energies

Article

Mine Intelligent Receiver: MIMO-OFDM Intelligent Receiver for Mine Information Recovery

Anyi Wang [1,2], Zhiyuan Feng [1,*], Xuhong Li [1] and Yong Pan [1]

[1] School of Communication and Information Engineering, Xi'an University of Science and Technology, Xi'an 710054, China
[2] Key Laboratory of Network Convergence Communication, Xi'an 710600, China
* Correspondence: fzy_0531@163.com

Abstract: With the advancement of an intellectual and numerical society, the coal mining industry has also begun to change to intelligence. As an important aspect of intelligent coal mine construction, coal mine communication has put forward more stringent standards for communication quality. For the complex communication environment in mines, the transmission of communication signals is always damaged by various noises and interferences, resulting in serious distortion of the communication signals received at the receiving end. Therefore, the use of traditional receivers for information recovery has the problem of high bit error rate (BER), which cannot meet the standard of intelligent coal mine construction. Based on this, the aim of this research is to combine convolutional neural networks (CNN) and multi-input multi-output orthogonal frequency division multiplexing (MIMO-OFDM) communication systems to design an intelligent receiver model for complex mine communication systems. At the receiver side, CNNs are used to take the place of all the information processing processes. First, features are extracted from the received IQ signal by the convolutional neural network, and then the original information bit is recovered using a multi-label classifier to finally realize end-to-end information restoration. The experimental results show that the intelligent receiver model designed in this research has more accurate information recovery capability in the complex mine channel environment compared with the traditional receiver. In addition, they also verify that the intelligent receiver can still recover information effectively when the traditional receiver cannot recover information properly in the case of partial loss of received data.

Keywords: intelligent coal mine communication system; mine information recovery; mine intelligent receiver; deep learning; end-to-end signal processing

check for updates

Citation: Wang, A.; Feng, Z.; Li, X.; Pan, Y. Mine Intelligent Receiver: MIMO-OFDM Intelligent Receiver for Mine Information Recovery. *Energies* **2022**, *15*, 6550. https://doi.org/10.3390/en15186550

Academic Editors: Jiusheng Bao, Xuewen Wang, Jianjian Yang and Qiang Zhang

Received: 15 August 2022
Accepted: 5 September 2022
Published: 7 September 2022

1. Introduction

With the advancement of the industrialization revolution, the coal mining industry is also changing regarding intelligence and intensification. As an important aspect of intelligent coal mine construction, the intelligence of a coal mine communication system has become a topic worthy of study [1–3]. As a restricted space, mine tunnels are much more complex than surface communication scenarios, and there are many branches and bends distributed in the narrow space. Therefore, there are serious transmission losses in mine communication. When electromagnetic waves propagate in mines, it will be absorbed by the denser coal dust and water vapor in the air or reflected by the uneven roadway rock walls and obstacles, thus causing serious transmission losses [4]. Due to multipath fading [5], the transmission characteristics of the mine signals are destroyed, which makes the communication system less reliable. With the innovation of communication technology, some of the communication technologies that have been used maturely in terrestrial communication have been introduced into mine communication systems. For example, MIMO-OFDM technology is considered as one of the most important transmission technologies in wireless communication systems because of its excellent transmission performance [6]. MIMO systems improve channel capacity and OFDM uses multi-carrier technology to resist frequency selective fading caused by non-ideal factors during transmission, which also improves the system reliability to some extent. However, MIMO-OFDM technology also has many limitations. For example, MIMO systems need to achieve a high level of accuracy in channel state information and keep the channel stable, which is not guaranteed in real communication. In addition, with the increased number of antennas, the complexity of signal processing at the receiver increases.

Recently, rapidly developing artificial intelligence (AI) has brought new solutions to many fields, especially deep learning, as one of the most outstanding branches of AI, which has made important contributions in fields such as computer vision (CV) and natural language processing (NLP) [7–9]. Therefore, a growing number of researchers have started to study the application of deep learning in communication systems, hoping that deep learning techniques can be used to solve communication challenges that are difficult to be solved by traditional communication algorithms. There are many studies on the introduction of deep learning into communication systems, including channel estimation [10], channel decoding [11], channel equalization [12], channel modeling [13], modulated signal identification [14], or other local performance optimization. For signal modulation identification, the literature [15] addresses cognitive radio and proposes the use of deep learning methods for automatic signal modulation identification. The authors used a data-driven approach to train CNNs on different datasets to achieve higher accuracy signal recognition. For channel estimation, the literature [16] utilizes deep neural networks for channel estimation and signal detection in OFDM systems and demonstrates that the deep learning approach has some improvements on the system BER performance under severe wireless channel interference. For signal decoding, a deep neural network scheme for polar coded short packet decoding was used in the literature [17]. A decoding method for decoding polar codes in a flat fading channel is designed using a deep learning approach. Simulation results show that the method can obtain the coding gain under the fading channel with a simple codebook structure. For MIMO communication systems, a self-encoder-based unsupervised deep learning scheme for the physical layer of single-user MIMO communication is proposed in the literature [18]. The study combines multiple MIMO assignments into one end-to-end optimization task as a way to reduce the BER of signal transmission. It is shown that deep learning techniques and self-encoders can transmit signals more efficiently at high signal-to-noise ratios and exceed the performance of conventional spatial diversity MIMO systems. Although the above studies are significant for performance optimization of wireless communication systems, they are still at the level of local optimization of a single module. Some scholars have also started to use neural networks to optimize multiple modules in communication systems. Deep neural networks are proposed in the literature [19] to replace two signal processing modules, equalization and decoding, as a way to improve the processing of multipath signals. However, there is still a performance gap compared to the minimum MSE method with known channel statistical states. In the literature [12], a deep learning-based channel estimation and equalization approach is used to address the problems of conventional channel estimation algorithms in the presence of interference. The results show that deep learning algorithms can effectively solve the dilemma of traditional algorithms. The above studies mainly use deep neural networks to optimize one or several signal processing modules, which are simply a combination of local optimization and do not achieve complete overall optimization. To achieve overall optimization at the receiver side, the literature [20] introduces the concept of a deep receiver model that achieves end-to-end recovery of information under non-ideal channel conditions and verifies that this receiver model outperforms the conventional hard-decision receiver in terms of BER. The authors use the classical DenseNet to construct the receiver model. However, the structural design of DenseNet makes the training very difficult and cannot be adapted to the mine communication scenario.

Inspired by the above work, this research aims to explore the integration of deep learning with MIMO-OFDM communication systems and design an intelligent receiver model based on convolutional neural networks. The CNN is used to substitute the whole information recovery process at the receiver side to achieve the overall optimization at the receiver side, which is used to further improve the information recovery accuracy at the receiver side of the MIMO-OFDM communication system in the complex mine environment. The main work of this research has the following points.

- A new intelligent receiver model is designed for information recovery of MIMO-OFDM wireless communication systems under complex mines. The model uses convolutional neural networks to replace the information recovery processes such as channel estimation, equalization, symbol synchronization, demodulation, and decoding in conventional receivers to realize end-to-end recovery of the received signal and global optimization at the receiver side. We used the IQ signal received by the receive antenna of the MIMO-OFDM system as the input to the network model and then recovered the original bits using a multi-label classifier after feature extraction by the convolutional neural network.
- We designed a VOVNet-based intelligent receiver model and conducted simulation experiments by setting a fixed modulation coding scheme in a constant channel scenario and a dynamic channel scenario, respectively. The simulation data were generated in MATLAB 2019b simulation software, and the data were fed into the model for training after a simple normalization process. The trained network model was used to predict the newly received IQ data and complete the decoding of the brand new data.
- Due to the complex and changeable communication scenarios in mines, it may lead to sudden communication interruptions, resulting in the loss of communication data. Therefore, we specially performed data loss tests on the intelligent receiver model designed in this paper.

