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# Deep Learning Based User Association in Heterogeneous Wireless Networks

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**ABSTRACT** Due to the high splitting-gain of dense small cells, Ultra-Dense Network (UDN) is widely regarded as a promising networking technology to achieve high data rate and low latency in 5G mobile communications. In UDNs, user association is an open NP-hard problem due to the high computational complexity. In this paper, we study the user association problem from a deep learning perspective. We propose a U-Net based deep learning scheme aimed at intelligently associating user equipments(UE) to the competing Macro Base Stations (MBS) and small Base Stations (SBS). We formulate the user association problem as a constrained combinatorial optimization problem and employ a cross-entropy algorithm to obtain its asymptotically optimal solution for labelling in supervised learning. We define a differentiable loss function by combining the Mean Squared Errors(MSE) criterion and the fairness and load balancing constraints for the supervised deep learning framework. We first train the U-Net based learning model and then evaluate the accuracy of the proposed scheme. Simulation results show that the proposed U-Net scheme approaches the asymptotically optimum Genetic Algorithm (GA) scheme in terms of minimum rate gain and sum rate gain, whereas outperforms the latter with significantly reduced computation time and robustness to network scales.

**INDEX TERMS** Deep learning, user association, Ultra-Dense Network, U-Net.

## I. INTRODUCTION

### A. USER ASSOCIATION AND RELATED WORKS

Ultra-Dense Network (UDN) is widely considered as a promising technology to meet the requirements of explosive data traffic and low latency in emerging 5G and beyond 5G (B5G) mobile communications. By densely deploying small cells (such as picocells and femtocells), cell splitting and densification in UNDs are considered to be one of the most effective means to deliver ever-increasing capacity and to offload the wireless data traffic from macrocells. In UDNs, a user equipment(UE) may receive signals from multiple BSs and interference in UDNs becomes more severe. Coordinated Multi-Point (CoMP) transmission technique is proposed to leverage the cooperation of multiple BSs to enhance the signal to interference and noise ratio (SINR), to counteract intercell interference and to enhance network capacity in UDNs.

Increased complexity and heterogeneity of cellular networks require a paradigm shift from traditional resource allocation mechanisms. In this paper, we study the user association mechanism, which plays a pivotal role in enhancing the load balancing, the spectrum efficiency, and the energy efficiency of networks.

In existing cellular networks, received signal power based user association is the most dominant rule, where a UE chooses to associate with the specific BS with the maximum received signal strength (max-RSS). In UDNs, the conventional max-RSS association rule will lead to over-loading at Macro cells, due to different maximum transmit powers and coverage ranges. Rather than being associated to the BS with max-RSS, a UE in CoMP based UDNs may be associated with one or more BSs before data transmission commences. Thus more sophisticated user association algorithms are needed to address the unique features of the emerging 5G and B5G networks.

In general, finding the truly optimal UE-BS association is a combinatorial optimization problem and the complexity grows exponentially with the scale of the network, which is a dead end [1]. Since a general utility maximization of (load-weighted) rate, subject to a resource or/and power constraint, results in a coupled relationship between user association

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and scheduling, which is NP hard and not computable even for median-sized cellular networks. It is shown that the load-aware association significantly improves resource utilization and mitigates the congestion of MBSs, resulting in a multi-fold gain to the overall rate for most UEs [2].

One way to make the user association problem convex is to assume a fully loaded model with the binary association relaxed to a real number between 0 and 1. Besides combinatorial optimization, game theory, Markov Decision Processes(MDP)and stochastic geometry are also widely used tools for solving the user association problem [3].

In [2], Ye *et al.* proposed a class of novel user association schemes that achieve load balance in heterogeneous networks through a network-wide utility maximization problem and designed a distributed algorithm via dual decomposition. A key observation is that the optimal biasing factors are nearly independent of BSs' densities for the various tiers, but highly dependent on the per-tier transmit powers. With these optimal biasing factors, the network nearly achieves the optimal load-aware performance. However, it is hard to determine the optimal bias value. In [4], Ge *et al.* investigated joint user association and user scheduling for load balancing over the downlink of a wireless heterogeneous network by formulating a network-wide utility maximization problem, and proposed an alternating direction method of multipliers to efficiently approximate and solve the nonconvex problem.

### B. APPLICATIONS OF DEEP LEARNING IN COMMUNICATIONS

Recently, deep learning has emerged as a state-of-the-art machine learning technique with promising potential to drive significant breakthroughs in wireless communications. Deep learning has been first investigated in decoding and codes for better error performance and lower complexity. Besides channel decoding, deep learning techniques have been recently investigated in a variety of wireless communications such as MIMO detection [5], radio signal classification [6] and channel estimation [7]. In [8], Zhou *et al.* studied network traffic predication based on deep long short-term memory (LSTM) structure learning model, to make localized prediction pertaining to future traffic characteristics from the past and current dataset.

Deep learning (DL) has also been considered as a powerful tool by which a multi-layer neural network can be trained to model resource management such as power allocation and subchannel allocation. By using the data generated by a suboptimum/near optimum algorithm and training the deep learning model, resource allocation decisions can be obtained without intensive online computations. Existing works on deep learning based resource allocation in wireless communications can be categorized into two groups: deep reinforcement learning (DRL) and deep supervised learning [9].

