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*Research Article*

# Equalization Network-Aided SCMA Codec Scheme with Deep Learning

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With the rapid development of the Internet of Things, sparse code multiple access (SCMA), which aims to promote spectrum efficiency and support massive connectivity in the future beyond fifth- and sixth-generation massive machine-type communication (mMTC) scenarios, has been widely investigated. To improve the bit error rate (BER) performance of the SCMA system in the uplink Rayleigh fading channel, we propose a novel deep learning-based SCMA codec scheme. The proposed scheme consists of an equalization network-aided decoder network and a denoising autoencoder- (DAE-) based encoder network. At the decoder, an equalization network and a multiuser detection network constitute the decoder network. The equalization network, composed of two deep neural network (DNN) units, compensates for the phase shift of the signal through the fading channel, which improves the antifading capability of the system. At the encoder, a complete DAE is constructed, which introduces an extra noise layer at the input of the encoder that yields a robust encoder output representation, improving the antinoise capability of the system. We use an end-to-end training method to train the SCMA codec and optimize the parameters and structural model of the neural network. Simulation results show that our proposed scheme can reduce the detection time and improve the BER performance of the system in the uplink Rayleigh fading channel.

## 1. Introduction

With the widespread popularity of mobile intelligent devices and the rapid development of Internet of Things technology, there are new challenges to satisfying the customer quality of service (QoS), such as those associated with the massive connectivity of the number of terminal devices [1], communication network security [2], and complex channel environments [3]. To improve the spectrum efficiency and the number of connections under the massive machine-type communication (mMTC) scenarios of beyond fifth-generation/sixth-generation (B5G/6G) technologies, nonorthogonal multiple access (NOMA) plays an indispensable role in mobile communication systems.

NOMA was proposed for 5G wireless communications [4]. Sparse code multiple access (SCMA) [5] is a code domain multiplexing NOMA technology in NOMA schemes. In SCMA, the information bits of coding are directly mapped to the multidimensional complex grid nodes, which are called codeword maps. Thanks to the design of a multidimensional constellation and the combination of constellation rotation and the spread spectrum, codebooks for each user can be achieved. In addition, compared with the traditional code division multiple access (CDMA) [6] modulation and spread spectrum coding mode under the same number of time and frequency resources, the SCMA system transmits the user codewords in a nonorthogonal way on a time-frequency resource block. In this way, the reuse rate of resource blocks is greatly improved; thus, the system can be connected to multiple user devices.

An excellent SCMA communication system requires effective multiuser detection algorithms and optimal codebook design. The multiuser detection issue is also called decoding in the SCMA system. Using the message passing algorithm (MPA) [7] based on the Tanner graph is a general method to solve the decoding problem of SCMA, with the performance of the algorithm being close to that of maximum posterior probability decoding. However, the high

complexity index in the MPA operation and multiplication and the high hardware performance requirements render practical application of MPA difficult to achieve. To apply the SCMA system to practical engineering, it is necessary to study how to reduce the decoding complexity of SCMA [8–13], although some bit error rate (BER) performance is sacrificed in these schemes. This problem was also investigated in [14–17] to improve the BER performance of the system in terms of the BER performance of the Rayleigh fading channel. A suboptimal SCMA codebook design algorithm for an uplink Rayleigh fading channel was proposed [15], which reduces the multidimensional parent constellation design to a nonconvex optimization problem and expands two factors to achieve better coding gain. To further promote the application of SCMA systems in practical engineering, we study a whole codec scheme to address multiuser detection and optimal codebook design issues under a Rayleigh fading channel.

Due to the universality of artificial intelligence in various fields, recent studies have also begun to apply neural networks to communication systems [18–29]. For example, some studies were based on deep learning technology to deal with the signal detection problem of MIMO systems [22–24], and there were also studies using artificial intelligence (AI) technology in UAV networks [25–27]. In addition, new ways of thinking about communications as an end-to-end joint optimization of the communication system, which utilizes autoencoders to jointly learn transmitter and receiver implementations as well as signal encodings without any prior knowledge, were introduced in [30]. The application of this method for the physical layer to the SCMA system is realized in an SCMA scheme that proposes codeword generation and signal detection based on deep learning [31] and an intermediate density code division multiple access (MDMA) based on deep learning [32], the algorithm of which is represented by a new Tanner graph to achieve multiuser detection without iteration by adjusting the edge weights in the neural network. In [33], according to a new deep neural network (DNN) method for SCMA to reduce the computational complexity and improve the BER performance, the author proposes dense code multiple access based on deep learning. The SCMA decoder is designed as a classifier and detected by deep learning methods to reduce the detection complexity in [34]. These algorithms can achieve better BER performance than the traditional MPA multiuser detection method in the Gaussian channel, but the BER performance limitation problem in the uplink Rayleigh fading channel is still not solved.

