Dynamic Power Allocation in NOMA-Based Federated Learning System

Shufeng Li
School of Information and Communication Engineering Communication University of China
Beijing, China
lishufeng@cuc.edu.cn

Ming Wang
School of Information and Communication Engineering Communication University of China
Beijing, China
wangming12136@163.com

Yujun Cai
School of Information and Communication Engineering Communication University of China
Beijing, China
tangentchase@cuc.edu.cn

Yao Sun
James Watt School of Engineering University of Glasgow
Glasgow, U.K
yao.sun@glasgow.ac.uk

***Abstract*—With the rapid rise of digital technology, artificial intelligence driven by big data has entered the fast lane of development, but it has also given rise to many problems, such as data silos and user privacy. A solution to solve these problems is federated learning. However, this framework also faces many challenges, with high communication costs in the first place. Non-orthogonal multiple access (NOMA) can be applied to alleviate the problem. In this paper, we focus on this issue and investigate multiple access technology based on federated learning. We build a NOMA-based federated learning system to improve the communication efficiency of federated learning. Then we propose a NOMA dynamic power allocation algorithm based on the real-time channel state at the edge user to improve the performance of the system. Experimental results show that the proposed algorithm can improve the training accuracy of the system model and reduce the energy consumption for uploading parameters.**

***Keywords*—Federated Learning, NOMA, Power Allocation**

I. Introduction

With the rapid innovation of digital technology, big data and artificial intelligence have brought many changes in the fields of computer vision, speech recognition, text classification, natural language processing, and so on. At the same time, artificial intelligence has also been rapidly applied in wireless communication networks, which is called a major innovation to realize intelligent communication networks. However, in the process of achieving efficient access to data generated by a large number of mobile terminals, the artificial intelligence technology driven by big data has encountered many challenges, such as the data silos problem, which means it is difficult to integrate data from different places, and the user privacy, which is difficult to avoid in data mining.

One approach to solving the data silos problem and the user privacy problem involves the use of federated learning. The concept of federated learning was originally proposed by Google[1]. This paper published by McMahan et al. made the first formal elaboration on the definition, application scenarios, and other characteristics of federated learning, and proposed the FedAvg algorithm to solve the problem of the high communication cost of federated learning. Later, leading companies in various fields started to promote the development of this machine learning framework. Up to now, there are many mature and widely used federated learning frameworks both in domestic and overseas, such as FATE proposed by WeBank[2], Paddle FL proposed by Baidu[3], and TensorFlow Federated proposed by Google[4]. However, federated learning has encountered many challenges in the process of development, such as high communication costs, increasing privacy and security protection requirements, in addition to system heterogeneity and statistical heterogeneity at the edge user. To solve these problems, a large number of experts and scholars have proposed many optimization solutions. In this paper, we focus on the problem of high communication cost of federated learning, and improve the communication efficiency of federated learning by optimizing the multi-access technology in the federated learning framework, so as to achieve the goal of reducing the communication cost of federated learning.

Currently, the prevailing multiple access techniques used in the federated learning framework are orthogonal multiple access (OMA). These classical OMA techniques allocate the edge users in the federated learning framework to orthogonal resources in the frequency, time, and code domains to achieve multiplexing of signals, thus avoiding or alleviating the interference among these edge users. Hu et al. proposed a device scheduling for energy-efficient federated learning based on time-division multiple access (TDMA) to optimize energy consumption[5]. Yang et al. proposed a bisection-based algorithm to minimize the energy consumption in frequency-division multiple access (FDMA) -based federated learning systems[6]. With the fast development of non-orthogonal multiple access (NOMA) technology, wireless resources have been applied more efficiently. The main idea of NOMA technology is to use power domain multiplexing or code domain multiplexing for several different users to achieve the sharing of time and frequency resources within the same spatial hierarchy [7]. Liu et al. fully compared the OMA technique with the NOMA technique from multiple perspectives and demonstrated the greater performance advantage of the NOMA technique [8]. Sun et al. proposed an adaptive gradient quantization and sparsification approach to implementing gradient updates for uplinks in a federated learning framework and further investigated the approach in NOMA [9]. Ma et al. transformed the edge user scheduling problem of federated learning under NOMA into a maximum weight independent set problem that can be solved by graph theory to improve communication efficiency while enhancing edge user testing accuracy [10]. Thus, the aim of the work in this paper is to build a NOMA-based federated learning system to improve the communication efficiency of federated learning and to analyze and optimize its model performance. The main contributions of this paper are summarized as follows:

