveillance, and emergency and disaster management with large-scale connection of devices [2]. In addition, more recently, research on the Internet of medical things (IoMT), which utilizes IoT devices for medical purposes [3], [4], and technologies that provide long-distance IoT communication via artificial satellites are attracting attention [5]. Due to the rapid increase in demand for these new IoT-based services, the total number of connected IoT devices is expected to reach approximately 80 billion by 2030 [6]. Therefore, it is becoming increasingly important to develop a suitable IoT communication framework that can efficiently serve large numbers of IoT users with limited resources.

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To this end, many recent studies have been conducted on resource and interference management of various wireless networks including IoT networks [7]–[14]. In [7], the authors have proposed resource allocation schemes to reduce the total energy consumption of non-orthogonal multiple access (NOMA) and time division multiple access (TDMA), respectively. Recent works [8] have studied the joint optimization of sub-band assignment and power control to maximize the achievable sum rate, in which interference exists both between IoT sub-bands and between IoT and long-term evolution (LTE) bands. The authors of [9] have proposed an energy efficient iterative algorithm for resource allocation in IoT networks by using Lagrangian dual decomposition (LDD) [10] under the imperfect channel state information (CSI) assumption. In [11], the stochastic optimization problem to minimize the total power consumption of NOMA-based IoT downlink networks have been studied. The authors of [12] have proposed a two-step optimization scheme with a genetic algorithm (GA) applied to each step to solve the resource block assignment and power allocation problem in NOMA networks. In [13], the authors have
proposed a three-step resource allocation scheme with convex relaxation and heuristic greedy algorithms for sub-carrier assignment and transmit power control to maximize the sum rate of multi-carrier NOMA (MC-NOMA) systems. In addition, in [14], an efficient weighted sum rate optimization algorithm based on iterative joint user selection and variable power allocation (VPA) has been proposed to solve sub-band assignment and power allocation problem for downlink multi-band NOMA (MB-NOMA) systems. Note that these previous works [7]–[9], [11]–[14] have considered iterative algorithms with relaxation strategies when solving their resource allocation problems.

Recently, deep learning with fully-connected neural network (FNN), convolutional neural network (CNN), and recurrent neural network (RNN) has been widely adopted to solve various types of complex combinatorial optimization problems in wireless communication [15]–[21]. In [15], the transmit power control based on CNN has been proposed to maximize spectral efficiency and energy efficiency. In [16], the RNN-based energy efficient resource allocation algorithm has been proposed for NOMA-IoT networks assuming that imperfect successive interference cancellation (SIC) is applied. The authors of [17] have proposed the FNN-based approach to solve linear sum assignment problems subject to integer programming constraints. In [18], a joint pilot and data power control scheme based on a deep neural network has been developed to maximize the sum spectral efficiency in uplink cellular massive multiple-input multiple-output (MIMO) systems. In [19], the FNN-based unsupervised learning approach has been studied to optimize beamforming vectors using uplink-downlink duality in multi-user multiple-input single-output (MU-MISO) downlink cellular systems. In addition, in [20], a deep belief network (DBN)-based algorithm has been proposed for a downlink simultaneous wireless information and power transfer (SWIPT)-enabled MC-NOMA system, which minimizes the total transmit power while satisfying the system quality-of-service (QoS) by optimizing the sub-band assignment and power allocation problem. The authors of [21] have developed an energy efficient algorithm for the joint resource allocation problem, which applies LDD and semi-supervised learning based on FNN structure to maximize energy efficiency in NOMA mmWave heterogeneous networks. From these recent works [15]–[21], deep learning based approaches have been shown to provide significantly improved performance with low computational complexity when solving various joint resource allocation problems in wireless communication systems compared to existing convex relaxation algorithms.