This paper is aimed at solving the problem of poor BER performance of the SCMA system in the uplink Rayleigh fading channel and further promoting the use of the SCMA system in practical engineering. We propose an equalization network-aided SCMA codec scheme based on deep learning. By using multiple DNN units, we present the SCMA encoder, equalizer, and multiuser detection module, optimize both the encoding and decoding ends, and train in an end-to-end manner. In the decoder network, which is composed of equalization and multiuser detection subnets, the equalization subnet is used to learn the parameters of the Rayleigh fading channel and compensate for the signal because it is affected by the fading channel. Moreover, the SCMA encoder is constructed by several DNN units of the denoising autoencoder (DAE) structure, which is a codeword mapped to improve the robustness of the codebook generated by introducing an extra noise layer at the input end. We use an end-to-end approach to train and optimize the parameters and structural model of the neural network so that the neural network can converge quickly. Simulation results show that our proposed SCMA codec scheme can reduce the detection time of the receiver and improve the BER performance of the system in the uplink Rayleigh fading channel. We now summarize our major contribution as follows:

(1) Equalization network-aided SCMA decoder design: To enhance the multiuser detection performance in the Rayleigh fading channel, an equalization network-aided SCMA decoder is designed. Compared with the deep learning-aided SCMA (D-SCMA) decoder [31], the decoder is composed of three DNN units instead of a single DNN unit. An equalization network composed of two DNN units has also been added, and by learning the parameters of the Rayleigh channel and compensating for the signal, the BER performance and the training time performance can be more effectively improved

(2) Denoising autoencoder structure-based SCMA encoder design: To enhance the robustness of the codebook, we introduce an extra noise layer at the encoder input. In the training phase, adding an appropriate amount of noise to the source data can improve the antinoise performance of the neural network. Simulation results verify that the proposed encoder is superior to its counterparts

## 2. System Model

For the uplink SCMA system, we assume that the number of users in the SCMA system is $J$ and the number of resource blocks is $K$. Due to the sparse structure of the system, the sparse code allocation for each user is extended to $K$ resource blocks. The number of users $J > K$ such that the overload rate of the SCMA system is defined as $\lambda = J/K$. For example, the factor diagram matrix of the SCMA system is expressed as Equation (1). In light of the SCMA codebook design, $m = \log_2(M)$ bit data are sent each time, and the system encoder encodes them into a $K$-dimensional composite codeword where the sparse codeword has only $N$ nonzero elements, with $N << K$.

$$F = \begin{bmatrix} 1 & 0 & 1 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 1 & 0 \end{bmatrix}. \tag{1}$$

The complex codewords of 6 users are superimposed onto 4 resource blocks to realize the nonorthogonal superposition and transmission of signals. Each connection line between user $j$ and resource block $k$ can be seen as the coding mapping of each user on the resource block.

The codeword of user $j$ can be written as $x_j = [x_{j1}, x_{j2}, \cdots, x_{jK}]^T$, and the received signal $y$ is expressed by the following formula:

$$y = \sum_{j=1}^{J} \text{diag}(h_j) x_j + n, \qquad (2)$$

where $h_j = [h_{j1}, h_{j2}, \cdots, h_{jK}]^T$ is the channel gain between the user and the resource block and, in the Rayleigh fading channel, $h_j \sim CN(0,1)$. diag $(\cdot)$ represents the logarithmic matrix, and the noise $n = (n_1, n_2, \cdots, n_K)^T$ is the additive white Gaussian noise with a mean value of 0 and a variance of $\sigma^2$.

## 3. Proposed Scheme

In this section, we propose a codec scheme, namely, the equalization network-aided SCMA DAE system, referred to as EN-DAE-SCMA. The SCMA system structure of this scheme is shown in Figure 1, where the number of users is $J = 6$ and the number of time-frequency resource blocks is $K = 4$. Multiple DAEs are used to construct the encoding end of the system, with each DAE composed of DNN units. The user codebook is modulated by the DAE-based DNN units, where each DNN unit represents a codeword mapper, and then, the user codebook is connected to the resource block according to the original factor graph to obtain a complete SCMA codebook. The decoding end of the system consists of an equalization network and a multiuser detection network to decode each user's sent data.

The DNN contains many hidden layers that have stronger learning and training capabilities and mapping capabilities than single-layer neural networks. The calculation formula of the $i$-th neuron in each hidden layer can be expressed as follows:

$$z_i = f\left(\sum_{t=1}^{T} W_{t,i} \times v_t + b_i\right), \qquad (3)$$

where $z_i$ is the output data, $v_t$ is the input data, $W_{t,i}$, $b_i$, and $T$ are the weight, bias, and number of neurons, respectively, and $f(\cdot)$ represents the nonlinear activation function formula.

The main purpose of the EN-DAE-SCMA system is to reconstruct user data $s = [s_1, s_2, s_3, s_4, s_5, s_6]^T$ through the designed encoding end and decoding end. After the user data are encoded, the received user signal is detected by the decoder through the fading channel and noise pollution, with the reconstructed user data being $\hat{s} = [\hat{s}_1, \hat{s}_2, \hat{s}_3, \hat{s}_4, \hat{s}_5, \hat{s}_6]^T$, where $s \neq \hat{s}$. By optimization of the network to minimize the mean squared error between the reconstructed data and the original data, it can be expressed by the following formula:

$$\min_{\theta} (\|s - \hat{s}\| ; \theta), \qquad (4)$$

where $\theta$ represents the set of weights and biases of the neural network of the entire system.

*3.1. SCMA Encoder.* To construct the encoding end of the EN-DAE-SCMA system, we make changes on the basis of the D-SCMA [20] encoder and introduce an extra noise layer at the input end. According to the factor graph, we use a DAE-based DNN unit to learn the mapping process for each edge connecting the user and the resource block to obtain the corresponding codeword. The DNN unit based on the DAE is called the SCMA codeword mapper. The structure of the codeword mapper is shown in Figure 2.