- Firstly, we build a NOMA-based federated learning system. Each edge user can simultaneously upload the parameters to the parameter server for aggregation, which improves the communication efficiency of federated learning.
- Secondly, we propose a NOMA dynamic power allocation algorithm based on the real-time channel state at the edge user to improve the performance of the NOMA-based federated learning system. The algorithm can make full use of the real-time channel state information at the edge user to find the optimal power allocation scheme.
- Finally, we conduct experiments on the proposed algorithm. Then we adjust and analyze the parameters in the algorithm to find appropriate parameters to optimize the performance of the system model. The simulation results show that the algorithm can improve the training accuracy of the system model and reduce the energy consumption for uploading parameters.

II. System Model

At first, we build a federated learning system consisting of a parameter server and a set $\mathcal{K} = \{1, 2, ..., K\}$ of K edge users. Edge users finish the training of machine learning models using local data respectively. The training task for edge user $k \in \mathcal{K}$ in round t is to find the mapping relationship between the features x_k^t and the labels y_k^t in the dataset. The model parameter w_k^t is used to describe the mapping relationship and the loss function $f(x_k^t, y_k^t; w_k^t)$ is used to describe the mapping error, then the main problem solved by this task can be described as:

$$\min F_k(w_k^t) = \frac{1}{|\mathcal{D}_k|} \sum_{i \in \mathcal{D}_k} f(x_k^t(i), y_k^t(i); w_k^t). \tag{1}$$

where $|\mathcal{D}_k|$ is denoted as the cardinality of the data sample used by edge user k in the training process of the machine learning model.

Now we temporarily hide the formulation for t, which is because the formula holds for all rounds of the training task, then the formula can be generalized as:

$$\min F(w) = \sum_{k=1}^{K} \frac{|\mathcal{D}_k|}{|\mathcal{D}|} F_k(w_k). \tag{2}$$

where w is the global model parameter generated by the sub-model parameter w_k. The ultimate goal of the model is to find the optimal solution that minimizes the loss function $F(w)$ by iterating the machine learning model parameters.

Based on this, we use NOMA to optimize the federated learning framework on the uplink transmission of edge user signals, and then build a NOMA-based federated learning system. The NOMA-based federated learning system is showed in the Figure 1. In this system model, the running process can be divided into 3 steps. Firstly, each edge user initializes their respective machine learning model to be trained according to the parameters passed down by the parameter server. Secondly, each edge user accesses the local dataset to train their respective models and uploads the trained parameters to the parameter server, using power domain-non-orthogonal multiple access (PD-NOMA) technology in the process of uploading. Finally, the parameter server aggregates the model parameters uploaded by each edge user and then passes the aggregated new parameters down to each edge user to update its local machine learning model, which is circulated in this way.

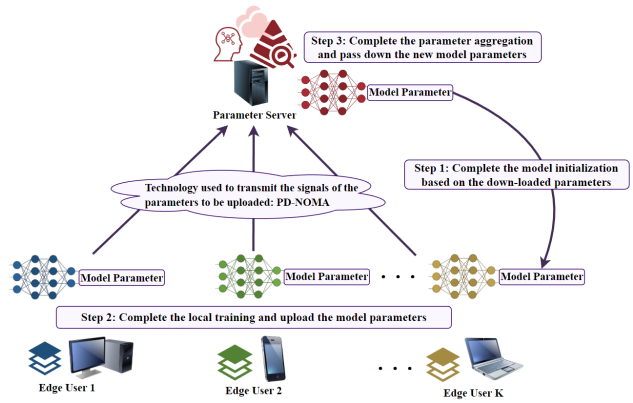

Fig. 1. NOMA-based federated learning system model

In particular, the elements that are continuously iterated in the built system model are important parameters that are trained by each edge user in the local machine learning model. In this paper, we use Convolutional Neural Network (CNN) [11] as the machine learning model to be trained in the NOMA-based federated learning system. The training task performed is image recognition, and the dataset trained by each edge user is MNIST. As shown in Figure 2, there are two convolutional layers in the training process of the machine learning model, corresponding to Convolutional Layer1 and Convolutional Layer2. The important parameters in the convolutional process are the parameters of the filters involved in the convolution, which are uniformly preset to w in this paper to facilitate the derivation of subsequent formulas.