The DRL is theoretically based on the finite Markov Decision Process (MDP) modelling, and attempts to achieve the maximum long-term utilities to obtain the optimum joint policy. However, the wireless environment states are more complicated rather than the simple Markov process under time-varying channel conditions and random mobility of UEs. Moreover, information exchange by passing the message among the BSs and UEs at each decision episode involves overwhelming overhead in wireless communications.

In [9], Ahmed *et al.* proposed a supervised Auto-encoder based DL model to jointly solve the sub-band and power allocation problem in a multi-cell network. However, the joint power and subchannel allocation is only considered in data generation phase by iteratively using Genetic Algorithm(GA), the maximum power and subchannel constraints are not considered in the DL training phase. More importantly, output sparsity is not considered for large-scale subchannel allocation, which may result in non-convergence in training.

In [10], supervised deep learning has been applied for power allocation based on Weighted Minimum Mean Square Error (WMMSE) benchmark. The WMMSE criterion is however not the global optimum and thus Liang *et al.* proposed an unsupervised deep learning by directly maximizing the sum rate utility function in the training phase [11]. The unsupervised learning method does not require the ground truth data labelling which is usually infeasible in practice due to non-convex optimization. However, the unsupervised learning cannot be generalized due to that the loss function in discrete allocation such as subchannel allocation and user association may be non-differential and may not converge in training phase. Rather than maximizing network throughput, Matthiesen *et al.* developed a deep learning power control framework for energy efficiency maximization in wireless interference networks [12].

In [13], Zhao *et al.* investigated a deep reinforcement learning scheme for user association and resource allocation in heterogeneous cellular networks. To solve the computationally expensive problem with the large action space, a multi-agent DRL method is proposed to obtain the nearly optimal policy through message passing. However, passing channel information and instant rewards among BSs for each UE at every decision episode will impose unacceptable overhead in time-sensitive 5G/B5G cellular networks. Moreover, the convergence of the DRL method highly depends on training parameters such as $\epsilon$-greedy exploration, discount rate of utility, episode length and step sizes, the optimal values of which are environment-dependent.

### C. CONTRIBUTIONS

In this paper, we investigate the user association problem from the supervised deep learning perspective, which does not assume the MDP of the environments. The inherent characteristics of environments are learned from collected past and current data. The main contributions are as follows.

- We study the user association problem of ultra dense mobile networks by using deep supervised learning

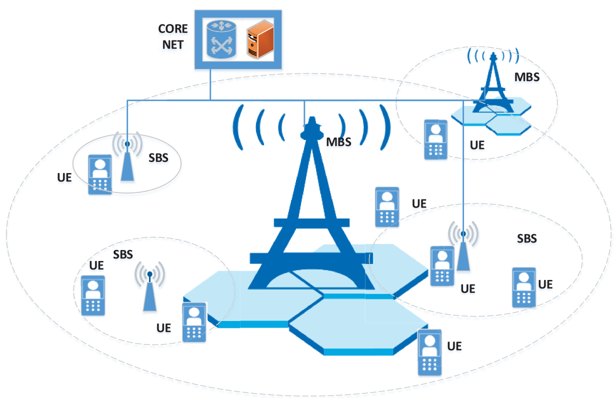


**FIGURE 1.** System model of UDN with JT-CoMP.

technologies to address the open NP-hard problem. We first map the user association problem into an image segmentation problem in typical convolutional networks with pixel-scale classification, and propose a U-Net based deep learning algorithm aimed at intelligently associating UEs to the competing Macro and small BSs.

- We formulate the user association problem as a constrained combinatorial optimization problem and employ a cross-entropy algorithm to obtain its asymptotically optimal solutions for labelling in supervised learning. We define a differentiable loss function by combining the MSE-criterion and the fairness and load balancing constraints for fast convergence in the supervised deep learning framework.
- Extensive simulations are performed for performance evaluation and the results show that the proposed deep learning user association scheme approaches the asymptotically optimum GA scheme in terms of maximum rates and sum rates, whereas outperforms the latter with significantly reduced computational complexity.
- We consider the user association to more than one BSs in the CoMP, the framework of which can be also suitable to non-CoMP transmission scenarios.

The rest of the paper is organized as follows. The system model and use association model are introduced in Section II. Problem formulation is presented in Section III as a constrained combinatorial optimization problem. In Section IV, the main contribution of this paper is presented to introduce a U-Net based deep learning framework for user association. Simulation results are given in section V. Conclusions of this study are drawn in Section VI.

## II. SYSTEM MODEL

### A. NETWORK MODEL

We consider a two-tier OFDMA heterogeneous Ultra Dense Network consisting of $N_{\text{MBS}}$ MBSs and $N_{\text{SBS}}$ SBSs. The system model is shown in Fig.1. Denote $P_i$ as the $i$-th tier transmit powers of BSs. Usually, there is a transmit power disparity among different tiers of BSs. For example, Macrocells have a typical transmit power 43 dBm, Picocells have classical transmit powers ranging from 26 dBm to 30 dBm, whereas the transmit powers of Femtocells are usually less than 23 dBm.