Since the input data transmitted by each user to the encoding end of the EN-DAE-SCMA system are expressed as $r$, $r$ is the binary bit data, and there are $m$ possible types of information, where $m = 2^b$, with $b$ representing the number of bits per transmission, where $b = 2$. Binary input data are randomly generated and encoded into a one-hot vector, which is an $M$-dimensional vector $s$, where only one element is 1 and all the other elements are 0. The encoded one-hot vector is used as the input data of the encoding end. To make the codeword sparse, the user binary vector $S_j = (S_1, \cdots, S_{2K})^T$ represents the SCMA mapping matrix corresponding to user $j$. The connection mode between the user and the resource block is determined by the SCMA factor matrix, which can be randomly generated according to the overload rate of the SCMA system.

Each DAE-based DNN unit autonomously learns the mapping process from a certain user to a certain resource block after receiving the user data and outputs a two-dimensional codeword that represents the real parts $R$ and imaginary parts $I$ of the complex codeword. Let $f_{kj}(s_j; \theta_f)$ be the two-dimensional codeword mapped from resource $k$ to user $j$, where $s_j$ represents the original input data vector sent by user $j$ to the neural network and $\theta_f$ represents the weight and bias of the EN-DAE-SCMA system encoder. The encoding end is based on a denoising autoencoder; that is, a noise layer is added after the input layer of each DNN unit. A certain proportion of noise is added to the input data to pollute the original user data $s$ with noise. The data after passing through the noise layer can be expressed as follows:

$$\hat{s} = s + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I). \qquad (5)$$

After the data are polluted with noise, the two-dimensional codeword mapped from user $j$ to resource $k$ can be expressed as $f_{kj}(s_j; \varepsilon; \theta_f)$. The number of hidden layers of the codeword mapper of the encoder network is set to 3, i.e., $L = 3$, and each hidden layer contains 32 hidden nodes.
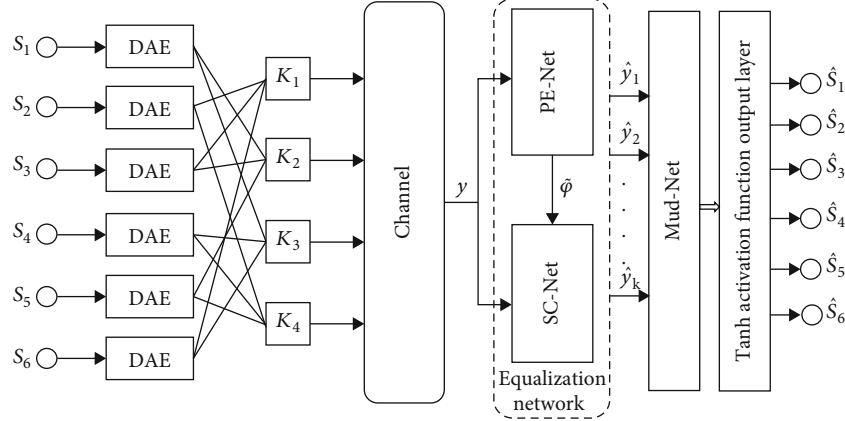
Figure 1: Equalization network-aided SCMA denoising autoencoder structure.
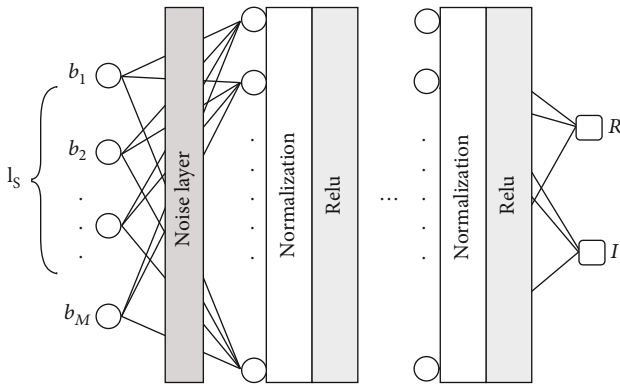


Figure 2: SCMA encoder structure.

The ReLU activation function is used in the hidden layer of the encoder network, and it can be expressed as follows:

$$f_{\text{Relu}}(x) = \max(0, x). \tag{6}$$

All the codewords sent on the same resource block are superimposed together and then transmitted by adding Gaussian white noise. Therefore, the data received on the resource block $k$ are expressed as follows:

$$y_k = \sum_{j=1}^{J} h_{kj} f_{kj}(s_j; \varepsilon; \theta_f) + n_k, \tag{7}$$

where $h_{kj}$ is the channel gain, each transmission is static, and $n_k$ is the additive white Gaussian noise over the resource block $k$.

*3.2. SCMA Decoder.* The receiver decoder of the system consists of an equalization network and a multiuser detection network, in which the network architecture of the equalization network is inspired by the spatial transform network used in the field of computer vision (maintaining the spatial invariance of the input data). As shown in Figure 3, the equalization network function plays a similar role to the

channel equalizer at the receiving end of the traditional SCMA transmission system. It is composed of two subnetworks, namely, the parameter estimation network $g_{\varphi}(\cdot)$ and the signal compensation network $g_{\omega}(\cdot)$. First, the phase offset $\varphi$ generated by the fading channel is estimated through the parameter estimation network. Then, the received signal $y$ and the estimated phase offset parameter $\varphi$ are subjected to reversed-phase rotation processing through the signal compensation network to compensate for the signal. In this way, the output of the channel can be equalized, and the fading distortion of the signal can be overcome.