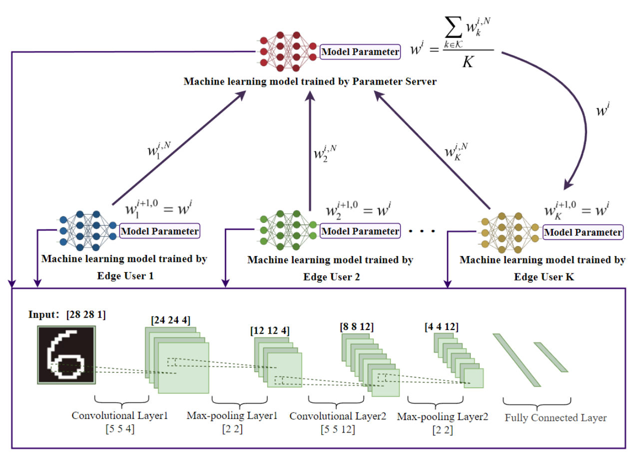

Fig. 2. The training process of the machine learning model

Furthermore, we describe the process of generating and updating the machine learning model parameters in the system model.

A. Global Parameter Update

In this paper, M is set as the global iteration count in the system model and N is the local iteration count, followed by $i \in \{1, 2, ..., M\}$ as the rounds of global iterations and $j \in \{1, 2, ..., N\}$ as the rounds of local iterations. Then $w_k^{i,j}$ denotes the model parameters updated locally by the edge user k at round j during the global parameter update at round i. Thus, for round $i+1$, the model parameters of the parameter server and each edge user are the global iteration parameters after the parameter server aggregates the local iteration parameters at round i:

$$w_k^{i+1,0} = w^i, \forall k \in \mathcal{K}. \tag{3}$$

B. Local Parameter Update

In the training of the local machine learning model by edge user k, it needs to calculate the gradient $\nabla F_k(w)$ of the loss function $F_k(w)$. So for the local iterations of round $j+1$, the local model parameters are the results of edge user k performing the following equation:

$$w_k^{i,j+1} = w_k^{i,j} - \alpha \nabla F_k(w_k^{i,j}). \tag{4}$$

where α denotes the learning rate.

C. Global Parameter Aggregation

After k edge users upload local machine learning model parameters using PD-NOMA technology, the parameter server aggregates the model parameters $w_k^{i,N}$ and then completes the update by averaging the aggregated parameters to obtain a new round of global model parameters:

$$w^i = \frac{\sum_{k=1}^{K} w_k^{i,N}}{K}. \tag{5}$$

III. PERFORMANCE OPTIMIZATION IN THE SYSTEM MODEL

There are many factors affecting the performance of the NOMA-based federated learning system. In this paper, we focus on the optimization of NOMA power allocation in the system to improve the model performance.

A. Model Performance Analysis

The model for uploading the parameters using PD-NOMA in the system model is shown in Figure 3. NOMA allows different edge users in the system model to transmit signals using the same time domain and the same frequency domain. The key principle of PD-NOMA is to allocate power and stack codes on the signals of different edge users first. Then, the parameter server uses Successive Interference Cancellation (SIC) technology to detect and separate the signals of each edge user step by step according to the power difference of the different signals [12]. This is a very subtle technology. For the NOMA-based federated learning system, we set the transmit power of edge user k at round t to be p_k^t, the Rayleigh fading channel power gain from edge user k to the parameter server to be h_k^t, and the signal sent by edge user k to be s_k^t. Then the signal received by the parameter server is:

$$y^t = \sum_{k=1}^{K} h_k^t \sqrt{p_k^t} s_k^t + z^t. \tag{6}$$

where z^t is the complex additive Gaussian white noise, $z^t \sim \mathcal{CN}(0, \sigma^2)$.