We consider a topology area of $D \times D$ square meters, where the MBSs are uniformly distributed to provide coverage and to support capacity, with the distance between MBSs no small than $d_M$. The small BSs are also randomly and uniformly distributed within the covering area. Let $B^\Omega = \{b|b = 1, 2, \cdots, |B^\Omega|\}$ denote the set of BSs consisting of both Macro BSs and Small BSs, where $|B^\Omega| = N_{\text{MBS}} + N_{\text{SBS}}$ is the total number of BSs. UEs are randomly and uniformly distributed around each SBS. The set of UEs is denoted by $M^\Omega = \{m|m = 1, 2, \cdots, |M^\Omega|\}$.

In an OFDMA network, the total transmission time and frequency bands are equally divided into multiple time slots and multiple subcarriers. Similar to that in 4G LTE and 5G New Radio (NR), a resource block (RB) is the smallest unit of resources that can be allocated to a UE, and each resource block consists of several consecutive subcarriers. As known in LTE network, the resource block is 180 kHz wide in frequency and 1 slot long in time. Without loss of generality, we denote $W_0$ and $N_{\text{RB}}$ as the bandwidth of each RB, and the total number of RBs, respectively.

The channel gain is modeled to capture path loss, shadowing and antenna gain, which is averaged over the allocated resource blocks for association. Denote $g_{m,b}$ as the averaged channel gain between UE $m$ and BS $b$, we then have the averaged channel gain matrix as

$$\mathbf{G} = \begin{bmatrix} g_{1,1} & g_{1,2} & \cdots & g_{1,|B^\Omega|} \\ g_{2,1} & g_{2,2} & \cdots & g_{2,|B^\Omega|} \\ \vdots & \vdots & \ddots & \vdots \\ g_{|M^\Omega|,1} & g_{|M^\Omega|,2} & \cdots & g_{|M^\Omega|,|B^\Omega|} \end{bmatrix} \tag{1}$$

UEs locating at the edges of cells usually suffer from severe intercell interference and low capacity. To reduce interference and enhance peak data rates of cell edge users, joint transmission Coordinated Multi-Point (termed as JT-CoMP) is considered in the network architecture, which allows multiple BSs in the neighborhood to cooperatively serve a specific UE simultaneously. Let $B_m^\Omega$ denote the set of coordinated BSs for joint transmission to UE $m$, the SINR of UE $m$ is given by

$$\gamma_m = \frac{\sum\limits_{b \in B_m^\Omega} P_b g_{m,b}}{\sum\limits_{b' \in B^\Omega \backslash B_m^\Omega} P_{b'} g_{m,b'} + \sigma^2} \tag{2}$$

where $P_b$ is the transmit power of BS $b$, $\sigma^2$ is the variance of Additive White Gaussian Noise (AWGN) denoting the noise power level.

Before data transmission, a user association mechanism is needed to determine whether a UE is associated with a particular base station (BS).

### B. USER/CELL ASSOCIATION MODEL

User association, namely associating a UE with a particular serving base station (BS), plays a pivotal role in enhancing the load balancing, the spectrum efficiency, and the energy efficiency of networks performance. The association relationship between UE $m$ and BS $b$ is denoted by a bit number $x_{m,b}(m \in M^{\Omega}, b \in B^{\Omega})$ defined as

$$x_{m,b} = \begin{cases} 1 & \text{UE } m \text{ is associated with BS } b \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

Thus, the entire association matrix between all UEs and all BSs can be represented as:

$$\mathbf{X} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,|B^{\Omega}|} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,|B^{\Omega}|} \\ \vdots & \vdots & \ddots & \vdots \\ x_{|M^{\Omega}|,1} & x_{|M^{\Omega}|,2} & \cdots & x_{|M^{\Omega}|,|B^{\Omega}|} \end{bmatrix} \tag{4}$$

In this paper, we consider downlink user/cell association, and assume that each BS always has data to transmit to its associated UEs. Assume that the association time is carried out in a large time scale compared to the change of channel. The SINR of a specific UE in a downlink transmission can be presented in terms of $x_{m,b}$ as follows,

$$\Gamma_m = \frac{\sum_{b \in B^{\Omega}} x_{m,b} P_b g_{m,b}}{\sum_{b' \in B^{\Omega}} (1 - x_{m,b'}) P_{b'} g_{m,b} + \sigma^2} \tag{5}$$

### C. RESOURCE BLOCK ALLOCATION

In [2], it was shown that under the consideration of load balancing, the optimal resource allocation is equal allocation under logarithmic utility function. Therefore, the optimal RB allocation for BS $b$ is equal allocation given by $\frac{W_0 \cdot N_{\mathrm{RB}}}{|M_b^{\Omega}|}$, where $|M_b^{\Omega}|$ denotes the number of UEs associated with BS $b$. Considering that UE $m$ may associate with different BSs in JT-CoMP networks, correspondingly, the optimal RB allocation for UE $m$ can be given by

$$\beta_m = \min \left\{ \frac{W_0 \cdot N_{\mathrm{RB}}}{|M_b^{\Omega}|} \middle| b \in B_m^{\Omega} \right\} \tag{6}$$

where $B_m^{\Omega} \subseteq B^{\Omega}$ denotes the set of BSs associated with UE $m$, i.e., $B_m^{\Omega} = \{b | b \in B^{\Omega}$, and $x_{m,b} = 1\}$, $M_b^{\Omega} \subseteq M^{\Omega}$ denotes the set of UEs associated with BS $b$, i.e., $M_b^{\Omega} = \{m | m \in M^{\Omega}$, and $x_{m,b} = 1\}$. The min operation is applied due to that JT-CoMP has to transmit on the same frequency band.