The parameter estimation network $g_{\varphi}(\cdot) z$ is a fully connected DNN whose input is the complex signal $y = [y_1, y_2, \cdots, y_K]^{\text{T}}$ after passing through the channel, which is used to predict and process the Rayleigh fading channel parameter information and generate the output scalar $\tilde{\varphi}$. The network consists of two hidden layers and an output layer, and the number of neurons in the hidden layer is $2K$. The parameter estimation scalar obtained by the neural network is expressed as follows:

$$\begin{aligned}
\tilde{\varphi} &= g_{\varphi}(\text{Re}(y), \text{Im}(y); \theta_1) \\
&= W_0 \tanh(W_2(\tanh(W_1(\text{Re}(y), \text{Im}(y)) + b_1))b_2) + b_0,
\end{aligned} \tag{8}$$

where $\theta_1$ represents the training parameters of the parameter estimation network, $W_1$, $W_2$ represent the weight matrix of the first layer and the second layer in the parameter estimation network, $b_1$, $b_2$ represent the bias vector of the first layer and the second layer in the parameter estimation network, and $W_0$, $b_0$ are the weight and bias of the output layer, respectively. The activation function in the hidden layer is the tanh activation function, which can be expressed as follows:

$$\tanh(W_l y_{l-1} + b_l) = \frac{\sinh(W_l y_{l-1} + b_l)}{\cosh(W_l y_{l-1} + b_l)} = \frac{e^{W_l y_{l-1} + b_l} - e^{-W_l y_{l-1} + b_l}}{e^{W_l y_{l-1} + b_l} + e^{-W_l y_{l-1} + b_l}}, \tag{9}$$
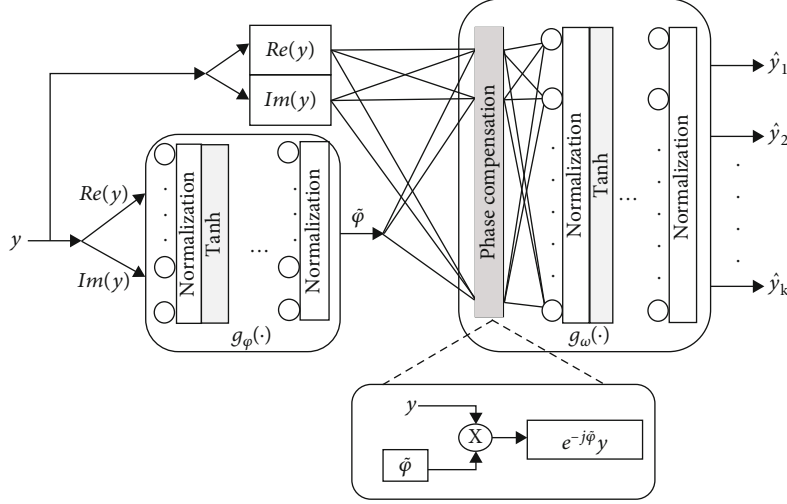
FIGURE 3: Equalization network.

where $W_l$ and $b_l$ represent the weight and bias of the $l$-th hidden layer, respectively, and $y_{l-1}$ is the previous layer output.

The original received signal $y$ and the output scalar $\tilde{\varphi}$ of the parameter estimation network $g_\varphi(\cdot)$ are sent to the input end of the signal compensation network $g_\omega(\cdot)$. A reversed-phase rotation operation is performed on the signal super-imposed on each physical resource block and the output of the parameter estimation network; that is, the received signal is multiplied by the inverse transformation of the channel impulse response. The transformed signal $\mu$ is expressed as follows:

$$\mu = \begin{bmatrix} \cos{(\tilde{\varphi})} \, \mathrm{Re}\,(y) + \sin{(\tilde{\varphi})} \, \mathrm{Im}\,(y) \\ \cos{(\tilde{\varphi})} \, \mathrm{Im}\,(y) - \sin{(\tilde{\varphi})} \, \mathrm{Re}\,(y) \end{bmatrix} = e^{-j\tilde{\varphi}} y. \quad (10)$$

The transformed signal $\mu$ is further optimized through a DNN, and the output of the entire signal compensation network is the signal $\hat{y} = [\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_K]^\mathrm{T}$ superimposed on each resource block to simplify the task of the multiuser detection network. The output $\hat{y}$ obtained after optimization by the signal compensation network $g_\omega(\cdot)$ is expressed as follows:

$$\hat{y} = g_\omega(\mu; \theta_2) = Q_0 \mathrm{Tanh}(Q_L(\cdots \mathrm{Tanh}(Q_1(\mu) + a_1) \cdots) + a_L) + a_0, \quad (11)$$

where $\theta_2$ is the weight and bias of the network, $Q_l$ represents the weight matrix of the $l$-th layer in the signal compensation network, and $a_l$ represents the bias vector of the $l$-th layer and the second layer in the signal compensation network. The activation function used in the hidden layer of the network is the tanh activation function, the number of hidden layers for the network is set to 3, and each hidden layer has 64 hidden nodes. Therefore, the channel output is equalized by an equalizing network to reduce the fading distortion problem in the fading channel.