Motivated by the aforementioned works, we develop a CNN-based joint optimizer for frequency sub-band assignment and transmit power control in uplink IoT cellular networks in this paper. In particular, in contrast to the previous studies that considered sub-band assignment and power control problems similar to our work [11]–[14], [20], [21], we consider spectral leakage between sub-bands to reflect the fact that low-cost IoT devices have limited ability to suppress out-of-band emissions [22]. We assume that multiple IoT users simultaneously communicate with a base station over multiple frequency sub-bands in the presence of spectral leakage, and our goal is to maximize the achievable sum rate of IoT users, as in [8]. However, in contrast to [8], we attempt to solve the joint optimization problem with deep learning instead of convex relaxation methods in this paper. It turns out that the proposed CNN-based algorithm provides near-optimal performance that can be obtained through exhaustive search and strictly outperforms the previous iterative algorithm with convex relaxation.
relaxation without deep learning presented in [8] with low computation time.

The main contributions of this paper can be highlighted as follows:
- We consider the practical environment of low-cost IoT cellular networks in which spectral leakage occurs between adjacent sub-bands and reflect its effect in the model learning process.
- We propose a novel low-complexity algorithm that divides a non-convex joint integer programming problem into separate two-step problems and solves them sequentially based on CNNs. We also present how to implement the proposed algorithm with FNNs.
- We demonstrate by simulation that the proposed scheme can achieve an improved sum rate with much lower computational complexity compared to the previous schemes that do not apply deep learning.

The remainder of this paper is organized as follows. We describe the system model and the problem formulation in Sections II and III, respectively. The proposed CNN-based and FNN-based optimization algorithms are explained in Section IV. In Section V, the sum rate performance of the proposed scheme is evaluated and compared with that of benchmark schemes through numerical simulations. Finally, we conclude the paper in Section VI.

**Notation:** We denote finite sets by calligraphic letters, for example, $X$. Boldface lowercase and uppercase letters represent vectors and matrices, respectively. Let $[1 : K] = \{1, 2, \ldots, K\}$. Denote the circularly symmetric complex Gaussian distribution with mean 0 and variance $\sigma^2$ by $\mathcal{CN}(0, \sigma^2)$.

### II. SYSTEM MODEL

We consider an uplink IoT cellular network with $K$ IoT users, in which both the base station and IoT users have one antenna each. There are $N$ frequency sub-bands in the network, and each IoT user can access only one sub-band among $N$ sub-bands to send its message to the base station. See Fig. 1. In addition, we assume orthogonal multiple access (OMA), i.e., multiple users cannot be assigned to the same sub-band at the same time. For convenience, we denote $c_i^m \in \{0, 1\}$ as a binary indicator such that $c_i^m = 1$ if sub-band $m$ is allocated to user $i$ or $c_i^m = 0$ otherwise, where $i \in \mathcal{K} = [1 : K]$ and $m \in \mathcal{N} = [1 : N]$. Due to the aforementioned assumptions, $c_i^m$ is required to satisfy the following two constraints:

$$\sum_{i=1}^{K} c_i^m \leq 1, \quad \forall m \in \mathcal{N}, \quad \sum_{i=1}^{N} c_i^m \leq 1, \quad \forall i \in \mathcal{K}. \tag{1}$$

Assuming that IoT user $i \in \mathcal{K}$ is assigned to sub-band $m \in \mathcal{N}$, the transmitted signal of user $i$ at time $t$, denoted by $x_i^m(t)$, can be expressed as

$$x_i^m(t) = \sqrt{P_i^m} c_i^m s_i(t), \quad \forall m \in \mathcal{N}, \tag{2}$$

where $s_i(t)$ denotes the independent information symbol of user $i$ at time $t$ that follows $\mathcal{CN}(0, 1)$ and $p_i$ is the transmit power associated with $s_i(t)$ satisfying the power constraint $P_max$, i.e., $p_i \leq P_{max}$ for all $i \in \mathcal{K}$.

We assume that spectral leakage occurs between frequency sub-bands due to out-of-band emissions from IoT devices, as similar to previous works [8], [23]. Let denote the channel coefficient from sub-band $m$ of user $i$ to sub-band $n$ by $h_{i}^{[n,m]}$ and assume that it remains fixed during communication\(^1\) and is known to the base station.\(^2\) Then the received signal of the base station at sub-band $n \in \mathcal{N}$ at time $t$, denoted by $\gamma^{[n]}(t)$, is given by