The rest of this paper is organized as follows. Section 2 introduces the knowledge of the mine fading channel model and MIMO-OFDM wireless communication system. Section 3 describes in more depth the process of building the intelligent receiver model for coal mines. Section 4 validates and discusses the experimental results of the model under a variety of conditions. Finally, Section 5 provides the conclusions of this paper and directions for future work.

2. Theoretical Basis

This section describes the theoretical basis of the coal channel fading model and MIMO-OFDM communication techniques. These descriptions are the theoretical basis for the subsequent research.

2.1. MIMO-OFDM Communication System Model

The MIMO-OFDM system uses multi-antenna technology to transmit OFDM modulated signals, which can effectively use the multipath effect to overcome signal fading, improve data transmission rate, and reduce the BER of signal transmission. In this paper, a centralized MIMO-OFDM system was used with the number of antennas, N_t and N_r, at the transmitter and receiver ends, respectively, as shown in Figure 1. The original information bit stream was encoded into N_t binary bit stream by constellation modulation and MIMO coding to be OFDM modulated data, and then the signal transmitted to the wireless channel by the transmitting antenna after being OFDM modulated. After the wireless channel transmission to the receiver side to obtain N_r received signals, OFDM demodulation to obtain the MIMO-OFDM system of multiplexed subcarriers, and finally MIMO decoding, demodulation and other operations obtain the recovery information bit stream.

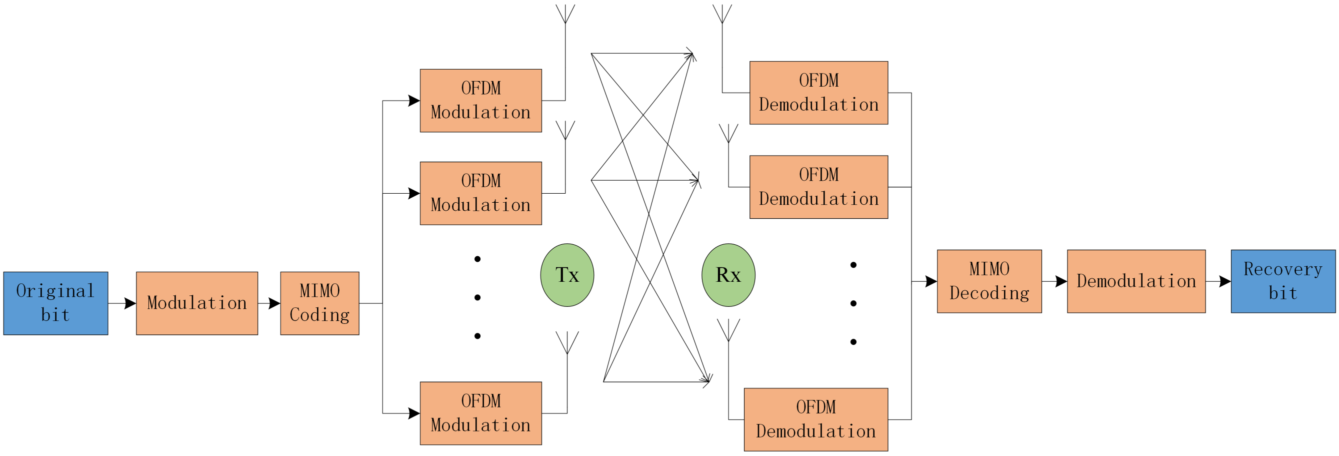

Figure 1. Conventional MIMO-OFDM system architecture.

Considering the channel as a flat fading channel, the channel pulse between the n_t-th transmitting antenna and the n_r-th receiving antenna is correspondingly $\mathrm{h}_{n_r,n_t}(t)$. If frequency bias and initial time delay are neglected, the signal received at the n_r-th receiving antenna can be expressed as:

$$y_{n_r}(t) = \sum_{n_t=1}^{N_t} \mathrm{h}_{n_r,n_t}(t) s_{n_t}(t) + v_{n_t}(t) \tag{1}$$

In terms of a matrixm this can be denoted as:

$$\mathbf{Y} = \mathbf{HS} + \mathbf{N} \tag{2}$$

where **S** denotes the signal after MIMO coding and OFDM modulation, **N** is Gaussian white noise with zero mean and variance σ^2, and **H** is the channel matrix, which can be expressed as:

$$\mathrm{H} = \begin{pmatrix} h_{1,1} & \cdots & h_{1,N_t} \\ \vdots & \ddots & \vdots \\ h_{N_r,1} & \cdots & h_{N_r,N_t} \end{pmatrix} \tag{3}$$

where $h_{i,j}(1 \leq i \leq N_r, 1 \leq j \leq N_t)$ is the channel coefficient with respect to the channel between the i-th receive antenna and the j-th transmit antenna.

There are two implementations of MIMO technology: spatial diversity and spatial multiplexing. Space-time coding is the most commonly used spatial diversity technique. Among them, space-time packet coding (STBC) is a widely used space-time coding scheme with its concise coding method. STBC is a reliable high-speed wireless communication transmission optimization scheme, which can effectively reduce the bit error rate and expand the channel capacity. Alamouti space-time coding [21] is a classic two-antenna transmit diversity method in which two symbols, s_1 and s_2, are transmitted in two consecutive time slots; in the first time slot, s_1 and s_2 are radiated to the wireless channel by the first antenna and the second antenna, respectively; in the second time slot, $-s_2^*$ is transmitted by the first antenna and s_1^* is transmitted by the second antenna. The coding matrix can be expressed as follows:

$$s = \begin{bmatrix} s_1 & -s_2^* \\ s_2 & s_1^* \end{bmatrix} \tag{4}$$

where each line represents the transmit data of each antenna in each time slot. With a single receive antenna, the signal received in the first time slot can be expressed as:

$$y(1) = h_{1,1}s_1 + h_{2,1}s_2 + n_1 \tag{5}$$

The signal received in the second time slot can be expressed as:

$$y(2) = -h_{1,1}s_2^* + h_{2,1}s_1^* + n_2 \tag{6}$$

where $y(k)$ denotes the signal received at the k-th time slot.

2.2. Mine Wireless Channel Model

The mine communication environment is complex, and there are many branches and bends in the narrow space, as well as obstacles, etc. Therefore, the mine wireless channel is susceptible to damage from external factors, such as noise and interference, and there is serious fading. Generally, underground wireless channels can be divided into two types: large scale fading and small scale fading.

The large-scale fading of the mine channel mainly consists of free-space path loss and specific electromagnetic wave transmission loss in the mine environment [22]. For an arbitrary distance, the path loss $\zeta(t,d)$ at a specific time and location follows a normal distribution in dB.

$$\zeta(t,d) = \zeta(t,d) + 10n\lg\frac{d}{d_0} + X_\sigma(t) \tag{7}$$

where t is time, d is signal transmission distance, d_0 is the reference distance, n is the path loss index, indicating the path loss growth rate, and $X_\sigma(t)$ is the shadow fading, obeying a normal distribution with mean 0 and variance σ^2.