Finally, we use a multiuser detection network instead of the MPA based on factor graphs in traditional algorithms to detect user information. The multiuser detection network $g_d(\hat{y}; \theta_3)$ decodes the received output signal $\hat{y} = [\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_K]^\mathrm{T}$ of the signal compensation network $g_\omega(\mu; \theta_2)$ and distinguishes the user data loaded in $K$ resource blocks. $\theta_3$ is the weight and bias of the network. The number of hidden layers of the network is set to 4, and the number of nodes in each hidden layer is 256. As shown in Figure 4, the rectified linear unit (ReLU) and tanh are the activation function of the hidden layer and the activation function of the output layer, respectively. Therefore, it is more appropriate to combine the mean squared error function since the value range of the tanh activation function is $[-1, 1]$.

The decoded data of the multiuser network can be expressed as follows:

$$\hat{s} = [\hat{s}_1, \hat{s}_2, \cdots, \hat{s}_6]^\mathrm{T} = g_d(\hat{y}; \theta_3) = \sum_{k=1}^{K} g_d\left(\hat{y}_k; \theta_3^k\right). \quad (12)$$

3.3. Neural Network Training. The EN-DAE-SCMA system uses an end-to-end training method to update the weights and biases of all neural networks in the system and to establish an end-to-end mean squared error loss function:

$$\begin{aligned} L\left(s, \hat{s}; \theta_f, \theta_1, \theta_2, \theta_3; \varepsilon\right) &= L\left(s, g\left(Hf\left(s; \theta_f; \varepsilon\right) + n; \theta_1, \theta_2, \theta_3\right)\right) \\ &= \frac{1}{N} \sum_{i=1}^{N} \left(s(i) - g\left(Hf\left(s(i); \theta_f; \varepsilon\right) + n; \theta_1, \theta_2, \theta_3\right)\right)^2. \end{aligned} \quad (13)$$

The mean squared error loss function averages the sum of the squared errors of the target value and the estimated value to reduce the sensitivity of sample data that deviate greatly. Here, $H = \sum_{k=1}^{K} \sum_{j=1}^{J} h_{kj}$ is the channel vector, and $n$ is the channel noise vector.

Based on the characteristics of the EN-DAE-SCMA system, we use the adaptive moment estimation (ADAM)
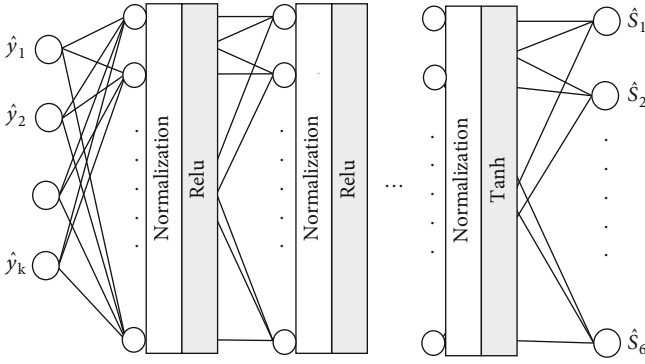
FIGURE 4: Multiuser detection network.

optimizer to update the network. The basic calculation expression is as follows:

$$\theta_t = \theta_{t-1} - \alpha \cdot \frac{\widehat{m}_t}{\sqrt{\widehat{v}_t} + \psi}, \tag{14}$$

where $t$ is the momentum time step, $\widehat{m}_t$ is the deviation correction of the gradient mean, $\widehat{v}_t$ is the deviation correction of the square gradient, $\psi = 10^{-8}$ prevents the divisor from being 0, and the parameters are optimized by continuously updating $m_t$ and $v_t$.

In the training process, user data are randomly generated, and one-hot encoding is performed on the data, $s$, as the input data of the encoder, and is also the target value for the prediction of the entire neural network. Similarly, $\widehat{s} = g(Hf(s(i); \theta_f; \varepsilon) + n; \theta_1, \theta_2, \theta_3)$, as the decoded data of the decoder, are also the estimated value of the entire neural network. At the same time, the training noise selected during neural network training has a greater impact on the BER performance of the system. The variance in the channel noise power is expressed as $\beta = E[|x|^2]/(\eta E_b/N_0)$, where $E[|x|^2]$ is the transmission signal power, $E_b/N_0$ represents the bit signal-to-noise ratio, and $\eta$ represents the spectral efficiency. In the following text, we use enumeration to select the appropriate training noise.

## 4. Simulation Results

In this section, the performance of our proposed deep learning SCMA codec scheme is analyzed and verified through simulation experiments. The experimental environment of this paper uses TensorFlow, KERAS, and other deep learning libraries to conduct simulation experiments based on Python 3.7.6. The SCMA system carries out simulation experiments with 6 users occupying 4 resource blocks, and the codebook size is set as 4. In addition, each user data point takes 2 bits as a group for single thermal coding and codebook mapping. Since we use deep learning methods to adoptively learn the codebooks, the codebook design of each user does not follow a certain modulation mode, and the codebooks between users have great differences. The total dataset includes 300,000 random data points for training, and the data size of each batch is 400. The ADAM optimizer

with an initial learning rate of 0.00001 is used to update the loss value of each sample with a gradient, and then, the weight and bias of the neural network are updated.

First, we study the influence of the number of encoder neural network hidden layers on the BER performance of the EN-DAE-SCMA codec scheme to seek a balance between BER performance and complexity. Figure 5 describes the influence of the number of layers of the encoder on the BER performance of the system under the channel environment of $E_b/N_0 = 8$ dB, $E_b/N_0 = 12$ dB, and $E_b/N_0 = 16$ dB. As the number of encoder layers increases, the BER performance improves, but it tends to converge after increasing to a certain number of layers. When the number of encoder layers reaches 3, the algorithm performance almost converges. Therefore, after the performance comparison of each algorithm, we set the number of encoder layers of the EN-DAE-SCMA system to 3.