$$\gamma^{[n]}(t) = \sum_{i \in \mathcal{K}} h_{i}^{[n,n]} x_{i}^{[n]}(t) + \sum_{i \in \mathcal{K}, m \in \mathcal{N}, m \neq n} h_{i}^{[n,m]} x_{i}^{[m]}(t) + z^{[n]}(t), \tag{3}$$

where $z^{[n]}(t) \sim \mathcal{CN}(0, \sigma^2)$ is the additive noise at sub-band $n$. As a result, the achievable rate of IoT user $i$ is [8], [24]

$$R_i = \log_2 \left( 1 + \frac{\sum_{n \in \mathcal{N}} c_i^{[n]} |h_{i}^{[n,n]}|^2 p_i}{\sum_{j \in \mathcal{K}, j \neq i} \sum_{n \in \mathcal{N}} \sum_{m \in \mathcal{N}} c_j^{[m]} |h_{j}^{[n,m]}|^2 p_j + \sigma^2} \right).$$

**Remark 1:** By setting $h_{i}^{[n,m]} = 0$ for all $n \neq m$ and $i \in \mathcal{K}$, our channel model can recover the conventional scenario that assumes no inter-subband spectral leakage. In addition, by removing the constraints (1), it can be extended to more general scenarios that allow NOMA and one IoT device to access multiple sub-bands.

\(^1\)It is a reasonable assumption considering that the time it takes to transmit a data packet is quite short due to the small size of the data packet in the case of IoT communication.

\(^2\)Since we consider an uplink communication scenario in this paper, channel state information (CSI) can be easily estimated at the base station (the receiver side) by receiving pilot signals from IoT users.
III. PROBLEM STATEMENT

Our goal is to maximize the achievable sum rate of the network by jointly optimizing sub-band assignment and power control of IoT users.\(^3\)

For convenience, we define the sub-band assignment matrix \( C \in \{0,1\}^{N\times K} \) whose the \((m,i)\)th element is \( c_{i}^{m} \). We also define the power control vector \( p \in [0, P_{\text{max}}]^{1 \times K} \) whose the \(i\)th element is \( p_{i} \). Then the optimization problem can be formulated as follows:

\[
\begin{align*}
\max_{C,p} & \quad \sum_{i \in K} R_i(C, p) \tag{4a} \\
\text{s.t} & \quad \sum_{i \in K} c_{i}^{m} \leq 1, \quad \forall m \in \mathcal{N}, \tag{4b} \\
& \quad \sum_{m \in \mathcal{N}} c_{i}^{m} \leq 1, \quad \forall i \in \mathcal{K}, \tag{4c} \\
& \quad 0 \leq p_{i} \leq P_{\text{max}}, \quad \forall i \in \mathcal{K}, \tag{4d}
\end{align*}
\]

where \( R_i(C, p) \) is given by (3) for fixed \( C \) and \( p \).

The joint optimization problem (4) is a non-convex integer programming problem due to the nature of the sub-band allocation and the presence of spectral leakage between sub-bands. Hence, it is difficult to solve efficiently with previous optimization methods using convex relaxation strategies. To overcome this challenge, in this paper, we develop a new optimizer based on deep learning that can considerably improve the sum rate performance with low computational complexity.

IV. PROPOSED ALGORITHM BASED ON DEEP LEARNING

To reduce the computational complexity of solving (4), we propose a two-stage optimizer that sequentially performs sub-band assignment and power control. Specifically, assuming that only on-off power control is applied, we first solve the sub-band assignment problem \( P_1 \) formulated as follows:

\[
P_1 : \quad \max_{C} \sum_{i \in K} R_i(C, p_{\text{max}}) \quad \text{s.t. (4b), (4c)}, \tag{5}
\]

where \( p_{\text{max}} \) denotes the power control vector when all IoT users have the maximum transmit power, i.e., \( p_{i} = P_{\text{max}}, \quad \forall i \in \mathcal{K} \). Then, after \( C \) is determined as \( C^{*} \) from solving \( P_1 \), a suitable power control vector is searched from solving the following optimization problem \( P_2 \) for given \( C^{*} \):

\[
P_2 : \quad \max_{p} \sum_{i \in K} R_i(C^{*}, p) \quad \text{s.t. (4d)}. \tag{6}
\]

In this paper, we apply supervised learning to both optimization problems \( P_1 \) and \( P_2 \). In the following, we will describe the detailed steps of the proposed approach.