The electromagnetic wave propagation loss in the mine tunnel is related to the roughness of the tunnel wall, the inclination degree, and the polarization mode of the antenna, etc., where the vertical polarization loss is

$$L_{ver} = 4.343\lambda^2 z\left(\frac{w^2}{a^3\sqrt{\varphi_1 - 1}} + \frac{\rho^2\varphi_2}{b^3\sqrt{\varphi_2 - 1}}\right) \tag{8}$$

where λ is the wavelength of the electromagnetic wave signal, z is the distance between the transmitting and receiving antennas, ω is the half-wave number in the horizontal propagation direction, a and b are the height and width of the alleyway, φ_1 and φ_2 are the relative dielectric constants of both sides and the top and bottom plates, and ρ is the half-wave number in the vertical propagation direction. The total loss of horizontal polarization wave is

$$L_{total} = L_{hor} + L_{rough} + L_{tile} \tag{9}$$

where L_{hor} is the horizontal polarization loss, $L_{rough}$is the roughness loss, and L_{tile} is the tilt loss.

$$L_{hor} = 4.343\lambda^2 z\left(\frac{w^2\varphi_1}{a^3\sqrt{\varphi_1 - 1}} + \frac{\rho^2}{b^3\sqrt{\varphi_2 - 1}}\right) \tag{10}$$

$$L_{rough} = 8.636\pi^3\Delta h^2 z\lambda\left(\frac{1}{a^4} + \frac{1}{b^4}\right) \tag{11}$$

$$L_{tile} = 4.343\pi^2\vartheta^2 z\frac{1}{\lambda} \tag{12}$$

where Δh is the height of the roadway surface undulation and ϑ is the inclination angle of the top wall roadway wall.

In this paper, Nakagami-m fading [23], which is commonly used for wireless channels in mines, is used as a small-scale fading model in the alleyway with the probability density function of

$$F(r) = \frac{2m^m r^{2m-1}}{\Gamma(m)\Omega^m}\exp\left(-(m/\Omega)r^2\right) \tag{13}$$

where r is the Nakagami-m envelope, m is the fading factor, characterizing the signal fading intensity, with larger m values indicating less signal fading, $\Gamma(\bullet)$ is the Gamma function, and Ω is the average power. The Nakagami-m distribution is used to accurately characterize the fading of multipath signals in complex scenes. The actual channel scenarios, such as long straight tunnels and turnouts in mine tunnels, are characterized by varying the value of m.

3. Network Model

This section describes the implementation of the MIMO-OFDM intelligent receiver. For the original information bit stream with M bits at the transmitter side, it is transmitted to the receiver side through a series of operations at the transmitter side via a wireless fading channel. The receiver side performs feature extraction on the received $IQ = (\mathrm{Re}[y(k)], \mathrm{Im}[y(k)])$ signal, and then the extracted feature vector is subjected to multi-label classification to finally achieve the recovery of the original information bit stream. Convolutional neural network, as an outstanding technology to promote the rapid development of deep learning, has significantly improved the feature extraction ability of neural network by superposition of convolutional layers. ReseNet [24] is proposed to solve the performance degradation problem caused by the accumulation of convolutional layers. Similarly, the introduction of DenseNet [25] pushed the feature extraction capability of convolutional neural networks to a new level. With the expansion of CNN in terms of depth and width, the ability of the network model to extract features from data becomes more outstanding, but the demand of the network model on computational resources also becomes more obvious, which makes the training process of convolutional neural networks difficult and time-consuming. In particular, DensNet has a serious feature redundancy problem, which makes the network model training very difficult. Therefore, Lee etal. improved the feature aggregation model on the basis of DenseNet and redesigned the activation function and finally proposed VOVNet [26], which significantly reduces the inference speed of the model. In response to the demand for instant mine communication systems, we used VOVNet to build a mine intelligent receiver model.

3.1. Feature Extraction Network

Owing to the dense connection structure of DenseNet, the extraction ability of data features is excellent, but it also brings problems, such as a long training time and serious feature redundancy. In response to these problems, VOVNet proposes the one-short aggregation (OSA) module to improve the dense connection structure of DenseNet and realize the efficient use of GPU. This module improves the dense connection structure in DenseNet and realizes the efficient use of GPU, which speeds up the model fitting speed and reduces the redundancy of features and the demand for computational resources.

Feature Aggregation Model

DenseNet is a special type of CNN, where each layer in the network is related to other layers to ensure that each layer has access to the maximum information flow. This ensures that each layer has direct access to the output feature information of all previous layers and passes the feature information extracted from this layer to the subsequent network layers, as shown in Figure 2. Due to the severe feature reuse in the middle convolutional layer of the densely connected structure, unnecessary redundancy is caused. Therefore, removing the feature transfer between intermediate convolutional layers and performing feature aggregation only in the final convolutional layer can effectively solve the feature redundancy problem. VOVNet is to reduce the intermediate layer feature reuse by aggregating the feature maps of all layers at once in the final layer while ensuring that the input and output channels are the same, as shown in Figure 3.

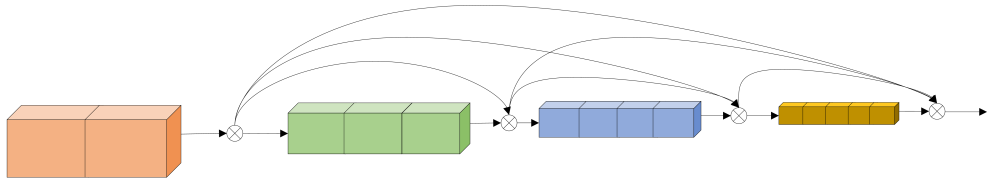

Figure 2. Dense aggregation model.

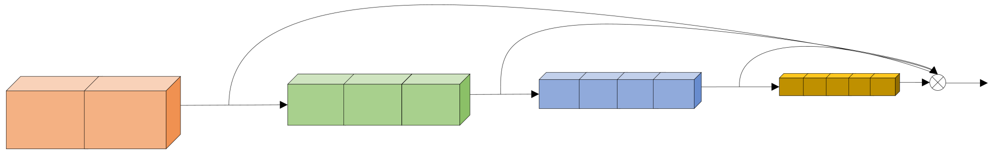

Figure 3. One-short aggregation model.

The core of DenseNet is the DenseBlock module, which consists mainly of 1 × 1 convolution and 1 × 3 convolution. Based on the problems of DenseNet, VOVNet proposed an OSA module to replace the DenseBlock module on the basis of the DenseNet network structure. The OSA module aggregates the feature maps of all layers at once only at the final layer, ensuring that the input and output channels are the same, and removes the 1 × 1 convolution operation from the DenseBlock. To increase the feature extraction effect of the model, the OSA module also incorporates the residual connectivity of ResNet and the channel attention mechanism in SENet [27], as shown in Figure 4.

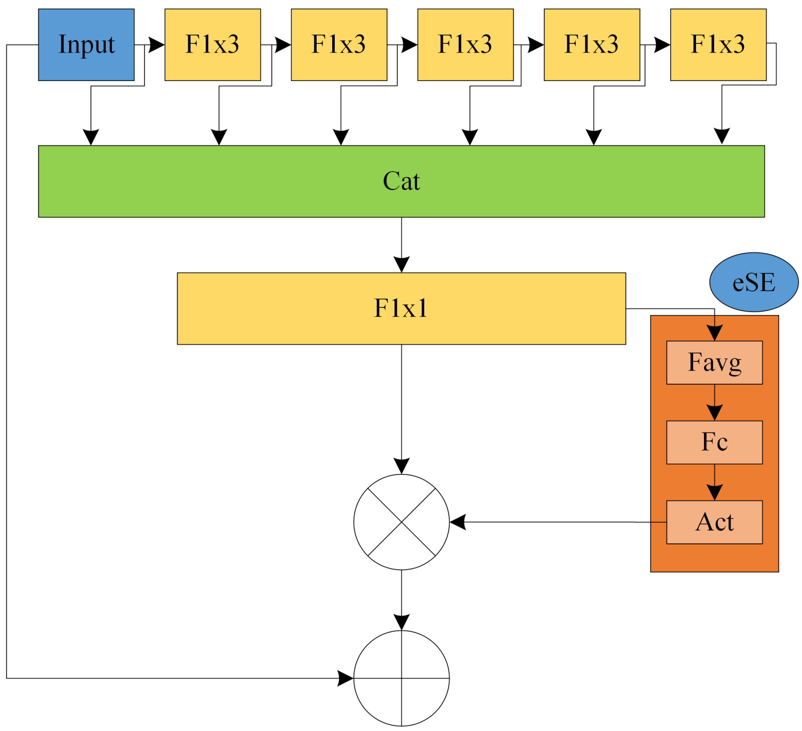

Figure 4. One-short aggregation module. F1x3 denotes the convolution operation with a convolution kernel of 1 × 3; Cat denotes the feature map connected in the channel dimension; Favg denotes the global average pooling; Fc is the fully connected operation; Act is the h-sigmoid activation function; X denotes element multiplication; + denotes element addition.