Second, we aim to determine the impact of the input noise layer in the encoder on the BER performance of EN-DAE-SCMA. We use the standard deviation $\sigma$ of the noise to represent the amount of noise added to the noise layer and carry out experiments under different $E_b/N_0$ values. As shown in Figure 6, the noise introduced by the input layer will have an impact on the performance of the system. When the noise standard deviation is $\sigma = 0$, which means no noise layer is added at the input, the BER performance is lower than the noise standard deviation $\sigma = 0.1$. However, as the noise increases, the BER performance begins to show a decreasing trend. If the neural network is trained by using noise-polluted data to learn some features of Gaussian noise, it can reduce the influence of Gaussian noise on the system to a certain extent. For the high noise in the low $E_b/N_0$ environment, the influence of the denoising network is very small, while the advantage of the denoising network is relatively obvious and shows better robustness for the low noise in the high $E_b/N_0$ environment. After many experiments and simulations, the optimal noise standard deviation $\sigma$ of the noise layer added in the proposed EN-DAE-SCMA codec scheme proposed is 0.1.

To study the influence of neural networks trained under different channel noise levels on the BER performance of EN-DAE-SCMA, keeping the input noise layer of the encoder unchanged, we select different channel noise levels $E_b/N_0$ to train the system. As shown in Figure 7, regardless of the $E_b/N_0$ values chosen for training, the BER performance of EN-DAE-SCMA is similar in low testing $E_b/N_0$ environments. In high $E_b/N_0$ environments, when the values of training $E_b/N_0$ are set to 4 dB, 6 dB, and 8 dB, the BER performance is poor. When the values of training $E_b/N_0$ are set to 10 dB and 12 dB, the BER performance is obviously advanced, especially for the high $E_b/N_0$ regime. The experimental results show that the training channel noise level $E_b/N_0$ greatly affects the BER performance of EN-DAE-SCMA and that the proper value of training $E_b/N_0$ should be carefully selected in the training phase. Through many experiments, the suitable value of training $E_b/N_0$ is 10 dB, and the system trained in this $E_b/N_0$ environment has better generalization ability, as shown in Figure 7. However, we
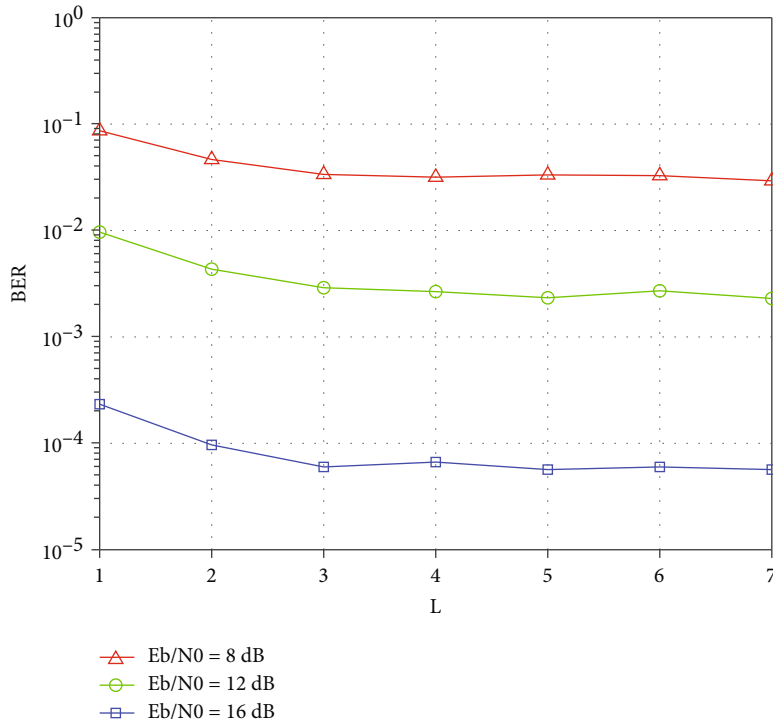
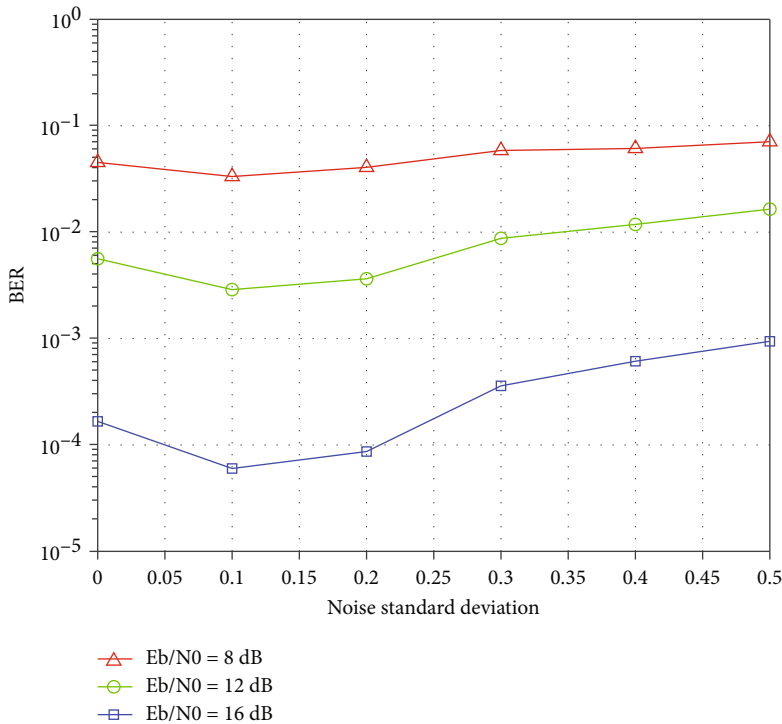FIGURE 5: BER performance under different numbers of encoder network layers.