Then the data rate of a downlink transmission to UE $m$ can be given by

$$R_m = \lceil \beta_m \rceil \log_2 (1 + \Gamma_m) \tag{7}$$

where $\lceil x \rceil$ is the minimum integer larger than or equal to $x$, $\Gamma_m$ is the SINR of UE $m$ defined by Eq. (5). The $\lceil x \rceil$ operation is applied due to that RB allocation is based on integer allocation of RBs in practice.

## III. PROBLEM FORMULATION

In this paper, we consider the user association problem under the consideration of load balancing. As shown in [2], logarithmic utility function is concave and has diminishing returns and thus promotes the load balancing. Therefore, logarithmic function is applied to the achievable rate. Considering the fairness of UEs, the network throughput of cell edge users is used as the performance metric, therefore, the objective function is to maximize the minimum logarithmic achievable rate of the cell edge user. Finally the problem is formulated as:

$$\begin{aligned} &\max_{\mathbf{X}} \ \min \sum_{m \in M_E} \log(U_m) \\ &s.t. \ C_1 : \ 1 \leq |B_m| \leq B_{max}, \quad \forall m \in M_{\Omega} \\ &\qquad C_2 : \ \sum_{m} x_{mb} \leq N_{max}, \quad \forall m \in M_{\Omega}, \ \forall b \in B_{\Omega} \end{aligned} \tag{8}$$

where the constraint $C_1$ indicates that for an arbitrary UE $m$, it can be served by at least one BS. In practice, the overhead may be unacceptably increasing with the number of cooperative BSs. Therefore, it is reasonable to assume that the number of associated BSs is upper-bounded by the maximum number of cooperative BSs as $B \leq B_{max}$. The constraint $C_2$ indicates that for an arbitrary BS $m$, the total number of associated UEs should not exceed the maximum allowable number $N_{max}$ by considering load balancing.

Problem (8) is a combinatorial problem with high complexity. Brute force search is only applicable for small scale network. For moderate scale network and large scale network, the computational complexity is prohibitively high. We have to determine for each UE which BSs are supposed to associate with. Mathematically, we have to determine the association matrix $\mathbf{X}$ from the input channel matrix $\mathbf{G}$, which can be regarded as an image segmentation problem and the class label (0/1) is supposed to be assigned to each pixel. Convolutional networks are investigated in this paper to solve the user association problem with significantly reduced computational complexity.

## IV. A U-Net BASED DEEP LEARNING FRAMEWORK FOR USER ASSOCIATION

### A. A MODIFIED U-Net ARCHITECTURE

The user association problem is to determine the value of each element of the association matrix $\mathbf{X}$, which can be mapped into the image segmentation problem in typical convolutional networks with pixel-scale classification. In particular, the channel gain matrices $\mathbf{G}$ can be mapped into the input "images" of a convolutional networks, and the output of the convolutional network can be regarded as the user association matrices $\mathbf{X}$. Considering that the U-Net architecture usually achieves good performance on various segmentation applications, the user association problem is modeled based on modified U-Net convolutional network as shown in Fig.2.

The network consists of a contracting path and an expansive path, which also gives it the U-shaped architecture. The contracting path follows the typical architecture of a convolutional network. It consists of four convolution blocks. Each convolution block has a $3 \times 3$ convolution operation with stride 2 and padding value 1, followed by a rectified linear unit (ReLU), and batch normalization. In the first convolutional block, a $5 \times 5$ kernel size is applied for convolution, with stride 1 and padding value of 2. At each downsampling step, the number of feature channels is doubled. There is

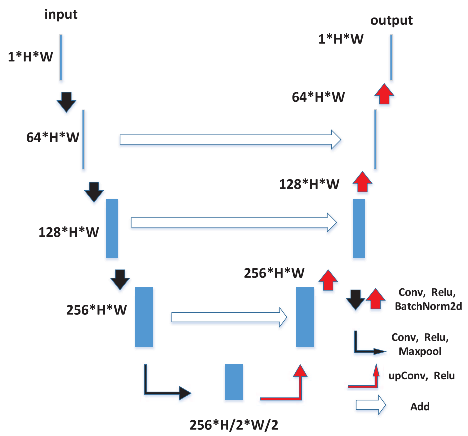


**FIGURE 2.** **A modified U-Net architecture for user association.**

an additional $2 \times 2$ max pooling operation in the fourth convolution block, which halves the feature map.