3.2. Multi-Label Classifier

Considering the original bit stream data as the labels for model training, if viewed as a regular multi-classification problem, the number of categories to be classified is 2^M, which is difficult to estimate for both the model parameters and the model training cost. Multiple binary classifiers are used in the literature [20] to reduce the classification complexity, but M classifiers are required. For this reason, we consider the problem as a multi-label classification problem and use the h-sigmoid activation function instead of the sigmoid activation function to output the feature map as a one-dimensional vector of length M that matches the original bit stream labels of M bits.

$\delta(x)$ is a sigmoid function, and it is very complicated to calculate the derivative of the sigmoid function directly. For this reason, the activation function can be redesigned in combination with the ReLU6 function to reduce the activation function derivative complexity and speed up the model training, as shown in Figure 5.

$$\delta(x) = \frac{1}{1+e^{-x}} \tag{14}$$

$$\mathrm{Re}LU6(x) = \min(\max(x,0),6) \tag{15}$$

$$h - sigmoid = \frac{\mathrm{Re}LU6(x+3)}{6} \tag{16}$$

Since the original bit stream is a sequence of [0 1], the label processing process is omitted and can be used directly as training labels. The network training loss function uses a binary cross-entropy loss function, which can be expressed as:

$$\mathrm{Loss} = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot \log(\hat{y}_i) + (1-y_i)\cdot\log(1-\hat{y}_i) \tag{17}$$

where y_i denotes the true label, $\hat{y}_i$ denotes the predicted value, and N is the number of samples.

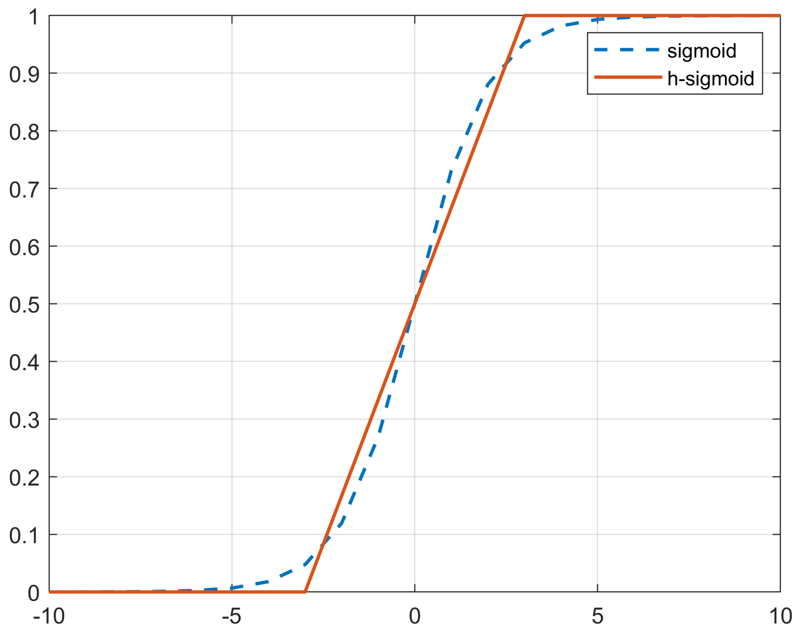

Figure 5. Sigmoid and h-sigmoid function curves.

3.3. Intelligent Receiver Model

In this paper, we use the powerful ability of DNN for data analysis to learn the damage law of the signal data autonomously and perform different types of modulation on the transmit signal in a non-ideal channel environment, as well as add different interference signals, which correspond to the randomly generated labels of the original bit stream and train the functional relationship between the damage signal and the labels through deep neural networks as a way to predict the new received signal and calculate the BER of the predicted signal. In the process of network training, different signals received through the channel transmission correspond to different labels. As the network converges iteratively, the loss function between the predicted signal and the real label is calculated, and the network parameters are automatically updated to finally achieve end-to-end recovery of the original signal. The structural model of the smart receiver is shown in Figure 6.

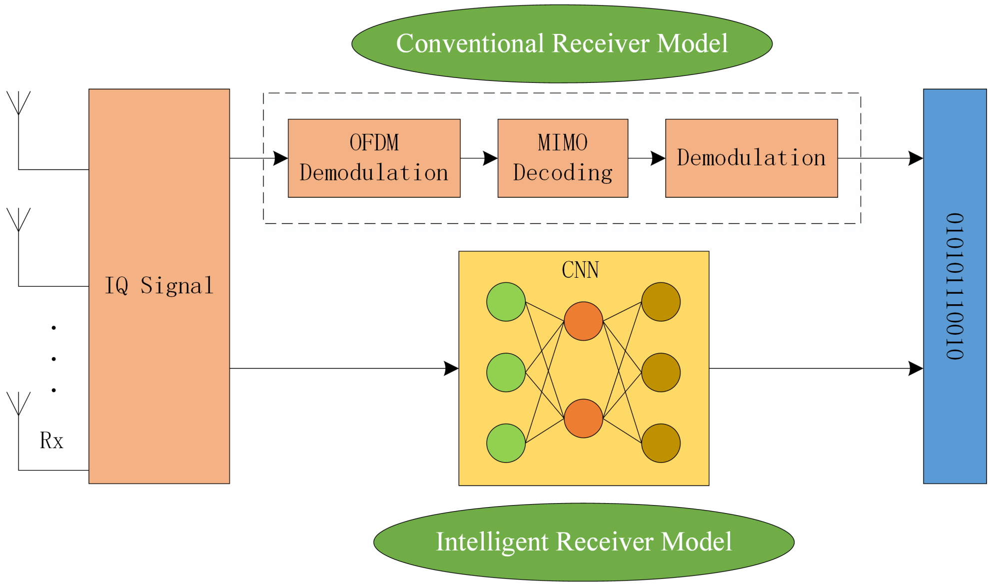

Figure 6. Structure comparison between traditional receiver and intelligent receiver.

The convolutional neural network takes the received IQ signal as the input to the network model, learns the signal change pattern dynamically on its own without knowing the signal modulation coding method, and recovers the original information bit stream. The receiver model uses deep neural networks for feature extraction of IQ signals and then recovers the data by multi-label classification.

3.3.1. Implementation Method of Intelligent Receiver

The network model structure of the VOVNet-based smart receiver designed in this paper is shown in Figure 7. The VOVNet-based intelligent receiver network model contains a total of 5 Stages, and each Stage is followed by a 1×3 maximum pooling layer with a step size of 2 for downsampling. Stage1 contains 3 layers of convolution, Stage2-Stage5 consists of OSA modules, and the classifier contains a fully connected layer, so the model has a total of 40 layers.

3.3.2. The Training Algorithm of the Intelligent Receiver

The parametric optimizer we used was Stochastic Gradient Descent with momentum (SGDM). A momentum mechanism was added compared to Stochastic Gradient Descent (SGD). The current momentum V is determined by the last iteration momentum, together with the current gradient. By adding the momentum factor, the model parameter update can maintain the previous update trend and avoid the local optimum. The iterative process of parameter update can be expressed as:

$$V_{dW} = mV_{dW} + (1 - m)dW \tag{18}$$

$$W = W - \alpha V_{dW} \tag{19}$$

where m is the momentum factor, W is the parameter to be updated in the network, and α is the learning rate.