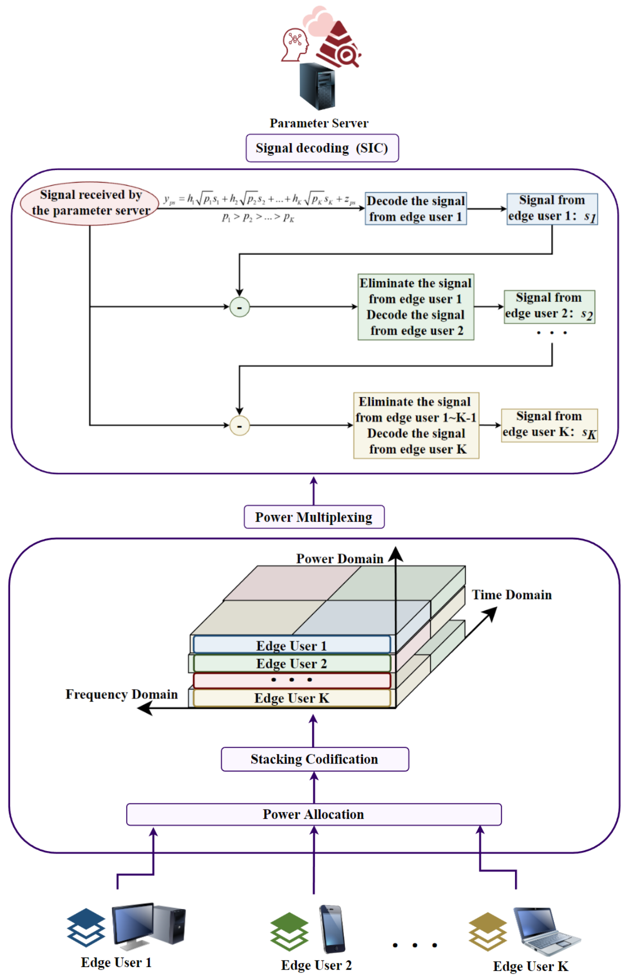

Fig. 3. The model for uploading the parameters using PD-NOMA

For the NOMA in the uplink, the signal of the edge user with the best channel gain has the highest power, and the parameter server detects and separates this signal at first. Therefore, after hiding the formulation for t, we assume that the channel gain of edge user 1 in the system model is the best and the allocated power of its signal is the largest: $p_1 > p_2 > ... > p_K$. Then the signal received by the parameter server can be expressed as:

$$\begin{aligned} y_{ps} &= h_1\sqrt{p_1}s_1 + h_2\sqrt{p_2}s_2 + ... + h_K\sqrt{p_K}s_K + z_{ps} \\ &= \sum_{k=1}^{K} h_k\sqrt{p_k}s_k + z_{ps}. \end{aligned} \tag{7}$$

Then, the parameter server detects and separates the signals step by step using SIC technology. Firstly, the parameter server sorts the signals of each edge user according to their power levels ($p_1 > p_2 > ... > p_K$) and then decodes them in the following order: $s_1, s_2, ..., s_K$. Specifically, the parameter server decodes the signal of edge user 1 at first, when the signals of other edge users are considered as noise. After that, the parameter server removes the signal of edge user 1, and then decodes the signal of edge user 2 from the reconstructed received signal. Finally, after removing the signal of edge user $K-1$, the parameter server decodes the signal of edge user K.

Based on the above analysis, we focus on the power allocation scheme for NOMA in the NOMA-based federated learning system, which enables the parameter server to detect and separate the signals after power multiplexing in higher quality by controlling the power differences of each edge user.

B. Model Performance Optimization

After the analysis of the system model performance, we start to optimize the power allocation algorithm of NOMA in the system. So far, a lot of research has been carried out in this area. The following are some of the classical power allocation algorithms summarized in this paper.

1) Full Search Power Allocation: The algorithm performs an exhaustive enumeration of power allocation schemes for all edge users in the federated learning system to find the optimal solution. However, the complexity of this algorithm grows nonlinearly with the increasing number of edge users, resulting in a large signal expense [13].

2) Iterative Power Allocation: The central idea is based on the greedy algorithm, and the biggest advantage of this algorithm is its lower complexity. However, the algorithm may not provide the optimal power allocation scheme.

