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Model-Driven Deep Learning Scheme for Adaptive Transmission in MIMO-SCFDE System

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ABSTRACT Adaptive transmission (AT) is considered as one of the critical technologies to enhance the effectiveness of communication systems. In this article, we propose a model-driven deep learning (DL) scheme for AT in multiple-input multiple-output single-carrier frequency-domain equalization (MIMO-SCFDE) systems, in which the adaptive modulation network (AMNet) and adaptive demodulation network (ADNet) are adopted to complete the modulation of the signal and the modulation recognition of the receiver. Under the target bit error rate (BER), the adaptive modulation (AM) scheme can adjust the modulation mode selection of different transmitting antennas adaptively according to the estimated channel information to improve the throughput. The features required by the AMNet are extracted from the received signal, and the labels are assigned according to the optimal modulation scheme got by analyzing the signal detection performance. Since the spectral correlation function has a powerful ability to suppress noise and the cyclic spectrum varies with the modulation mode, we take the preprocessed cyclic spectrogram as the input of ADNet to achieve the adaptive modulation recognition (AMR). Comparative experiments demonstrate that the proposed scheme gets better performance in terms of throughput and reliability in MIMO-SCFDE systems than the traditional scheme and the existing DL scheme.

INDEX TERMS Model-driven, deep learning, adaptive transmission, MIMO-SCFDE, adaptive modulation, adaptive demodulation.

I. INTRODUCTION

Adaptive transmission (AT) refers to the technology that the transmitter utilizes the channel state information (CSI) to adjust the transmission strategy adaptively, including changing the transmission power, adjusting the modulation mode, or adjusting the channel coding scheme so that the system can improve the information transmission rate or reliability [1]. Traditional AT technology mostly enhances the performance of the communication system through sophisticated algorithms [2]. However, for 5G communications that require high efficiency and high density, the increase in computational complexity will inevitably reduce the effectiveness of communications. With the resurgence of artificial intelligence (AI) technology, deep learning (DL) as an advanced data processing algorithm has been widely used in image analysis and speech recognition [3]. The organic combination of DL and wireless communication will become a breakthrough in physical layer transmission [4].

The research on applying DL to the physical layer is mainly divided into two types: data-driven network and model-driven network [5]. The data-driven DL network regards the multiple function blocks of the wireless communication system as an unknown black box replaced by the DL model and then relies on a large number of labeled data to complete the input-output training [6]. In [7], the receiving module after removing the cyclic prefix (CP) in the orthogonal frequency division multiplexing (OFDM) system is regarded

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as a whole and replaced by the offline trained deep neural networks (DNN) to accomplish the process from the radio frequency (RF) receiver to the sink directly. After revisiting the idea of using DNN for one-shot decoding of random and structured codes, [8] introduces the metric normalized validation error (NVE) to investigate further the potential and limitations of DL-based decoding concerning performance and complexity. The author of [9] develops a novel DL-based CSI sensing and recovery network called CsiNet-long short-term memory (LSTM), which not only considerably enhances recovery quality, but also improves the trade-off between compression ratio and complexity. Aiming at the problem that the traditional adaptive modulation (AM) scheme does not consider the channel correlation, [10] proposes a machine learning-based AM model for the MIMO-OFDM system to adjust data transmission rate according to the channel condition. In [11], a novel signal detection scheme based on the adaptive ensemble deep learning algorithm in single-carrier frequency-domain equalization (SC-FDE) systems is proposed, which adopts an integrated LSTM model to replace the channel estimation and frequency domain equalization process. Compared with the traditional physical layer technology, the above data-driven DL schemes improve performance by replacing multiple modules of the communication system in an end-to-end way. However, this kind of model discards these existing wireless communication knowledge, and the slight change of model structure will lead to the decline of accuracy.

The model-driven DL network maintains the original physical layer structure and uses the DL model with high training efficiency to replace a module or trainable parameters to optimize the overall performance [12]. The work in [13] introduces a peak-to-average power ratio (PAPR) reducing network (PRNet) to determine the constellation mapping and demapping of symbols adaptively on each subcarrier. To achieve higher data recovery accuracy, [14] combines DL with the expert knowledge and introduces a model-driven approach by adopting the block-by-block signal processing method that divides the receiver into channel estimation subnet and signal detection subnet. In [15], the author extends the idea of end-to-end learning of communications systems through DNN-based autoencoders OFDM with CP, which enables reliable communication over multipath channels and makes the communication scheme suitable for commodity hardware with imprecise oscillators. The author of [16] proposes a model-driven DL network for MIMO detection by inheriting the advantages of Bayes-optimal signal recovery algorithm and DL technology, and the network is easy and fast to train because only a few adjustable parameters are required to be optimized. To circumvent the challenge for precoding design brought by the use of low-resolution digital-to-analog converters (DAC) for each antenna and RF chain in downlink transmission, [17] develops a model-driven DL network for massive multiuser MIMO with finite-alphabet precoding, which shows significant advantages in performance, complexity, and robustness to channel estimation error under Rayleigh fading channel. Based on the existing physical layer module, the model-driven DL network can significantly reduce the dependence on data and become one of the most potential development directions for physical layer transmission technology.