For the loss function, the binary cross-entropy loss function was used, as shown in Equation (17). The training batch size was 256 and the number of training epochs was 10. The specific training method is shown below (Algorithm 1):

Algorithm 1: Training algorithms for intelligent receiver

Load training data set $(\mathrm{Re}[y(k)], \mathrm{Im}[y(k)])$;
Initialize network parameters W;
for *epoch in range(10)* **do**
    if *model loss reduction* **then**
        randomly select the minimum batch sample data from $(\mathrm{Re}[y(k)], \mathrm{Im}[y(k)])$ for training;
        model losses are calculated according to equation(17);
        model parameters are updated according to equation(18).
    else
        end of training.
    end
end
return *network model with minimal training loss*

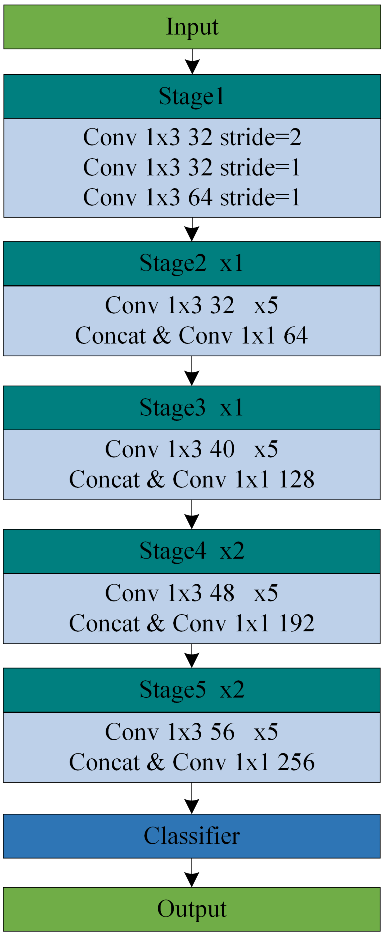

Figure 7. Network structure of mine intelligent receiver based on VOVNet.

4. Experimental Demonstration

In this section, the practical performance of the intelligent receiver for the mining MIMO-OFDM system proposed in this paper is verified by experimental simulations. In this paper, MATLAB2019b is used as an experimental platform to build a model of a mine MIMO-OFDM communication system that generates simulation datasets, and the intelligent receiver network model is built on an NVIDIA RTX3090 GPU using the Tensorflow2.0 deep learning framework. For the mine fading channel, we consider mine large scale fading and small scale fading. Large-scale fading involves the roughness and inclination of the tunnel walls in the mine channel, as well as the fading coefficient of some dust; Nakagami fading is chosen as the small-scale fading model, and the damage of the mine fading channel to the transmitted signal is characterized by varying the fading coefficient m.

To verify the end-to-end information recovery capability of the mine smart receiver under different channel scenarios, a 16-bit raw information bit stream was randomly generated and the channel was coded using (7, 4) Hamming codes, followed by BPSK digital modulation. Different coefficients m under Nakagami fading channel model were selected. m values were chosen to contain 0.5, 1, and 2, m = 0.5 for one-sided Gaussian distribution and m = 1 for Rayleigh distribution. m values are larger, and a smaller fading degree indicates a better channel state. The quantity of antennas receiving/transmitting was set to 2, the Eb/No (bit signal-to-noise ratio in dB) range was 0–10 dB, and the step size was 1 dB. A total of 20,000 training samples and 10,000 test samples were generated under each Eb/No, totalling 220,000 training samples and 110,000 test samples.

Observing Figure 8, it was found that, for different channel scenarios, smart reception had a superior information recovery performance compared to conventional reception. The error bit rate of conventional receivers reached only 10^{-3} at Eb/No of 10 dB and m = 0.5 due to the accumulated error, while the error bit rate of the intelligent receiver designed in this paper reached 10^{-5}. Overall, the change of channel fading had little effect on the smart receiver, which indicates that the smart receiver is less sensitive to the channel environment transformation, has good robustness, and shows more stable noise resistance performance.

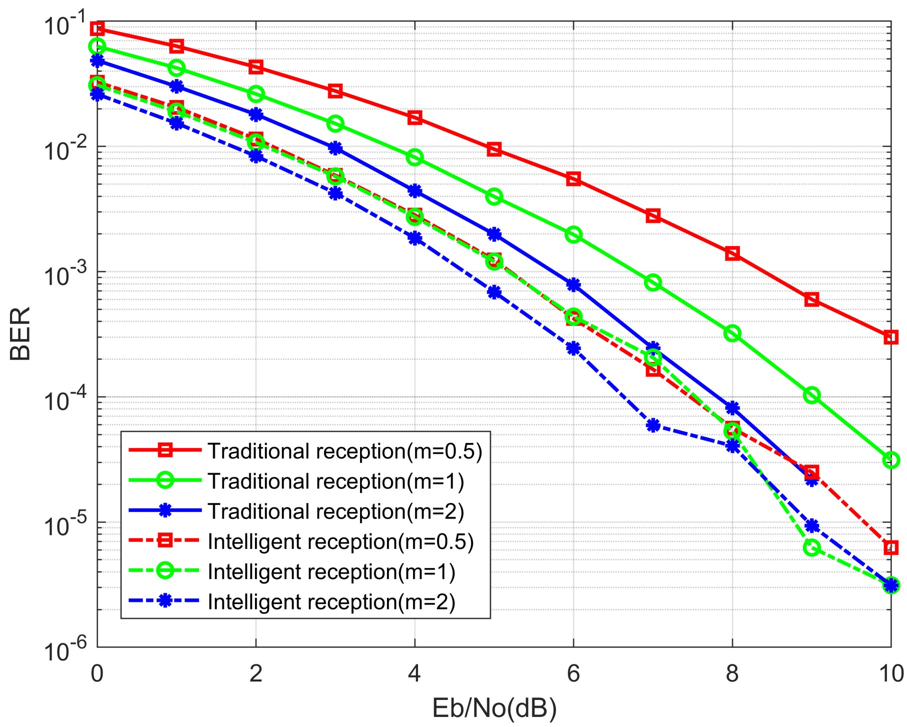

Figure 8. Comparison of information recovery capability for different channel scenarios.

Figure 9 shows the comparison of the information recovery performance of the mine smart receiver designed in this paper (noted as a multi-label classifier reception) and the literature [20] receiver model (noted as the binary classifier reception). It can be found that, although both belong to the overall optimized information recovery method, the multi-label classifier receiver model has a more excellent information recovery capability. When Eb/No = 10 dB, the error bit rate of the receiver model designed in this paper is lower than 10^{-5}, which is slightly better than the binary classifier reception model.