The first step in the expansive path consists of an upsampling operation of the feature map followed by a $2 \times 2$ transpose convolution (''up-convolution'') that doubles the height and width of the ''feature map''. Every other step consists of a $3 \times 3$ convolution with stride 1 and padding value 1, followed by a ReLU function, batch normalization and a concatenation with the corresponding feature mapping from the contracting path. At the final layer, a $1 \times 1$ convolution is used to map each 64-component feature vector to the desired number of classes. The activation function is defined as

$$y = \begin{cases} 0, & x < 0 \\ x, & 0 \leq x \leq 1 \\ 1, & x > 1 \end{cases} \tag{9}$$

In practice, the convolutional kernel size, stride and padding value can be adjusted by considering feature extraction dimensions and avoiding over-fitting, for both the contracting path and the expansive path.

We take an ''image'' for example to explain the image transform through each step of the modified U-Net architecture to get the desire output. The input ''image'' is of size $C \times H \times W$, where $C$, $H$ and $W$ denote the number of the U-Net ''channel'', height and width of the input data respectively. In this paper, $C = 1$, $H = |M^{\Omega}|$ denotes the number of UEs, and $W = |B^{\Omega}|$ corresponds to the number of BSs. The $10 * \log_{10}(\cdot)$ operation is applied to the channel gain matrices $\mathbf{G}$ followed by a normalization, we then obtain the normalized channel gain matrices $\hat{\mathbf{G}}$ as the input of the U-Net architecture.

In the contracting path of the first convolution block, 64 filters with $5 \times 5$ kernel size are applied to the normalized channel gain matrices $\hat{\mathbf{G}}$, with stride 1 and padding value of 2, followed by a ReLU activation function and batch normalization. In the second convolution block, the number of filters is set as 128 then the size of the feature maps becomes $128 \times H \times W$. In the third and fourth convolution block, the numbers of filters are both 256 whereas the fourth block has a max pooling operation. Therefore, the third and the fourth feature maps are of size $256 \times H \times W$ and $256 \times H/2 \times W/2$ respectively.

In the expansive path of the first upsampling block, a $2 \times 2$ ''up-convolution'' is applied and we double the size of the image and obtain a $256 \times H \times W$ feature map. With a concatenation by adding the associated feature map from the contracting path, we get a fused $256 \times H \times W$ feature map. In the following steps of the expansive path, the feature map is applied by a $3 \times 3$ convolution with stride 1 and padding value 1, followed by a ReLU function and batch normalization, as well as an add operation from the contracting path. The feature maps are halved with the size from $256 \times H \times W$, $128 \times H \times W$, to $64 \times H \times W$ respectively. At the final step, a $1 \times 1$ convolution is applied to map the 64-feature map to the desired number of classes.

## B. SUPERVISED LEARNING

### 1) DATA PREPROCESSING

#### a: DATA GENERATION

Ideally, we have to obtain the input channel gain matrix $\mathbf{G}$ and the optimal association matrix $\mathbf{X}$ for supervised learning. However, the problem of (8) is a constrained combinatorial optimization problem and brute search is practically infeasible for moderate-scale networks. To generate data to train and test our modified U-Net learning model, the input channel gain matrices have to be labeled. In this paper, a cross-entropy algorithm is applied [14] to obtain labels $\mathbf{X}_l$, which is the suboptimal solution of problem (8) by essentially a heuristic search Genetic Algorithm. The training dataset is divided into training set, validation set and testing set.

#### b: TRAINING PHASE

The training phase consists of pretraining and training phase. The goal of the pretraining phase is to find a good inial weight and bias of the learning network. We define the Minimum Mean Squared Error(MMSE) loss function as

$$L_M = \mathbf{E}(||\mathbf{X}_k - \mathbf{X}_L||^2) \tag{10}$$

where $\mathbf{X}_k$ denotes the output matrix of the learning network at the $k$th training epoch, $\mathbf{X}_L$ is the label matrix, and $\mathbf{E}(.)$ denotes the expectation operation.

After pretraining, the learning network can usually obtain a good initial value. By considering the constraint $C_1$ in (8), we denote $L_U$ as the loss function under the constraint of the number of BSs that a UE can be associated with,

$$\begin{aligned} L_U = \lambda_1 * \mathbf{E}_m \left( \mathrm{ReLu} \left( \max_i \sum_{j=1}^{B_\Omega} \lfloor x_{ij}^m \rfloor - B_{max} \right) \right) \\ + \lambda_2 * \mathbf{E}_m \left( \mathrm{ReLu} \left( 1 - \min_i \sum_{j=1}^{B_\Omega} \lfloor x_{ij}^m \rfloor \right) \right), \end{aligned} \tag{11}$$

where $x_{ij}^m$ denotes the association value of the $m$-th sample between user $i$ and BS $j$, $\lfloor x \rfloor$ denotes the rounding operation to map $x$ to a binary indicator 0/1. Note that $x_{ij}^m$ is a real value in the training process and is different from the final association indicator $x_{i,j}$ which only takes the value 0 or 1. The ReLu

**Algorithm 1** Procedure of Deep Learning Based User Association

1: Generate channel gain data set and do data preprocessing.
2: Find labels of input data by the cross-entropy based heuristic algorithm.
3: Train data set offline with training data set and validation data set.
4: Test the dataset and process the outliers.

function promotes the model to satisfy the constraint of the number of allowable BSs as $f(x) = \max(0, x)$. When the associated number of BSs exceeds $N_{max}$, there will be a positive loss on the loss function and the learning model will trace the path towards the minimum loss.