In this article, we propose a model-driven DL scheme for AT in MIMO-SCFDE systems. The main contributions of this work can be summarized as follows:

- We adopt improved DL models, called AMNet and ADNet, to replace the modulation and modulation recognition processes of traditional communication systems, respectively. The feature input into the AMNet is sequentially learned through a one-dimensional convolutional neural network (1D CNN), LSTM, and fully connected deep neural network (FC-DNN). Also, ADNet uses CNNs with different depths to construct an integrated model to achieve the adaptive selection of modulation recognition networks.
- We analyze the relationship between the MIMO channel parameters and the optimal modulation scheme. It leads us to select the estimated SNR, frequency-domain sub-channel marking information, frequency-domain sub-channel rank information, and channel equalization information as the feature required for model training, and assign labels according to the optimal modulation scheme obtained by a comprehensive analysis of signal detection performance.
- We analyze the path delay and received power relationship and prove that the received power under different path delays can be selected as the adaptive factor to realize the adaptive ensemble of the output of each sub-network in AMNet. Since the cyclic spectrum features change with SNR and modulation mode, we utilize ADNet to achieve adaptive modulation recognition (AMR) according to the cyclic spectrogram's complexity.

The remainder of this article is organized as follows. Section II describes the structure of the model-driven MIMO-SCFDE system. Section III introduces the proposed AT scheme, where the related DL algorithms implemented by the AM and AMR models are also presented. The throughput performance and modulation recognition accuracy based on the proposed scheme are simulated and discussed in Section IV. Finally, Section V concludes the article.

II. SYSTEM MODEL

Figure 1 shows the model-driven MIMO-SCFDE system for AT. The MIMO-SCFDE system is built up with N_T transmitting antennas and N_R receiving antennas. The bit information to be transmitted is converted into multi-channel signals and distributed to different antennas after serial-to-parallel conversion [18]. Then, the signal of each channel adaptively selects the optimal modulation mode according to the channel information fed back by the received signal and sent it through different antennas with cyclic prefix (CP) inserted. After passing the additive white Gaussian noise (AWGN)

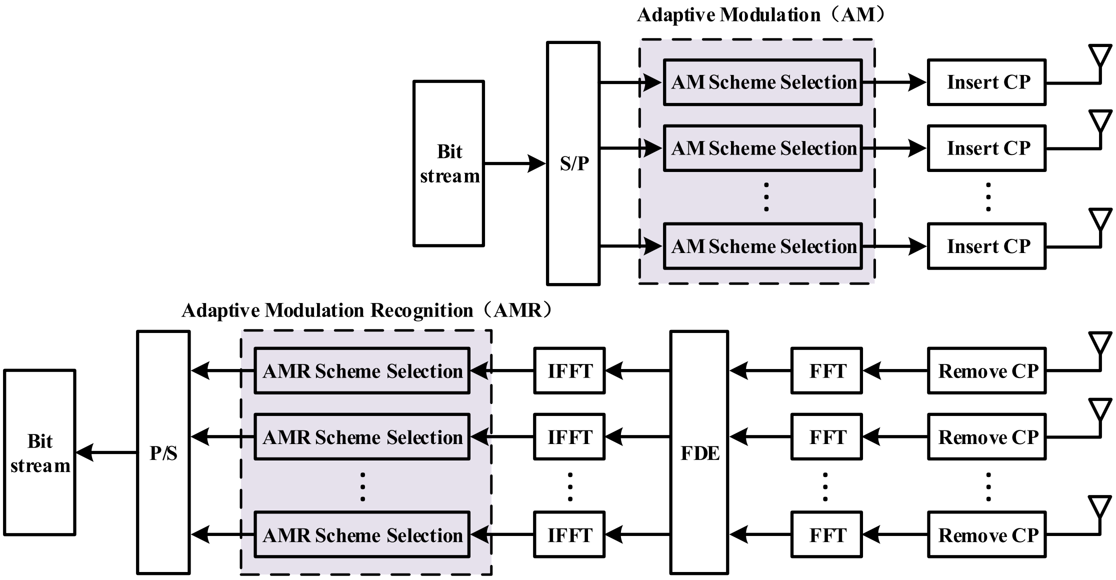

FIGURE 1. **Model-driven MIMO-SCFDE system model for AT.**

channel, the received signal is first processed to remove CP [19]. At this time, the time-domain vector obtained by the l-th receiving antenna can be expressed as