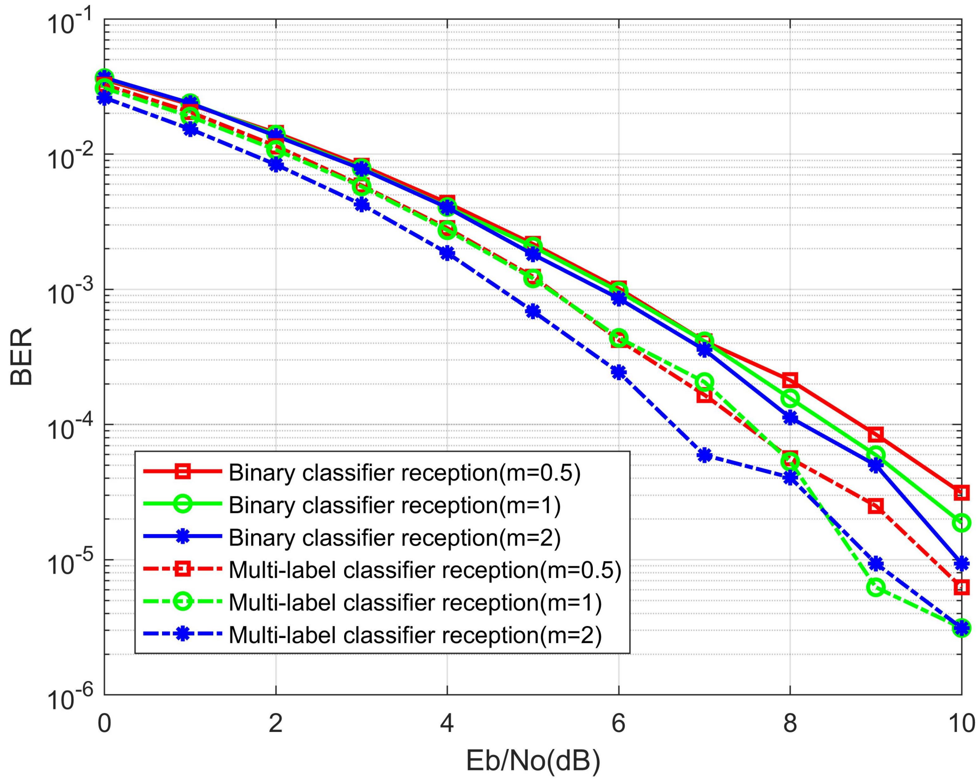

Figure 9. Comparison of information recovery capability for different modulation methods.

To demonstrate the end-to-end information restoration capability of the smart receiver with different digital modulated signals, we randomly generated 32-bit raw information bit stream. Three digital modulation methods were set: BPSK, QPSK and 16QAM, the Nakagami fading factor was chosen as 1, the number of transmitting/receiving antennas was 2, and the range of Eb/No was 0–10 dB in 1 dB steps.

Observing Figure 10, it was found that conventional receivers had significant variability for different modulated signals. The performance of information recovery was poorer for higher order modulation. The mine smart receiver designed in this paper was more adaptable to signal modulation variations. Although the BER of the 16QAM signal was about 10^{-4} at Eb/No = 10 dB, it was better than the conventional receiver overall. Especially for BPSK signals and QPSK signals, the mine smart receiver can accurately recover the initial information with similar performance.

To validate the information recovery capability of smart receivers with different antenna combinations, the experiment set the antenna combinations as 2×1, 2×2, 3×2. 16-bit raw information bit streams were randomly generated. Channel coding was performed using (7, 4) Hamming codes, followed by BPSK digital modulation. The Nakagami fading channel coefficient m was set to 1, the Eb/No range was 0–10 dB, and the step size was 1 dB.

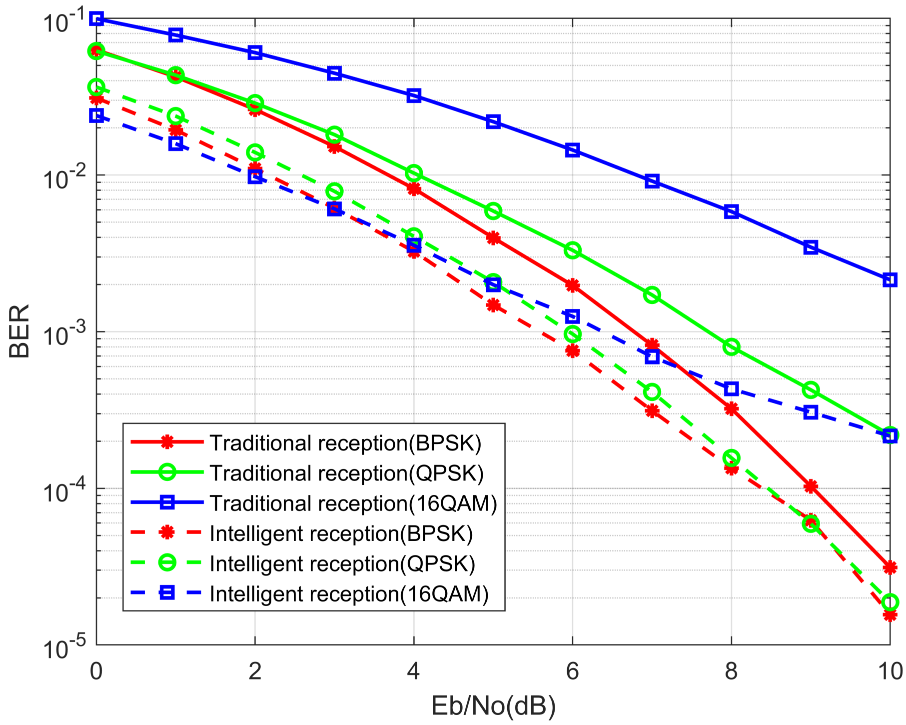

Figure 10. Comparison of information recovery capability for different modulation methods.

Observe Figure 11. When the antenna combination was 2 × 1 and Eb/No was 10 dB, the conventional reception bit error rate was only 10^{-3} and the intelligent reception bit error rate was close to 10^{-4}. The accuracy of information recovery for both conventional and intelligent reception was not satisfactory, which indicates that the change in the number of antennas has a greater impact on the intelligent receiver in the mine. We conjecture that the main reason is that the decrease in the number of receiving antennas corresponds to a decrease in the amount of data used for model training under the same conditions, and the model fails to reach the optimal state. Another state can be found. For conventional receivers, the antenna combinations of 2 × 2 and 3 × 2 are close to each other in terms of information recovery capability. This indicates that there is an upper limit to improve the information recovery capability of the conventional receiver by increasing the antennas. However, there is still a significant performance improvement for the smart receiver. This indicates that there is room for further improvement in the antenna combination for the smart receiver.

To validate the end-to-end information recovery capability of smart receivers in dynamic environments, three channel scenarios, Eb/No = 0 dB, Eb/No = 3 dB, and Eb/No = 6 dB, were selected to represent the mining face scenario, the occlusion scenario, and the long straight channel scenario in the mine, respectively. A 16-bit raw information bit stream was randomly generated. In addition, the channel encoding was (7, 4) Hamming code and BPSK digital modulation was used. The Nakagami fading channel coefficient m was set to 1, and the number of transmitting/receiving antennas were both 2.

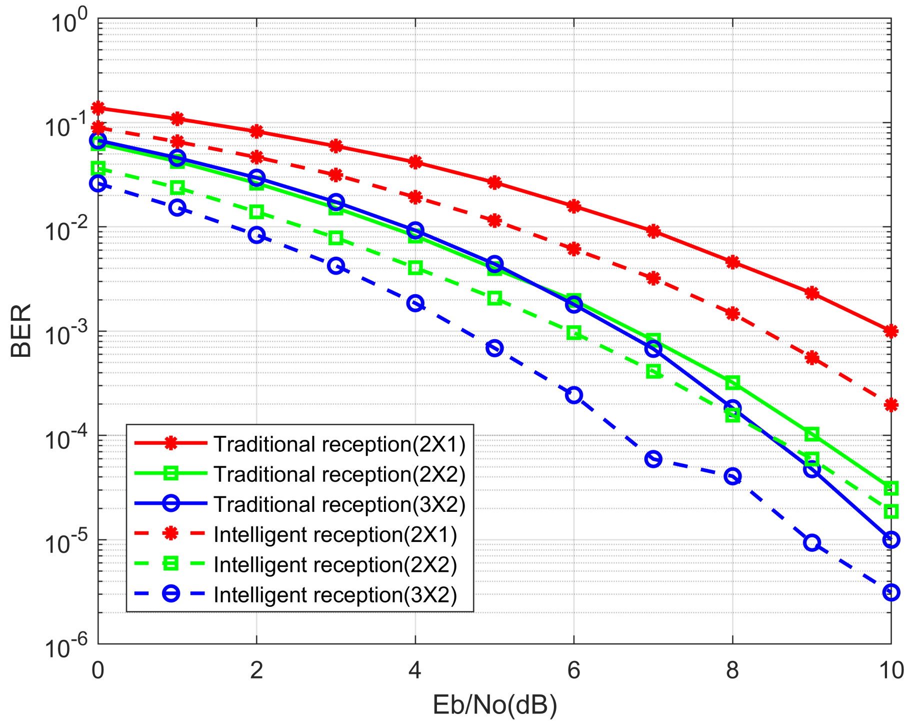

Figure 11. Comparison of information recovery capability for different antenna combinations.