3) Fixed Power Allocation: The algorithm is to sort the channel gain at each edge user and set a recursive coefficient for power allocation. It is assumed that the total power at the edge user end is P_s. There are K edge users, and the power assigned to edge user k after the ordering can be expressed as:

$$P_k = \begin{cases} \mu P_s, k = 1. \\ \mu\left(P_s - \sum_{i=1}^{k-1} P_k\right), 1 < k \le K. \end{cases} \tag{8}$$

The algorithm completes the recursion to achieve the power allocation according to (8). Its complexity is low and it utilizes the channel gain condition [14]. However, this algorithm fails to take full advantage of the real-time channel state of each edge user, and its applicability decreases as the channel gain changes in real time, which does not guarantee the system performance.

Based on the analysis above, we propose a NOMA dynamic power allocation algorithm based on the real-time channel state at the edge user to improve the performance of the NOMA-based federated learning system. First of all, to calculate the real-time channel state information of each edge user, the transmit power p_k^t of each edge user with its power gain h_k^t is taken into consideration. Given that there are a total of K edge users, the real-time channel state information of edge user k at round t when uploading is: $p_k^t \| h_k^t \|_2^2$. where $\|\cdot\|_2$ denotes the two-parametric number of real-time channel state of each edge user. Thus, it can be set that the interference from the noise of other devices except the signal of edge user k is:

$$n_k^t = \sum_{\substack{i=1 \\ i \ne k}}^{K} p_i^t \| h_i^t \|_2^2 + \sigma^2. \tag{9}$$

Then the allocated power coefficient $\alpha_{PA,k}^t$ for each edge user at round t is:

$$\alpha_{PA,k}^t = \frac{1}{\sum_{\substack{j=1 \\ j \ne k}}^{K} \left(\frac{p_j^t \| h_j^t \|_2^2}{n_j^t} \right)^{\mu_{PA}}} \left(\frac{p_k^t \| h_k^t \|_2^2}{n_k^t} \right)^{\mu_{PA}} . \tag{10}$$

where μ_{PA} denotes the dynamic power allocation exponent of the system model.

Algorithm 1: NOMA Dynamic Power Allocation Algorithm Based on the Real-Time Channel State at the Edge User

Initialization: dynamic power allocation exponent μ_{PA}, global iteration count M, local iteration count N;

for $i = 1 : M$
  for (each edge user k) **do**
    for $j = 1 : N$
      Calculate $w_k^{i,j} = w_k^{i,j-1} - \alpha \nabla F_k(w_k^{i,j-1})$;
      Calculate $acc_k^{i,j}$;
    end for
    Calculate acc_k^i according to $acc_k^{i,j}$;
    Calculate $n_k^i = \sum_{\substack{u=1 \\ u \ne k}}^{K} p_u^i \| h_u^i \|_2^2 + \sigma^2$;
    Calculate $\alpha_{PA,k}^i = \frac{1}{\sum_{\substack{u=1 \\ u \ne k}}^{K} \left(\frac{p_u^i \| h_u^i \|_2^2}{n_u^i} \right)^{\mu_{PA}}} \left(\frac{p_k^i \| h_k^i \|_2^2}{n_k^i} \right)^{\mu_{PA}}$;
  end for
  Transmit signals using PD-NOMA;
  Calculate $y_{ps} = \sum_{k=1}^{K} h_k \sqrt{p_k} s_k + z_{ps}$;
  Detects and separates the signals using SIC;
  Complete global parameter aggregation $w^i = \frac{\sum_{k=1}^{K} w_k^{i,N}}{K}$;
end for

IV. Simulation Results

In this section, we conduct the simulation of the NOMA dynamic power allocation algorithm based on the real-time channel state at the edge user proposed in the NOMA-based federated learning system and analyze the results. We assume that $K = 3$, the distance from the parameter server to edge user 1 is 100 m, to edge user 2 is 150 m, and to edge user 3 is 200 m. To analyze the optimization results of this power allocation algorithm more intuitively, the initial global iteration count M is set to 30 and the local iteration count N is set to 5, and then the Rayleigh fading channel is considered in this paper.