FIGURE 6: BER performance under different noise standard deviations.

also note that the optimal value of training $E_b/N_0$ may need to be revised according to the $E_b/N_0$ level of the actual communication channel.

In Figure 8, we compare the EN-DAE-SCMA codec scheme with the traditional 6-iteration MPA decoding algo-

rithm, the traditional scheme with an optimal codebook design method [15], the deep learning-based codec scheme of D-SCMA [31], and the DAE-SCMA scheme without the equalization network of EN-DAE-SCMA. We set the number of nodes in the hidden layer of the multiuser detection
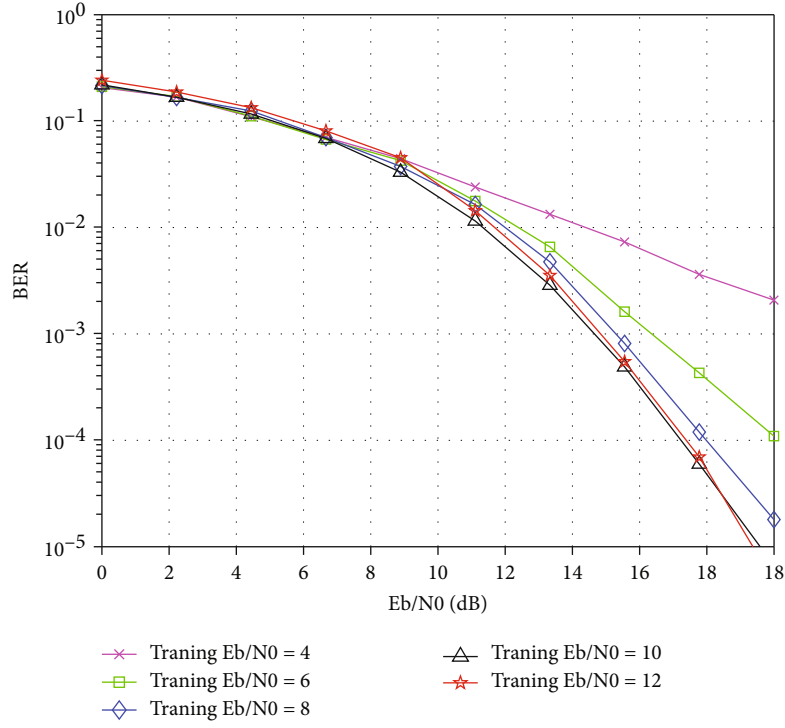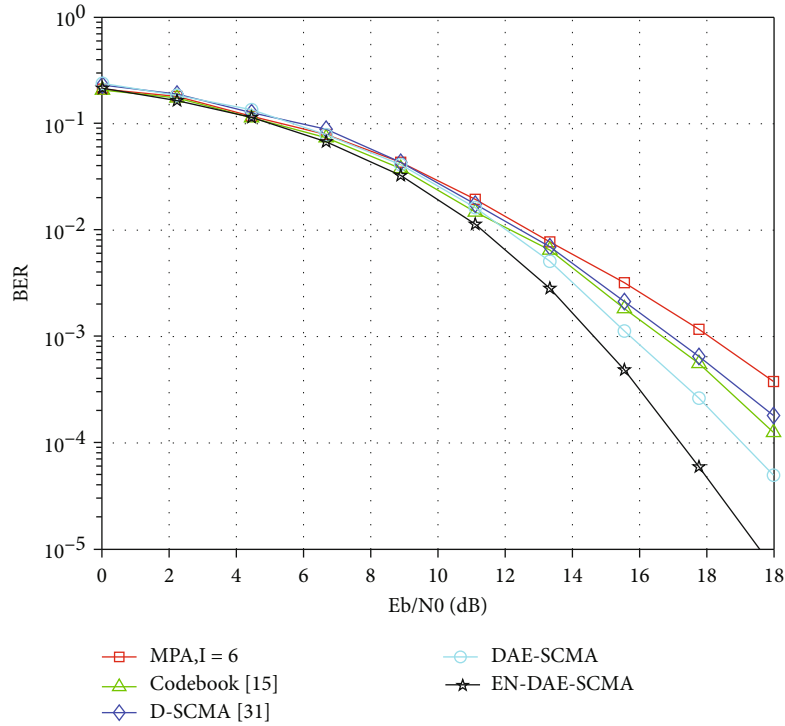
Figure 7: BER performance of EN-DAE-SCMA trained under various $E_b/N_0$.



Figure 8: Comparison of the BER performances of different algorithms.

Table 1: MAC operations of SCMA decoders.