Remark 2: Comparing to solving the original problem (4) directly, solving the problem in two steps (5) and (6) may degrade performance. However, it turns out that our proposed two-stage method can achieve performance close to that of the exhaustive search on (4) with much lower computational complexity, as shown in Section V.

A. STRUCTURE OF CNN

We employ CNNs to effectively extract the spatial features of (5) and (6). As shown in Fig. 2, the structure of the considered CNN model consists of three parts: convolution part, flattening part, and activation part [25]. In the convolution part, the spatial features of \( P_1 \) and \( P_2 \) are extracted by performing a convolution operation between the high-dimensional input data and the convolution filter of the CNN model. Then, in order to input the feature map extracted from the convolutional part to the activation part, it is vectorized in the flattening part. At the end of the activation part, the output of the flattening part is mapped using an activation function suitable for each optimization problem, allowing the model to effectively infer feasible outputs.

To be specific, the convolution part is composed of \( N_{c} \) concatenated layers. For each layer, the size of filter is set to \( 3 \times 3 \), and the depth of the filter is set to \( F_{c} \).\(^4\) Each convolution layer is activated by the rectified linear unit (ReLU) function to prevent the vanishing gradient problem [26]. The output of convolution part is then flattened for the final activation in the flattening part. Finally, the output of flattening part is fed into the activation part. It is worth mentioning that unlike the previous CNN-based works [15], [18], the additional fully connected part is not concatenated after the convolution part in the proposed CNN structure in order to reduce complexity. Note that if the fully connected layer exists, it increases the model complexity by increasing the number of model parameters. It will be shown through simulation in Section V that near optimal performance can be achieved even without an additional fully connected layer.

Note that CNN structures used to solve \( P_1 \) and \( P_2 \) have different activation parts, whereas the rest parts are the same. Specifically, for \( P_1 \), the final output is activated by the softmax function for the purpose of multi-class classification, i.e., when the input of activation part is given by \( x \), the \( i \)th element of the final output becomes \( \frac{\exp(x_i)}{\sum_{j=1}^{N} \exp(x_j)} \), where \( x_i \) denotes the \( i \)th element of \( x \). In the deep learning model used in \( P_1 \), the output of the model needs to be mapped to a probability value representing which user can be assigned to each sub-band. Therefore, the softmax function is connected to the activation part to enable this multi-class classification. On the other hand, for \( P_2 \), the sigmoid function is employed in the activation part to satisfy the transmit power constraint (4d) more easily, i.e., the \( i \)th element of the output vector is set to \( \frac{1}{1+\exp(-x_i)} \). More specifically, the deep learning model applied to \( P_2 \) needs to predict the normalized optimal power control vector, and hence the sigmoid function that maps

\(^3\)Note that since a cellular IoT network is considered in this paper, the base station can centrally manage both sub-band allocation and power control of each user by utilizing CSI.

\(^4\)\( N_{c} \) and \( F_{c} \) will be specified in Section V.
Moreover, we add the column all-zero vector to the left side of only one of the elements is 1 and all the others are 0 [17].

N gradient descent to update model parameters [27]. The problem of falling to a local optimal solution when applying the process to converge quickly and makes it robust against the problem.

\[ \hat{R}_{i,j} = \frac{|R_{i,j}|}{\sqrt{E(|R_{i,j}^2|^2)}}, \] (7)

Here, this standardization on the input data allows the training process to converge quickly and makes it robust against the problem of falling to a local optimal solution when applying gradient descent to update model parameters [27].

Due to the constraint (4b), the original problem can be decomposed into N classification problems by considering each column of \( \mathbf{C}^* \) as an one-hot target vector, in which only one of the elements is 1 and all the others are 0 [17]. Moreover, we add the column all-zero vector to the left side of \( \mathbf{C}^* \) to apply one-hot encoding even when no user is assigned to a given sub-band. Hence, the optimal sub-band assignment matrix now becomes \( \mathbf{C}^* \in \{0,1\}^{N \times (K+1)} \).