We firstly simulate the proposed NOMA dynamic power allocation algorithm based on the real-time channel state at the edge user from two perspectives: the accuracy of the machine learning model trained by each edge user and the energy consumption of the model parameters uploaded by each edge user. For each global iteration round, the training accuracy can be calculated while training, and the energy consumption needs to be further calculated. As noted above, the system model uses PD-NOMA to upload model parameters, and to facilitate the elaboration of this process, we temporarily assume that the ranking numbers of the K edge users are in descending order according to the decoding order of SIC: edge user K is decoded first and edge user 1 is decoded last. Then, for edge user k, the reached rate at round i of the global iteration is described as:

$$R_{NOMA,k}^{i}=B\log_2\left(\frac{\sum_{l=1}^{k}p_l^i a_l^i+\sigma^2}{\sum_{l=1}^{k-1}p_l^i a_l^i+\sigma^2}\right). \tag{11}$$

where B is the transmission bandwidth, a_l^i is the power allocation coefficient of the edge user l at round i of the global iteration, p_l^i is the transmit power, and σ^2 is the variance of the complex additive Gaussian white noise. The data size to be uploaded by edge user k is set to be S_k^i. Therefore, the time consumed can be expressed as:

$$t_{up,k}^{i}=\frac{S_k^i}{R_{NOMA,k}^{i}}. \tag{12}$$

At this point, P_k^i is set to be the transmit power of edge user k. Then we can build a model of the energy consumption of edge user k for uploading the model parameters:

$$E_{up,k}^{i}=P_k^i t_{up,k}^{i}=\frac{P_k^i S_k^i}{R_{NOMA,k}^{i}}. \tag{13}$$

The comparison of the optimization results of the NOMA power allocation algorithm is shown in Figure 4. Firstly, we compare the average accuracy of the machine learning models trained by each edge user in each round of the global iteration. After the arithmetic analysis of the values in the figure, we find that using the proposed NOMA dynamic power allocation algorithm based on the real-time channel state at the edge user can improve the training accuracy rate by 6.84%. Then, we compare the total cumulative energy consumption of the model parameters uploaded by all edge users in each round of the global iteration. We find that the proposed NOMA dynamic power allocation algorithm can reduce the energy consumption of the model parameters uploaded by each edge user. Thus, we can conclude that the proposed NOMA dynamic power allocation algorithm based on the real-time channel state at the edge user can reduce energy consumption while improving the training accuracy, which can improve the performance of the NOMA-based federated learning system.

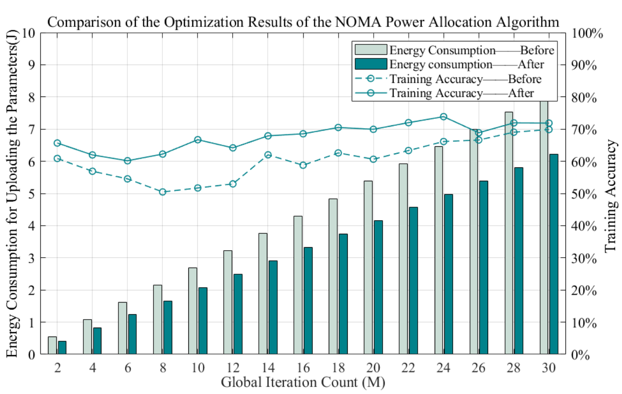

Fig. 4. The comparison of the optimization results of the NOMA power allocation algorithm

Based on this, we conduct the simulation of the BER of the NOMA-based federated learning system using new algorithm. The result is shown in Figure 5. We can find that the distance between the edge user and the parameter sever can cause influence on BER in the NOMA-based federated learning system using the new algorithm. The further the distance between the edge user and the parameter server, the greater will be the BER. Thus, selecting the appropriate distance between the edge user and the parameter server is also significant in the NOMA-based federated learning system using the NOMA dynamic power allocation algorithm based on the real-time channel state at the edge user.