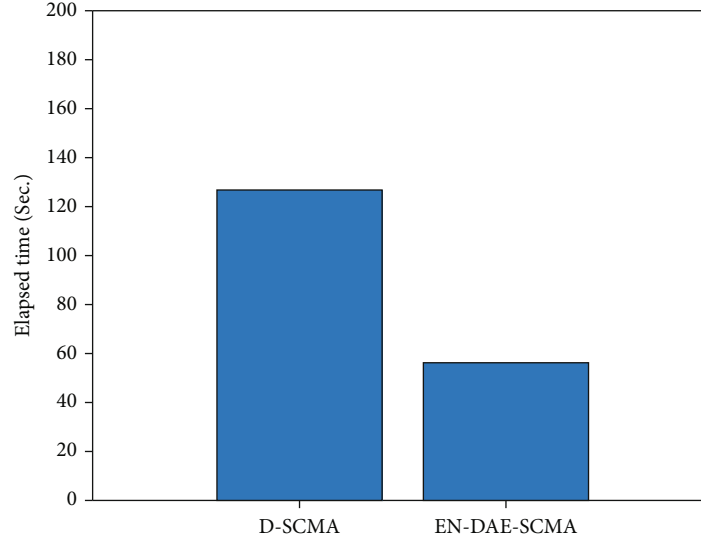|      | D-SCMA [31] | EN-DAE-SCMA |
| --- | --- | --- |
| MAC  | 794,694 | 214,208 |

FIGURE 9: Comparison of elapsed time for different algorithms.

network to 512 to achieve its better decoding performance in DAE-SCMA. The BER performance is shown in Figure 8. Figure 8 shows that the three deep learning-based SCMA codec schemes outperform the traditional SCMA schemes. These deep learning-based schemes have better encoders than the traditional handcrafted codebook. The BER performance of the proposed EN-DAE-SCMA codec scheme is significantly better than that of the traditional MPA scheme, the traditional codebook optimal design scheme [15], and the codec scheme of the D-SCMA system [31]. Because the system has joined the equalization network, it can reduce the fading distortion caused by the influence of the transmission channel, and it is more practical than other solutions when applied to Rayleigh fading channels that are closer to the real environment. It is worth noting that the DAE-SCMA scheme without the equalization network also outperforms the D-SCMA scheme. This is because the DAE-SCMA scheme artificially introduces a noise layer to make the training of the system more robust, so the encoder learns a better codebook than D-SCMA.

Finally, we analyze the algorithm complexity of the proposed EN-DAE-SCMA scheme. The multiply accumulated (MAC) operations of the EN-DAE-SCMA decoder are as follows:

$$
\begin{aligned}
\text{MAC} = {} & 2KN_{P,1} + \sum_{n=1}^{L_P-1} \left( N_{p,n} N_{p,n+1} \right) + 2KN_{S,1} + \sum_{n=1}^{L_S-1} \left( N_{S,n} N_{S,n+1} \right) \\
& + N_{S,L_S} N_{D,1} + \sum_{n=1}^{L_D-1} \left( N_{D,n} N_{D,n+1} \right) + N_{D,L_D},
\end{aligned}
$$

(15)

where $K$ represents the number of resource blocks and $L_P$, $L_S$, and $L_D$ represent the number of hidden layers of the parameter estimation network, signal compensation network, and multiuser detection network, respectively. Simi-larly, $N_{p,n}$, $N_{p,n}$, and $N_{D,n}$ represent the number of nodes of the $n$th hidden layer of each network.

For the sake of fairness, we choose to compare various algorithms that all use deep learning and the same experimental platform and simulation machine, where the CPU processor is an i7-6700 and has 8 GB of running memory and where the elapsed time of the program is exploited to represent the complexity. Table 1 shows the number of MAC operations of deep learning- (DL-) based SCMA decoders. The obtained results in Figure 9 show that the computing time of the proposed scheme is lower than that of the D-SCMA scheme. Consequently, the proposed EN-DAE-SCMA scheme has a lower computational complexity.

## 5. Conclusions

In this paper, we proposed a novel DL-based SCMA codec scheme for the uplink Rayleigh fading channel. On the one hand, we designed a decoding network based on DL. Compared with other conventional decoders, an equalization network composed of two DNN units was added to the decoder. Obtaining the parameter characteristics of the Rayleigh fading channel and compensating for the phase shifts of the received signals are executed by this equalization network. The decoder combined with the equalization network and multiuser detection network can achieve better BER performance. On the other hand, we make changes on the basis of the D-SCMA encoder and introduce an extra noise layer at the input in the training phase. It enhances the robustness of the encoder. Moreover, by adjusting the structure and scale of the neural network, the whole encoding and decoding network convergence speed was accelerated. Simulation and analysis results show that our proposed SCMA codec scheme requires significantly less training data and that the decoding complexity is reduced compared with that of D-SCMA, which also adopts DL schemes. Finally, unlike traditional codebooks based on handcrafted designs, our scheme can autonomously learn ideal codebooks with robustness

through denoising autoencoder technology, which can improve the applicability of the system in actual engineering. At present, our proposed scheme has achieved a significant performance improvement compared with the traditional SCMA scheme and D-SCMA scheme when the channel state information remains unchanged. In the future, we will study the use of a generative adversarial network to simulate the influence of Rayleigh fading channels or try to introduce transfer learning methods so that the system can still obtain performance advantages compared to traditional communication systems when the channel state information changes rapidly.

## Data Availability

The data used to support the findings of this study are included within the article.

## Conflicts of Interest

The authors declare that there are no conflicts of interest.

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