Then we construct \( N \) distributed models to find a suitable sub-band assignment matrix by training based on \( \mathbf{C}^* \). To be specific, each model \( m \in \mathcal{N} \) is separately trained to minimize the following loss function

\[ L_{p_1,m} = -\sum_{i=1}^{K+1} u_{m,i}^{*} \log \left( \frac{\exp(\hat{u}_{m,i}^{*})}{\sum_{j=1}^{K+1} \exp(\hat{u}_{m,j})} \right), \quad m \in \mathcal{N}, \] (8)

which is the categorical cross entropy widely adopted for multi-class classification problems, where \( u_{m,i}^* \) denotes the \( i \)th element of one-hot target vector \( \mathbf{u}_m^* \in \{0,1\}^{1 \times (K+1)} \), where \( \mathbf{u}_m^* \) is the \( m \)th row vector of \( \mathbf{C}^* \), and \( \hat{u}_{m,i}^{*} \) denotes the \( j \)th element of the output vector \( \hat{\mathbf{u}}_m \in \mathbb{R}^{1 \times (K+1)} \), which is the predicted vector of the model updated at the end of every training epoch to minimize (8). By setting a loss function as (8), the output of the trained model can effectively represent the probability of being assigned to a particular integer class, and as a result, the integer constraint in (4) can be effectively considered in the optimization process.

However, there is no guarantee that the resulting sub-band assignment matrix obtained from the aforementioned decomposition approach satisfies (4c). This is because each model is trained independently, and thus the inference of each model can be the same for some cases, which leads that one user is assigned to multiple sub-bands at the same time. To resolve this problem, we propose a sequential optimization algorithm based on the \( k \)-best algorithm that finds the best \( k \) candidates in the search space and controls its computational complexity by adjusting \( k \). Specifically, using the fact that each element of the output vector \( \hat{\mathbf{u}}_m \) represents the probability of which user is assigned to the corresponding sub-band \( m \), \( k \) candidate users are selected in descending order of probability, and the selected users are sequentially optimized to satisfy (4c).

Let denote the set of all possible permutations of the set \( \mathcal{N} \) by \( \mathcal{S} \). In addition, denote the \( n \)th element of \( s \in \mathcal{S} \) by \( s_n \). For given permutation \( s \) and \( k \), our proposed \( k \)-best algorithm consists of the following steps:

1. Let \( \tilde{\mathbf{u}}_m \) denote the modified version of \( \hat{\mathbf{u}}_m \) such that the \( k \) largest elements of \( \tilde{\mathbf{u}}_m \) are set to one and the other elements are set to zero.

![Algorithm 1](attachment:algorithm.png)

**FIGURE 3.** Standardized channel matrix for each optimization problem.
2) Define the $k$-best candidate user matrix as $\hat{C} = [\hat{u}_1]^T, \ldots, [\hat{u}_k]^T$. Let $c_{ij}$ denote the $(i, j)$th element in $C$. In addition, let $c_i$ and $\hat{c}_i$ denote the $i$th row vectors of $C$ and $\hat{C}$, respectively.

3) Initially, set $C$ to the $N \times K$ all zero matrix, $n = 1$, and $\hat{C}_{s1}, \ldots, \hat{C}_{sN}$, where $\hat{C}_{sn}$ denotes the set of positions of ones in $\hat{c}_{sn}$. For example, if $\hat{c}_{sn} = [1, 0, 1, 0, 1, 1]$, then $\hat{C}_{sn} = \{1, 3, 5, 6\}$.

4) For given $n$, sub-band assignment is sequentially performed to sub-bands $s_n$ and $s_{n+1}$. Note that the first column of $\hat{C}$ indicates whether a user is assigned to each sub-band, i.e., $i = 1 \in \hat{C}_{sn}$ means that no user is assigned to sub-band $s_n$. In that case, set $c_{sn} = 01 \times K$. Otherwise, set $c_{sn} = 1$ for $i \in \hat{C}_{sn}$ to select one of the candidate users from $\hat{C}_{sn}$ and allocate it to sub-band $s_n$.