Observing Figure 12, it was found that the information recovery accuracy of the mine smart receiver model designed in this paper was higher than that of the conventional receiver in all dynamic scenarios. The three channel scenario changes were distinguished obviously, and the scenario transition area was basically the same. At scenario 3, the BER of the mine smart receiver was lower than 10^{-3}, and the performance of the smart receiver information recovery ability was stable at the same scenario.

Due to the complex working scenarios of coal mine communication systems, communication data loss due to unexpected situations is a problem that needs to be dealt with. Therefore, we specifically considered the end-to-end information recovery performance of the intelligent receiver in case of data loss. The randomly generated 16-bit original information bit stream channel coding using (7, 4) Hamming code and digital modulation method was BPSK. Data loss degrees (ratio of lost data volume to complete data volume) were 1%, 3%, 5%, and 10%. The set Nakagami fading channel coefficient m was 1, and the number of transmitting/receiving antennas was 2. The Eb/No range was 0–10 dB, and step size was 1 dB.

Observation of Figure 13 reveals that the false bit rate of the smart reception at 5% data loss was similar to that of the conventional reception at complete data, and the false bit rate was about 10^{-5} when Eb/No was 10 dB at 1% and 3% data loss, which indicates that the smart receiver has better information recovery performance compared to the conventional receiver and can cope with more complex communication scenarios with certain emergency communication capability. However, the smart receiver designed in this paper also has a data loss tolerance, and the accuracy of information recovery is significantly reduced when the data loss is 10%.

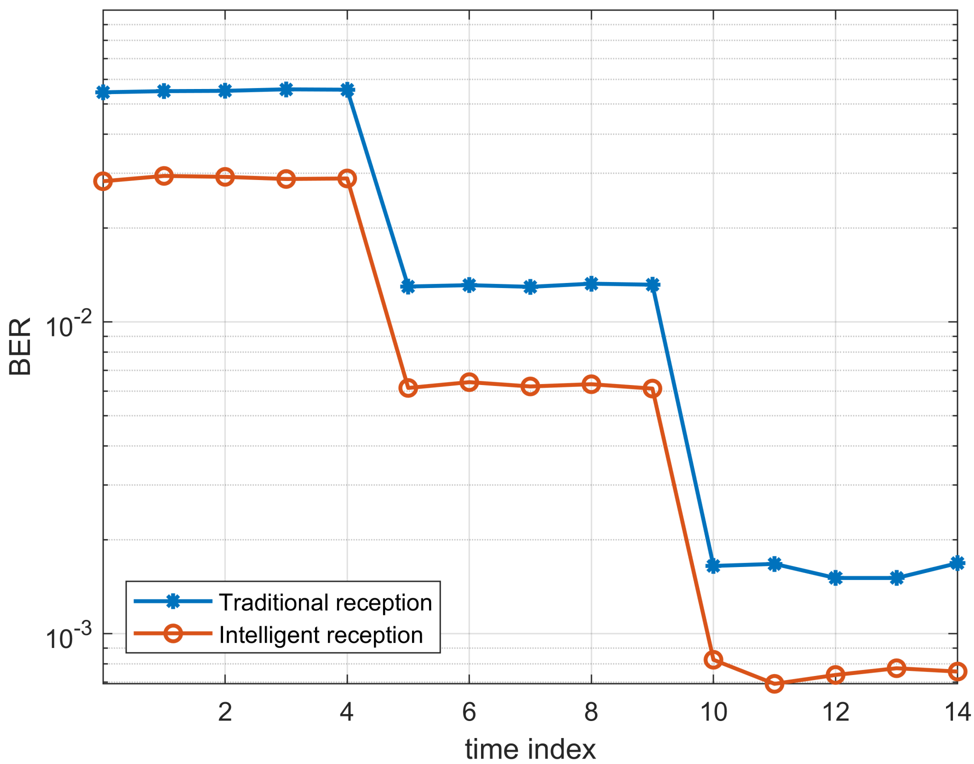

Figure 12. Comparison of information recovery capabilities in dynamic environments.

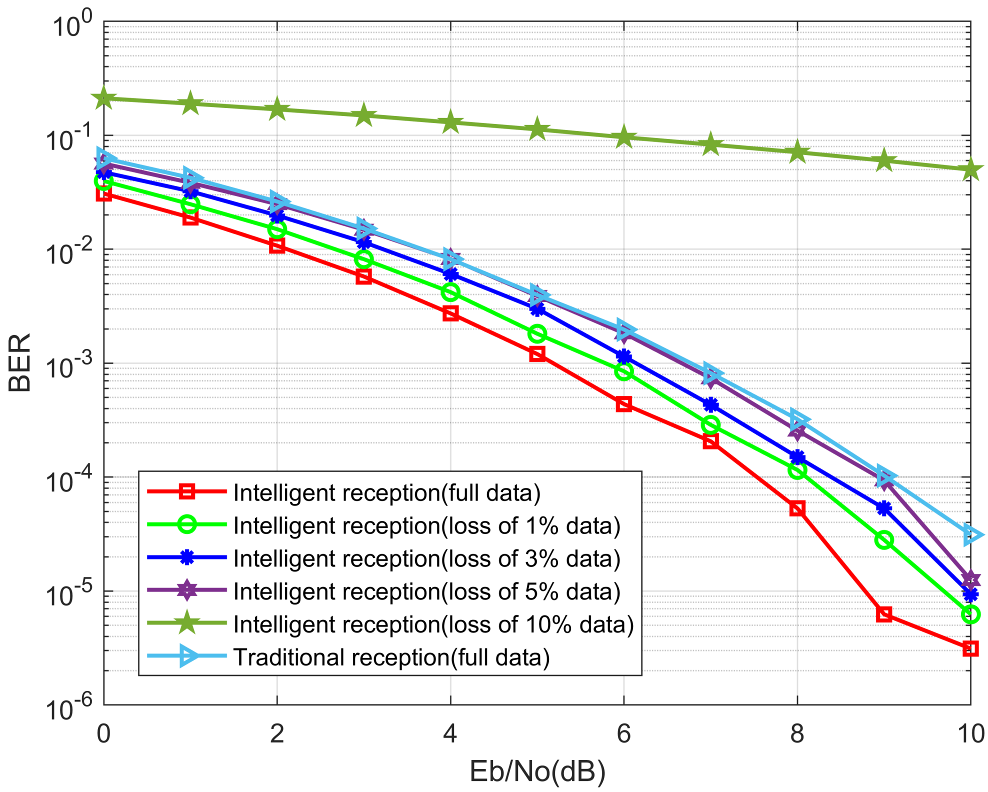

Figure 13. Information recovery performance for some lost data.