By considering the constraint $C_2$ in (8), we denote $L_B$ as the loss function under the constraint of the maximum number of UEs that a BS can associate,

$$L_B = \lambda_3 * \mathbf{E}_m \left( \text{ReLu} \left( \max_j \sum_{i=1}^{M_\Omega} \lfloor x_{ij}^m \rceil - N_{max} \right) \right). \quad (12)$$

Finally, the loss function of training phase is given by

$$L_C = L_M + L_U + L_B. \quad (13)$$

### *C. LEARNING PROCEDURE*

Because of the rounding operation of $\lfloor x_{ij}^m \rceil$, for each sample $m$, there may exist an outlier situation where a "lucky" UE cannot find a single BS to associate. Mathematically, we have

$$i^m = \underset{i}{arg} \left( \sum_{j=1}^{B_\Omega} \lfloor x_{ij}^m \rceil = 0 \right) \quad (14)$$

To deal with this situation, we let the outlier UE $i$ choose from the light-loaded BSs set $B'_\Omega$ with the maximum $x_{ij}$,

$$j_i^m = \underset{j}{arg} \left( \max_{j \in B'_\Omega} x_{ij}^m, \text{ and, } \sum_{i}^{M_\Omega} \lfloor x_{ij}^m \rceil \leq N_{max} \right) \quad (15)$$

Because of the rounding operation of $\lfloor x_{ij}^m \rceil$, there may exist another outlier situation where a "lucky" BS associates too much UEs, that is,

$$j^m = \underset{j}{arg} \left( \sum_{i}^{M_\Omega} \lfloor x_{ij}^m \rceil > N_{max} \right) \quad (16)$$

Similarly, we would find the UE which has the smallest association value $x_{ij}$ and at least is associated with more than one BS iteratively, until the load condition is satisfied

$$i_j^m = \underset{i}{arg} \left( \min_i x_{ij}^m, \text{ and, } \sum_{j=1}^{B_\Omega} \lfloor x_{ij}^m \rceil > 1 \right) \quad (17)$$

In practice, the above procedure to deal with the outlier's situations may be implemented iteratively until all outliers are removed.

**Algorithm 2** Procedure to Deal With the Outlier's User Association

1: **if** UE $i$ is an outlier without an associated BS **then**
2:     Associate UE $i$ with BS $j_i^m$ based on (15).
3: **end if**
4: **if** BS $j$ is an overloaded outlier **then**
5:     Remove the associated UE $i$ from BS $j$ based on (17).
6: **end if**

**TABLE 1.** Simulation parameters' setting.

| Parameters | Value |
|---|---|
| Plane of Topology | $600 \times 600$ m$^2$ |
| Number of MBSs $N_{\text{MBS}}$ | 2 |
| Minimum distance between MBS | 300 m |
| Number of SBSs $N_{\text{SBS}}$ | 8 |
| Number of UEs | 28∼44 |
| Number of RBs $N_{RB}$ | 20 |
| Bandwidth per RB | 180 KHz |
| Cell range bias | 6 dB |
| Channel Model | WINNER |
| Transmit Power of MBS | 40 W |
| Transmit Power of SBS | 2 W |
| Maximum number of BSs per UE | $B_{max}$= 3 |
| Maximum number of UEs per BS | $N_{max}$= 20 |
| Noise level | 174 dBm/Hz |

## V. PERFORMANCE EVALUATION AND SIMULATION

In this section, system level simulations are performed to evaluate the performance of the proposed scheme in terms of achievable rates and computational complexity.

### *A. SIMULATION SETTINGS*

Some important parameters settings are presented in Table 1. In the simulations, the maximum number of BSs serving for one UE is 3, by considering that a large number of cooperative BSs will cause huge overhead and intolerant network delay [15].

The total number of BSs $|B^\Omega| = N_{\text{MBS}} + N_{\text{SBS}} = 10$. For computational simplicity, we only consider the number of UEs ranging from 28 to 44 in the simulations, which means UEs are generally far from each other geologically at the space of 600 times 600 square meters and the adjacent channel gains/pixels are generally uncorrelated. In the U-Net model, the height of U-Net "images" denotes the number of the UEs as $H = 28 \sim 44$, and the width of U-Net "images" corresponds to the number of BSs as $W = |B^\Omega| = 10$.

The data set is collected by following the WINNER channel model and randomly spreading UEs around each SBS. We collect 15000 samples for each scale of network (fixed number of UEs and BSs). Among each total 15000 samples, 10% samples are used for validation, 10% for testing and the left 80% for training. In the first 10 epochs of training, the Adaptive Moment Estimation (Adam) optimizer is applied with learning rate 0.00001 for fast adaptation. Then the optimizer is changed to the well-known Stochastic Gradient Descent (SGD) method with learning rate dynamically reduced 10% every 20 epochs for steady convergence. The activation function in simulations is defined in (9).