5) Assign candidate users in $\hat{C}_{n+1}$ one by one. Similar to Step 4, if $j = 1 \in \hat{C}_{n+1}$, set $c_{n+1} = 01 \times K$. In addition, if a user is already assigned to sub-band $s_n$, then no user is assigned to sub-band $s_{n+1}$, i.e., if $j = i$, set $c_{n+1} = 01 \times K$, where $i \in \hat{C}_{sn}$ and $j \in \hat{C}_{n+1}$. Moreover, add $\{1\}$ to $\hat{C}_{n+1}$ for these cases for the next iteration. Otherwise, set $c_{n+1} = 1$ for $j \in \hat{C}_{n+1}$. Then calculate $R_{\text{sum},i,j} = \sum_{l \in K} R_l(C, p_{\text{max}})$ for all $i \in \hat{C}_{sn}$ and $j \in \hat{C}_{n+1}$.

6) Find the $(i, j)$ pair that maximizes $R_{\text{sum},i,j}$ in the previous step and assign users to sub-band $s_n$ and sub-band $s_{n+1}$ accordingly. Then, exclude these assigned users from the remaining set of candidate users. This is because users already assigned in the previous step can no longer be assigned to other sub-bands in order to satisfy (4c).

7) Set $n$ to $n + 1$, and repeat Steps 5-6 until $n = N - 1$.

8) Return the final result for sub-band assignment matrix $C$.

The pseudocode of the proposed sequential algorithm is stated in Algorithm 1. Finally, Algorithm 1 can be performed over all possible $s$ to obtain the optimal sub-band assignment matrix $C$ that maximizes (5).

Remark 3: The computational complexity of Algorithm 1 is determined by the $k$-factor and $N$. For a given permutation $s \in S$, since the size of the candidate user set is proportional to the $k$-factor, it has complexity of $O(k)$ (This also can be numerically observed in Table 1 in Section V). Moreover, the overall algorithm iterates over all $s \in S$. Consequently, the overall computational complexity of Algorithm 1 considering all possible permutations is given by $O(kN!)$.

C. POWER ALLOCATION

After solving P1, we now solve the power control problem P2 to maximize (6) for the sub-band assignment matrix determined in the previous stage. Since a sub-band assignment matrix is determined in the previous stage, the standardized channel matrix for power control, $\hat{H}_{p2} \in C^{N \times N}$, is given as in Fig. 3(b), where $d_n \in K$ denotes the user index assigned to sub-band $n \in N$ in the previous stage. To construct training samples, the set of standardized channel matrices is obtained by once again performing the sub-band assignment for randomly generated channels. For the training target, the optimal power vector that maximizes (6) is exhaustively searched in the power range $(4d)$ with sufficiently small quantization level and then normalized in the range $[0, 1]^1 \times N$. Consequently, the dataset for training is composed of the standardized channel matrix $\hat{H}_{p2}$ and the normalized optimal power vector $p^* \in [0, 1]^1 \times N$.

After the training data set is constructed, the power control model is trained to minimize the following mean squared error (MSE)

$$L_{p2} = \frac{1}{N} \sum_{i=1}^{N} (p_i^* - \hat{p}_i)^2, \quad (9)$$

where $p_i^*$ and $\hat{p}_i$ denote the $i$th element of $p^*$ and the output vector $\hat{p}$, respectively. Since the final output of the model for optimizing $P2$ is activated by the sigmoid function, the model can be trained to predict the normalized power vector $\hat{p} \in [0, 1]^{1 \times N}$ close to $p^*$ by minimizing (9). Finally, the transmit power control vector is determined as $p = P_{\text{max}} \hat{p}$ after the training process.

We summarize the overall procedure of the proposed algorithm in Fig. 4.

D. PROPOSED ALGORITHM BASED ON FNN

So far, we have developed a resource allocation scheme based on CNNs. Now, we will explain that the proposed scheme
can also be implemented via FNNs. Unlike the CNN model, which learns by extracting local information between adjacent elements of the input data in the convolutional part, the FNN model has the difference that it learns the input and output relationship directly from the fully connected part without the extraction process. Compared to the CNN-based scheme, the FNN-based method can effectively analyze the input and output relationship with a simpler model structure. To avoid the duplication of explanation, we will focus on the modifications introduced by FNN.