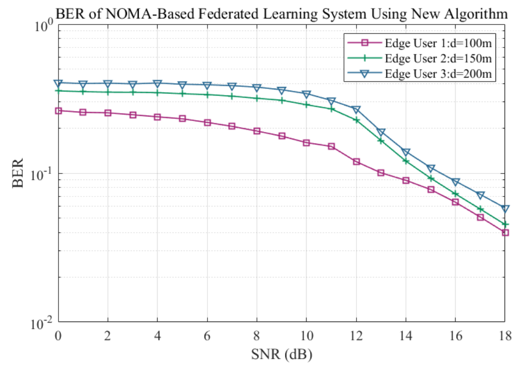

Fig. 5. BER of NOMA-based federated learning system using new algorithm

During the experiment, we find that the dynamic power allocation exponent μ_{PA} also has an influence on the performance of the system model. Therefore, we need to find the best value for the performance of the current system model by changing μ_{PA}. As shown in Figure 6, we present the comparison results of the dynamic power allocation exponent of the new algorithm. When $0\le\mu_{PA}\le0.5$, the difference in the power among the edge users increases accordingly as μ_{PA} increases, the training accuracy increases as well. When $0.6\le\mu_{PA}\le1$, the training accuracy shows a fluctuating trend. For the total energy consumption for uploading the parameters by edge users, when $0\le\mu_{PA}\le0.2$, the total energy consumption decreases as μ_{PA} increases. In the case of $0.3\le\mu_{PA}\le1$, as μ_{PA} increases, the power allocated to edge user 1 becomes larger and the total energy consumption of the system increases.

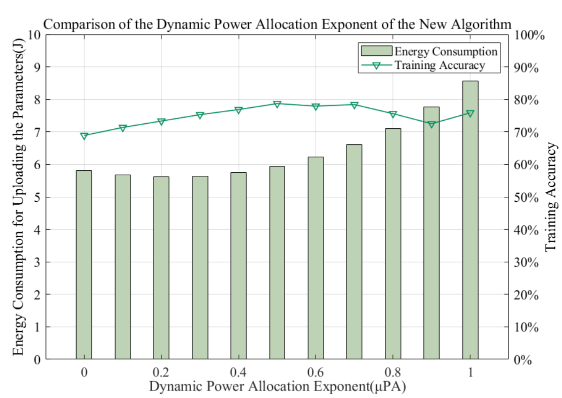

Fig. 6. The comparison of the dynamic power allocation exponent of the new algorithm

Therefore, to ensure the energy consumption for uploading parameters in the system not be too high while improving the training accuracy of the machine learning model as much as possible, we consider that the optimal solution for μ_{PA} should be $0.5 \le \mu_{PA} \le 0.7$.

In the experiment, we find that different values of the local iteration count N also influence the performance of the NOMA-based federated learning system. To determine the value of the local iteration count N that can best optimize the performance of the system model, we use the NOMA dynamic power allocation algorithm based on the real-time channel state at the edge user, and set the global iteration count $M = 30$, the dynamic power allocation exponent $\mu_{PA} = 0.6$, and then compare the average accuracy of the machine learning models trained by each edge user in each round of the global iteration when N is set to different values.

As shown in Figure 7, we present the comparative analysis of the local iteration count N in the NOMA-based federated learning system. It can be seen that the training accuracy increases as N increases. However, when N is large enough, there is no obvious increase in the training accuracy. In particular, when $N = 25$, the average accuracy is the best and the value is even better than that when $N = 30$. Therefore, we conclude that the performance of this system model is the best when $20 \le N \le 25$ in the NOMA-based federated learning system.

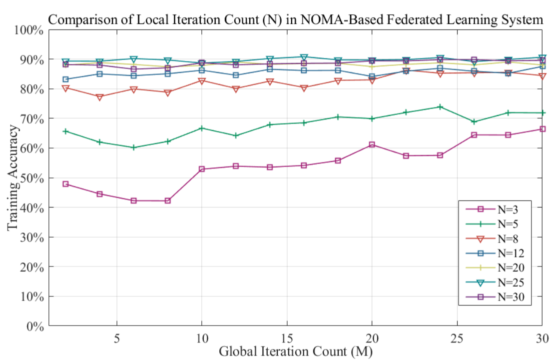

Fig. 7. The comparison of the local iteration count in NOMA-based federated system

V. CONCLUSION

In this paper, we studied the performance of the NOMA-based federated learning system. Firstly, we built a NOMA-based federated learning system, which improved the communication efficiency of federated learning. Secondly, we proposed a NOMA dynamic power allocation algorithm based on the real-time channel state at the edge user to improve the performance of the NOMA-based federated learning system. The algorithm made full use of the real-time channel state information at the edge user to find the optimal power allocation scheme. Finally, we simulated the proposed algorithm, and then we adjusted and analyzed the parameters in the algorithm to find appropriate parameters to optimize the performance of the system model. The results showed that the proposed algorithm improved the average training accuracy of the system model by 6.84% and reduced the energy consumption for uploading parameters. The performance of the system model was the best when $0.5 \le \mu_{PA} \le 0.7$ and $20 \le N \le 25$.

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