5. Conclusions

In this paper, a mine intelligent receiver model was designed based on the MIMO-OFDM wireless communication system in a complex mine environment. This receiver model uses an improved CNN model to replace the traditional receiver signal processing process and achieves accurate recovery of the original information through autonomous learning of IQ data. Compared with the traditional receiver model, the mine intelligent receiver model designed in this paper has the following features:

- The mine intelligent receiver model designed in this paper achieves the overall optimization effect at the receiver end. The conventional receiver model relies on theoretical assumptions between modules and has a serious error accumulation problem. Even single-module optimization and multi-module optimization based on deep learning only achieve the effect of local optimization, and the problem of error accumulation is not solved. The mine smart receiver designed in this paper is a model of overall joint optimization at the receiver side, which can realize blind reception of multiple digital modulation and coding combinations. Through autonomous learning of training data, data laws are extracted to achieve intelligent recovery of information.
- The mine intelligent receiver designed in this paper has stronger robustness. For the communication data loss caused by unexpected conditions in the complex communication environment of mines, the mine intelligent receiver has certain emergency performance and can better serve the actual mine communication scenarios.
- The mine intelligent receiver designed in this paper has rapid inference speed. By improving the structure of the CNN model, the inference speed of the model is accelerated, which is of application value to the actual mining wireless communication system and can better meet the requirement of immediacy of the mining communication system.

Through the verification of the data generated by the simulation experimental platform, the mine smart receiver designed in this paper has good information recovery performance. However, the best enhancement has not been achieved for the number of antennas, and since this receiver model is dependent on the amount of data, this will be the area we need to enhance and improve. In the future, we will test this receiver model in a real mine communication scenario and improve and optimize it accordingly for possible problems in the real communication scenario.

Author Contributions: For this research article, A.W. was in charge of the methodology; Z.F. was in charge of the writing, review, and formal analysis; X.L. was in charge of the data curation and field inspection; Y.P. was in charge of the testing and verification. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Natural Science Foundation of China under the project "Theory and Methodology of Marine Communication Channel Identification and Model Optimization", Project No. U19B2015.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The study was approved by Xi'an University of Science and Technology.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Gao, L. Discuss the construction of the wisdom mine. *Copp. Eng.* **2013**, 43–46+76.
2. Qingsong, H.; Wei, Y.A.; Enjie, D.I.; Shiyin, L.; Binghao, L. State-of-the-art and trend of emergency rescue communication technologies for coal mine. *J. Commun.* **2019**, *40*, 163–179.
3. Shi-Rong, G.E. Key technology of intelligent coal mining equipment. *Coal Sci. Technol.* **2014**, *42*, 0253–2336.
4. Boutin, M.; Benzakour, A.; Despins, C.L.; Affes, S. Radio wave characterization and modeling in underground mine tunnels. *IEEE Trans. Antennas Propag.* **2008**, *56*, 540–549. [CrossRef]
5. Liu, Z.; Wang, Y.; Zeng, Q.; Yang, Y.; Dai, Z. Research on optimization measures of Zigbee network connection in an imitated mine fading channel. *Electronics* **2021**, *10*, 171. [CrossRef]
6. Stuber, G.L.; Barry, J.R.; Mclaughlin, S.W.; Li, Y.; Ingram, M.A.; Pratt, T.G. Broadband MIMO-OFDM wireless communications. *Proc. IEEE* **2004**, *92*, 271–294. [CrossRef]

7. Xie, J.; Zheng, Y.; Du, R.; Xiong, W.; Cao, Y.; Ma, Z.; Cao, D.; Guo, J. Deep learning-based computer vision for surveillance in its: Evaluation of state-of-the-art methods. *IEEE Trans. Veh. Technol.* **2021**, *70*, 3027–3042. [CrossRef]
8. Lyons, N. Deep Learning-based Computer Vision Algorithms, Immersive Analytics and Simulation Software, and Virtual Reality Modeling Tools in Digital Twin-driven Smart Manufacturing. *Econ. Manag. Financ. Mark.* **2022**, *17*, 67–81. [CrossRef]
9. Landolt, S.; Wambsganss, T.; Söllner, M. A taxonomy for deep learning in natural language processing. In Proceedings of the Hawaii International Conference on System Sciences, Maui, HI, USA, 5–8 January 2021.
10. Bai, Q.; Wang, J.; Zhang, Y.; Song, J. Deep learning-based channel estimation algorithm over time selective fading channels. *IEEE Trans. Cogn. Commun. Netw.* **2019**, *6*, 125–134. [CrossRef]
11. Pang, X.; Yang, C.; Zhang, Z.; You, X.; Zhang, C. A channel-blind decoding for LDPC based on deep learning and dictionary learning. In Proceedings of the 2019 IEEE International Workshop on Signal Processing Systems (SiPS), Nanjing, China, 20–23 October 2019; pp. 284–289.
12. Cheng, X.; Liu, D.; Wang, C.; Yan, S.; Zhu, Z. Deep Learning-Based Channel Estimation and Equalization Scheme for FBMC/OQAM Systems. *IEEE Wirel. Commun. Lett.* **2019**, *8*, 881–884. [CrossRef]
13. Wang, D.; Song, Y.; Li, J.; Qin, J.; Yang, T.; Zhang, M.; Chen, X.; Boucouvalas, A.C. Data-driven optical fiber channel modeling: A deep learning approach. *J. Light. Technol.* **2020**, *38*, 4730–4743. [CrossRef]
14. Fan, C.; Wang, Y.; Liu, M. A Hybrid Approach for Signal Modulation Recognition Using Deep Learning Methods. *J. Phys. Conf. Ser.* **2021**, *1757*, 012074. [CrossRef]
15. Wang, Y.; Liu, M.; Yang, J.; Gui, G. Data-driven deep learning for automatic modulation recognition in cognitive radios. *IEEE Trans. Veh. Technol.* **2019**, *68*, 4074–4077. [CrossRef]
16. Ye, H.; Li, G.Y.; Juang, B.H. Power of deep learning for channel estimation and signal detection in OFDM systems. *IEEE Wirel. Commun. Lett.* **2017**, *7*, 114–117. [CrossRef]
17. Irawan, A.; Witjaksono, G.; Wibowo, W.K. Deep learning for polar codes over flat fading channels. In Proceedings of the 2019 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), Okinawa, Japan, 11–13 February 2019; pp. 488–491.
18. Dörner, S.; Cammerer, S.; Hoydis, J.; Ten Brink, S. Deep Learning Based Communication Over the Air. *IEEE J. Sel. Top. Signal Process.* **2017**, *12*, 132–143. [CrossRef]
19. Ye, H.; Li, G.Y. Initial Results on Deep Learning for Joint Channel Equalization and Decoding. In Proceedings of the IEEE 86th Vehicular Technology Conference (VTC-Fall), Toronto, ON, Canada, 24–27 September 2017.
20. Zheng, S.; Chen, S.; Yang, X. DeepReceiver: A deep learning-based intelligent receiver for wireless communications in the physical layer. *IEEE Trans. Cogn. Commun. Netw.* **2020**, *7*, 5–20. [CrossRef]
21. Alamouti, S.M. A simple transmit antenna diversity technique for wireless communications. *IEEE J. Sel. Areas Commun.* **1998**, *16*, 1451–1458. [CrossRef]
22. Peng, C.; Ai-Jun, L.; Lu-Feng, L. Study on mine electromagnetic environment and electromagnetic wave propagation. *Commun. Technol.* **2010**, *43*, 54–56.
23. Jang, Y. Average BER performance of MPSK with noisy phase reference in Nakagami-m fading channel. *Electron. Lett.* **2021**, *57*, 823–825. [CrossRef]
24. He, K.; Zhang, X.; Ren, S.; Sun, J. Deep residual learning for image recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, NV, USA, 27–30 June 2016; pp. 770–778.
25. Huang, G.; Liu, Z.; Van Der Maaten, L.; Weinberger, K.Q. Densely connected convolutional networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 21–26 July 2017; pp. 4700–4708.
26. Lee, Y.; Hwang, J.W.; Lee, S.; Bae, Y.; Park, J. An energy and GPU-computation efficient backbone network for real-time object detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, Long Beach, CA, USA, 16–17 June 2019.
27. Hu, J.; Shen, L.; Sun, G. Squeeze-and-excitation networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 18–23 June 2018; pp. 7132–7141.