Consider the FNN structure depicted in Fig. 5. In the considered FNN model, there are \( N_c \) hidden layers as with the CNN model, and each layer contains 64 neurons. Each hidden layer is activated by the ReLU function, and the activation part is the same as that of the CNN model. In addition, the FNN-based approach applies the FNN model instead of the CNN model to solve sub-band allocation and power control problems sequentially and individually. On the other hand, since matrix-type data cannot be entered as an input to the FNN structure, the standardized channel matrices in Fig. 3 now need to be vectorized before entering to the FNN structure, as shown in Fig. 5. The rest of the parts are the same as in the CNN-based scheme.

V. NUMERICAL EVALUATION

In this section, we numerically evaluate the achievable sum rate of the proposed scheme. We assume that the bandwidth of each sub-band is 15 kHz, \( \sigma^2 = -168 \text{ dBm/Hz} \), and \( P_{\text{max}} = 23 \text{ dBm} \). In addition, we set the radius of the cell \( D \) as \( D[\text{km}] = 0.1 \) and assume that the base station is located in the center of the cell while IoT users are randomly and uniformly located in the cell, in which the distance between the base station and IoT user \( i \) is given by \( d_i[\text{km}] = (120.9 + 40 \log_{10}(d_i)) \). We assume the spectral leakage ratio from sub-band \( m \) to sub-band \( n \), denoted by \( \rho_i^{[m,n]} \), as follows:

\[
\rho_i^{[m,n]} = \begin{cases} 
0 & \text{if } |n-m| = 0, \\
\rho_i^{[n-m]} & \text{if } |n-m| \neq 0,
\end{cases}
\]

where \( \rho_i \) will be specified later, \( \rho_2 = \rho_1 - 20 \text{ dB}, \rho_3 = \rho_1 - 30 \text{ dB}, \) and \( \rho_i^{[n-m]} = \rho_1 - 35 \text{ dB} \) for \( |n-m| \geq 4 \). The channel coefficient \( h_i^{[n,m]} \) is then assumed to follow \( \mathcal{CN}(0, \rho_i^{[n,m]}/\beta_i) \).

In the learning process of both the optimization stages, we set \( N_c = 5 \) and \( F_c = 4 \) in the CNN structure and generate 10,000 data samples for training set and 2,000 samples for test set. In addition, we adopt Adam algorithm [28], which is a mini-batch stochastic gradient descent algorithm, to update the weight and bias of the model in every training epoch, and the learning rate is set to 0.005.

In Table 1, the ratio of the achievable sum rate of the proposed algorithm to that of the exhaustive search is expressed as a percentage according to the \( k \)-factor. It is observed that Algorithm 1 provides a good trade-off between the computational complexity and the sum rate performance and can achieve near-optimal performance when \( k \) is large enough, i.e., \( k \geq 6 \). Since the sum rate nearly saturates at \( k = 6 \), we set the \( k \)-factor to 6 for the entire simulation.

In addition, we compare the FNN-based scheme and the CNN-based scheme in Table 2. From Table 2, it can be seen that the FNN model can be trained with a shorter training time compared to the CNN model. However, since there is no spatial feature extraction in the learning process, the FNN-based scheme performs worse than the CNN-based scheme. Moreover, note that CNN models are generally more robust against overfitting problems because they have significantly fewer model parameters than FNN models [29].

For comparison, the following benchmark schemes are considered.

- The full search scheme maximizes (4) by considering all possible combinations of sub-band assignment matrix \( \mathbf{C} \) and discretized power control vector \( \mathbf{p} \) with sufficiently small quantization level.
- The two-stage full search scheme first exhaustively finds the best sub-band assignment matrix for problem P1. Then, for the given sub-band assignment matrix, it exhaustively finds the optimal \( \mathbf{p} \) for problem P2.
- The weighted minimum mean square error power control (WMMSE PC) scheme determines a suitable sub-band assignment matrix in the same way as the proposed scheme. On the other hand, the power control vector is obtained by the MMSE-based iterative calculation [30] instead of the learning process explained in Section IV-C for the given sub-band assignment matrix.
- The no power control (No PC) scheme in which each IoT user can only perform on-off power control is considered. As in the WMMSE PC scheme, a sub-band assignment matrix is chosen in the same way as the proposed scheme.
- The simplified sub-band assignment scheme simply assigns the user with the largest channel gain to each sub-band.
sub-band without learning process and without considering inter-band interference due to spectral leakage. In order to satisfy the condition (4c), users are sequentially assigned to each sub-band using Algorithm 1. For a given sub-band assignment, the power control vector is obtained in the same manner as the proposed scheme.