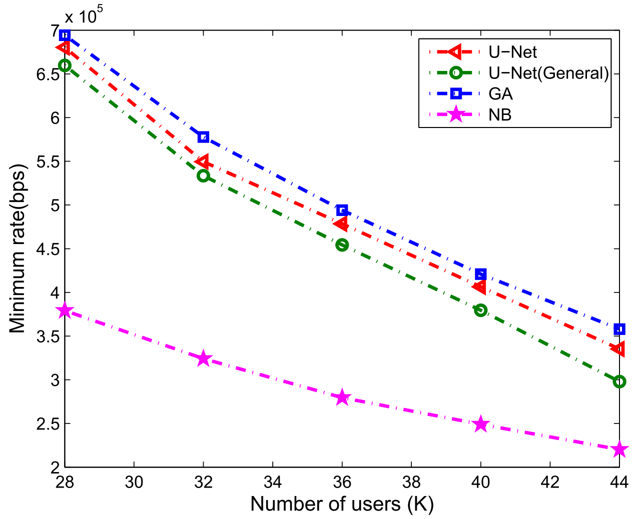


**FIGURE 3.** The minimum rate comparison of different association schemes versus different numbers of UEs.

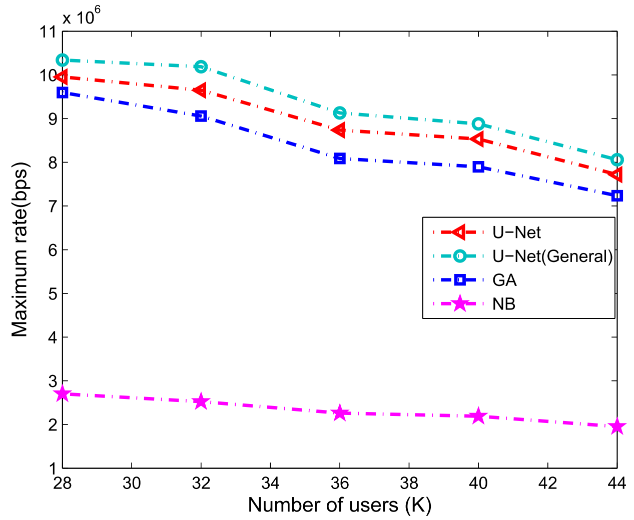


**FIGURE 4.** The maximum rate comparison of different association schemes versus different numbers of UEs.

### *B. SIMULATION RESULTS*

In this section, we first evaluate the performance of different user association schemes in terms of the minimum rate, the maximum rate and the sum rate of the network in Fig.3, Fig.4 and Fig.5 respectively. In particular, we compare the performance of the proposed deep learning scheme with the conventional genetic algorithm(GA) scheme and the N-best association scheme ($N = 3$ in the simulations, that is, each UE is associated first 3 BSs with maximum RSS).

To evaluate the generalization of the U-Net model, a much larger sample set under different numbers of UEs are used to train the network, which is termed as "U-Net(General)" in this paper. By "U-Net(General)" model, we mean multi-scale training. By training the U-Net architecture with input "images" (channel gain matrices) of different sizes, we expect the trained network can adapt to different numbers of UEs to some extent in practical wireless environments.

Under the fixed U-Net architecture, training and testing data of the U-Net(General) model have to be preprocessed by

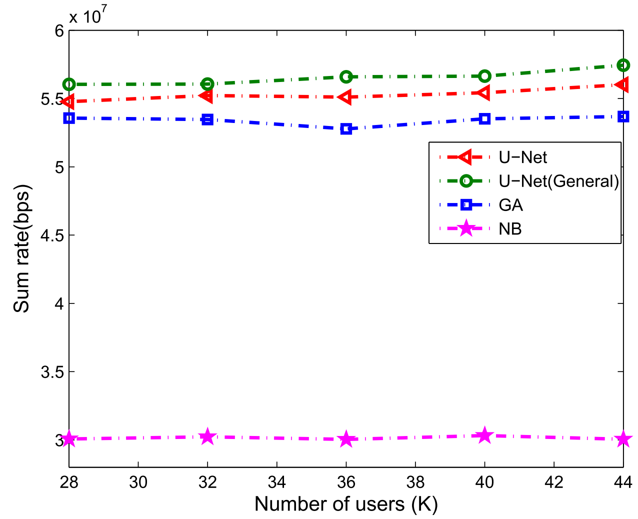


**FIGURE 5.** The sum rate comparison of different association schemes under different numbers of UEs.

interpolation to the same size. More specifically, the training data of the U-Net(General) model are the same and fixed as height $H = 32$ and width $W = |B^{\Omega}| = 10$, whereas the channel gain data with the height $H$ ranging from 28, 36, 40, 44 have to be preprocessed by interpolation. The "U-Net(General)" model is trained to evaluate whether to adapt the practical time-varying channel data and mobility of UEs.