- The previous convex relaxation scheme based on the Hungarian algorithm [8] is considered.

The average achievable sum rates of the considered schemes with respect to $K$, $N$, and $\rho_1$ are depicted in Figs. 6, 7, and 8, respectively. Overall, the results demonstrate that the proposed scheme with CNNs provides performance close to that of the full search or the two-stage full search schemes despite much lower complexity and also significantly outperforms the scheme in [8].

To be specific, in Fig. 6, it is observed that the achievable sum rates of the CNN-based schemes with the proposed sub-band assignment algorithm increase with $K$ in contrast to the simplified sub-band assignment, since inter-band interference due to spectral leakage is properly considered in the learning process. In addition, the proposed power control algorithm is shown to considerably improve the sum rate compared to the WMMSE PC or No PC schemes. However, it is observed that the performance of the FNN-based scheme is not improved as $K$ increases. This is due to the fact that the depth of the input channel matrix increases in proportion to $K$. To be more specific, as the depth of the input channel matrix increases, more spatial features that are not reflected in the learning process of the FNN structure exist, leading to performance degradation. On the other hand, the CNN-based scheme can improve sum rate performance as $K$ increases, since more hidden spatial features of the input channel matrix can be trained in the training phase even when $K$ increases.

It is also observed in Fig. 8 that the proposed two-stage optimization method can achieve performance close to that of the full search, which is the exhaustive joint optimizer. As expected, the sum rates of all the considered schemes increase with $N$ as shown in Fig. 7 and decrease as spectral leakage becomes more severe as shown in Fig. 8.

Moreover, the required simulation time for some chosen cases is summarized in Table 3. The simulation is performed by Python 3.8 with Tensorflow 2.5.0, Intel i7-10700F CPU, 32GB RAM, and NVIDIA GeForce RTX 3060 Ti GPU. It is clearly observed that the proposed scheme has much lower computational complexity than the two-stage full search and has a similar level of computational complexity to the previous convex relaxation method [8]. In addition, since the gap of simulation time between the FNN-based scheme and
the CNN-based scheme is negligible whereas the CNN-based scheme strictly outperforms the FNN-based scheme, it can be concluded that CNNs are more efficient deep learning structures for our proposed scheme considering both performance and complexity.

VI. CONCLUSION AND FUTURE WORKS

In this paper, we have studied deep learning-based algorithms that sequentially optimize sub-band assignment and transmit power control to maximize the sum rate of uplink IoT cellular networks in the presence of spectral leakage. CNN and FNN were considered as deep learning structures, and the proposed schemes based on each structure were analyzed and compared in detail. As a result, the proposed CNN-based scheme has been shown to achieve near-optimal performance and strictly outperform previous schemes without deep learning with low computation time.

Based on our work, several interesting further research directions can be considered. For example, extending the proposed algorithm to NOMA and analyzing its additional benefits would be a good follow-up study. In addition, extending to the case in which the base station has multiple antennas is also an interesting future direction.

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TABLE 3. Simulation time (sec) for 100 samples with \((N, K) \in \{(4, 8), (5, 10), (6, 12)\).

| Schemes               | Cases \((N, K)\) | \((4, 8)\) | \((5, 10)\) | \((6, 12)\) |
|-----------------------|----------------|-----------|-----------|-----------|
| Two-stage full search |                | 37.53     | 516.04    | 10,144.2  |
| Proposed scheme (CNN)|                | 4.63      | 39.21     | 223.56    |
| Proposed scheme (FNN)|                | 4.77      | 38.91     | 223.45    |
| WMMSPE PC             |                | 27.22     | 62.99     | 297.23    |
| Previous scheme [8]   |                | 78.45     | 100.72    | 131.93    |
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