In Fig.3-Fig.5, "U-Net" represents the performance of the loss function $L_C$-based U-Net learning scheme ($L_C$ is defined in (13)). "NB" and "GA" represent the performance of the conventional the N-best scheme and the cross-entropy based Genetic Algorithm in [14] respectively.

Fig.3 shows the minimum rates of the wireless network achieved by the proposed deep learning schemes, the conventional N-best (NB) association scheme and the asymptotic optimal GA association scheme in [14]. Let $K$ denote the number of UEs and we have $K = |M^{\Omega}|$. We can see that the proposed U-Net deep learning scheme with customized loss function and the "U-Net(General)" scheme can achieve respectively 80% and 74% minimum rate gain compared with the N-best scheme under the number of UEs $K = 28$. Under the number of UEs $K = 44$, the U-Net and the "U-Net(General)" scheme can achieve respectively more than 52% and 35% minimum rate gain.

Moreover, both the proposed U-Net scheme and the "U-Net(General)" scheme approach closely the asymptotic optimal GA association scheme in [14], with more than 97% minimum rates under the number of users $K = 28$. Under the number of users $K = 44$, the minimum rate of the proposed U-Net scheme and the "U-Net(General)" scheme are respectively 93% and 83%, compared to that of the GA scheme.

Fig.4 shows the maximum rates of the wireless network achieved by different association schemes.

We can see that the proposed U-Net scheme and "U-Net(General)" scheme significantly outperform the

**TABLE 2.** Computation time comparison of different association schemes.

| scheme \ time(s) | K=28 | K=32 | K=36 | K=40 |
|---|---|---|---|---|
| GA | 10.5692 | 11.8218 | 12.6176 | 13.5125 |
| DL/GPU | 0.0062 | 0.0059 | 0.0058 | 0.0058 |
| DL/CPU | 0.0452 | 0.0447 | 0.0401 | 0.0366 |

simple N-Best scheme with about three times maximum rate gain, and even outperform the asymptotically optimal GA scheme with around 5% maximum rate gain.

Fig.5 shows the sum rates of the wireless network achieved by different association schemes.

In Fig.5, we can see that the proposed "U-Net(General)" deep learning scheme has the best performance in terms of sum rates compared to the other schemes under different number of UEs. The proposed U-Net and U-Net(General) scheme can achieve respectively 82% and 86% sum rate gain compared to the N-best scheme.

As expected, in Fig.3, the proposed U-Net schemes perform slightly inferior compared to the asymptotic optimum GA scheme. This is reasonable because the objective function is to maximize the minimum rates. However, we can see from Fig.4 and Fig.5 that both the proposed U-Net and U-Net(General) scheme approach and even outperform the GA scheme, in terms of maximum rates and sum rates under different network scales, with about 12% maximum rate gain and 7% sum rate gain respectively. The achieved rate gains show the effectiveness of the proposed method to the outliers, otherwise, the maximum rates and sum rates of the proposed methods would not exceed that of the asymptotic GA method.

Table 2 shows the computation time complexity of different association schemes with unit second (sec.) in the testing phase. We evaluate the proposed deep learning based association scheme under both GPU and CPU configuration, termed as DL/GPU and DL/CPU respectively. We used the NVIDIA Tesla V100 GPU and the Intel(R) Xeon(R) Gold 5118 CPU @ 2.30 GHz to run the simulations. We can see in Table 2 that, the computation time of the DL/GPU association and the DL/CPU association is remarkably decreased compared to the asymptotic optimal GA-based association scheme, on the order of 1% and 0.1% respectively. Moreover, the computation time of the conventional GA based association increases with network scales, whereas the computation time of the two DL based schemes keeps almost invariable with the number of UEs $K$ with little fluctuation and this property is crucially important for practical application, especially helpful for large scale network with hundreds and thousands UEs in a cell. The computation time of the DL-based association schemes fluctuate on the order of millisecond due to the negligible instability of GPU and CPU. In addition, the computation time of the the DL/GPU scheme is about 10% compared to that of DL/CPU scheme, this is because deep learning on GPU can run in parallel. We can expect that the GPU for acceleration of DL algorithm would be more significant in large-scale networks.

## VI. CONCLUSION

In this paper, we study the user association problem of ultra dense mobile networks from a new perspective, by using deep learning technologies to address the open problem of high complexity of the NP-hard problem. We first map the user association problem into an image segmentation problem in typical convolutional networks with pixel-scale classification, and propose a U-Net based deep learning algorithm aimed at intelligently associating UEs to the competing MBSs and SBSs. We formulate the user association problem as a constrained combinatorial optimization problem and employ a cross-entropy algorithm to obtain its asymptotically optimal solutions for labelling in supervised learning. We define a differentiable loss function by combining the MSE criterion and the fairness and load balancing constraints for fast convergence of the supervised deep learning framework. Simulation results show that the proposed deep learning user association schemes approach the asymptotically optimum GA scheme in terms of maximum rate gains and sum rate gains, whereas outperform the latter with significantly reduced computation time and robustness to network scales.

Resource blocks' allocation and power control are important to improve network performance and it is an interesting topic to investigate the joint allocation for ultra dense networks. We leave this open problem for our future work.

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