$$r_{N,l} = y_{N,l} + v_{N,l} = \begin{bmatrix} y^0_{N,l} \\ y^1_{N,l} \\ \vdots \\ y^{N-1}_{N,l} \end{bmatrix} + \begin{bmatrix} v^0_{N,l} \\ v^1_{N,l} \\ \vdots \\ v^{N-1}_{N,l} \end{bmatrix}, \tag{1}$$

where $y_{N,l}$ and $v_{N,l}$ denotes the useful signal part and noise part of the received signal, respectively. Also, N denotes the number of fast Fourier transform (FFT) points, and $l = 1, 2, \cdots, N_R$. If the noise is assumed to satisfy the AWGN with a mean of 0 and a variance of σ_v^2, the frequency-domain signal after performing FFT by the l-th receiving antenna can be obtained as

$$\begin{aligned} R_{N,l} &= FFT_N(y_{N,l}) + FFT_N(v_{N,l}) \\ &= \begin{bmatrix} Y^0_{N,l} \\ Y^1_{N,l} \\ \vdots \\ Y^{N-1}_{N,l} \end{bmatrix} + \begin{bmatrix} V^0_{N,l} \\ V^1_{N,l} \\ \vdots \\ V^{N-1}_{N,l} \end{bmatrix}. \end{aligned} \tag{2}$$

For the SC-FDE system, the cyclic convolution transformation in the time domain to the frequency domain can be expressed as a point-by-point multiplication of the frequency domain signal and the corresponding frequency domain sub-channel gain [20]. Thus, the signals received by all N_R receiving antennas on the k-th frequency-domain sub-channel can be written as

$$\begin{aligned} R^k_N = Y^k_N + V^k_N &= \begin{bmatrix} Y^k_{N,1} \\ Y^k_{N,2} \\ \vdots \\ Y^k_{N,N_R} \end{bmatrix} + \begin{bmatrix} V^k_{N,1} \\ V^k_{N,2} \\ \vdots \\ V^k_{N,N_R} \end{bmatrix} \\ &= \begin{bmatrix} H^k_{N,1}X^k_{N,1} \\ H^k_{N,2}X^k_{N,2} \\ \vdots \\ H^k_{N,N_R}X^k_{N,N_R} \end{bmatrix} + \begin{bmatrix} V^k_{N,1} \\ V^k_{N,2} \\ \vdots \\ V^k_{N,N_R} \end{bmatrix}, \end{aligned} \tag{3}$$

where Y^k_N and V^k_N denotes the useful signal and noise of the received signal on the k-th frequency-domain sub-channel, respectively. $k = 0, 1, \cdots, N-1$. Also, X^k_N denotes the signal component, and H^k_N denotes the channel matrix of the k-th frequency-domain sub-channel, which can be expressed as

$$H^k_N = \begin{bmatrix} H^k_{1,1} & H^k_{1,2} & \cdots & H^k_{1,N_T} \\ H^k_{2,1} & H^k_{2,2} & \cdots & H^k_{2,N_T} \\ \vdots & \vdots & \ddots & \vdots \\ H^k_{N_R,1} & H^k_{N_R,2} & \cdots & H^k_{N_R,N_T} \end{bmatrix}. \tag{4}$$

In the MIMO-SCFDE system, in addition to solving the problems of noise and channel fading, the receiver also needs to adopt equalization technology to overcome multi-antenna interference (MAI) caused by the superposition of received signals from multiple receiving antennas [21]. When the signal is equalized, the equalization matrix corresponding to the sub-channel is first calculated according to the channel matrix, and then the frequency domain equalization (FDE) on each sub-channel is performed to compensate the frequency selectivity of the channel directly [22]. The commonly used linear equalization methods include zero-forcing (ZF) equalization and minimum mean square error (MMSE) equalization [23]. The ZF receiver can eliminate the MAI by distinguishing the data streams of different antennas, and the equalization matrix can be expressed as

$$G^k_{ZF} = ((H^k)^H H^k)^{-1}(H^k)^H, \tag{5}$$

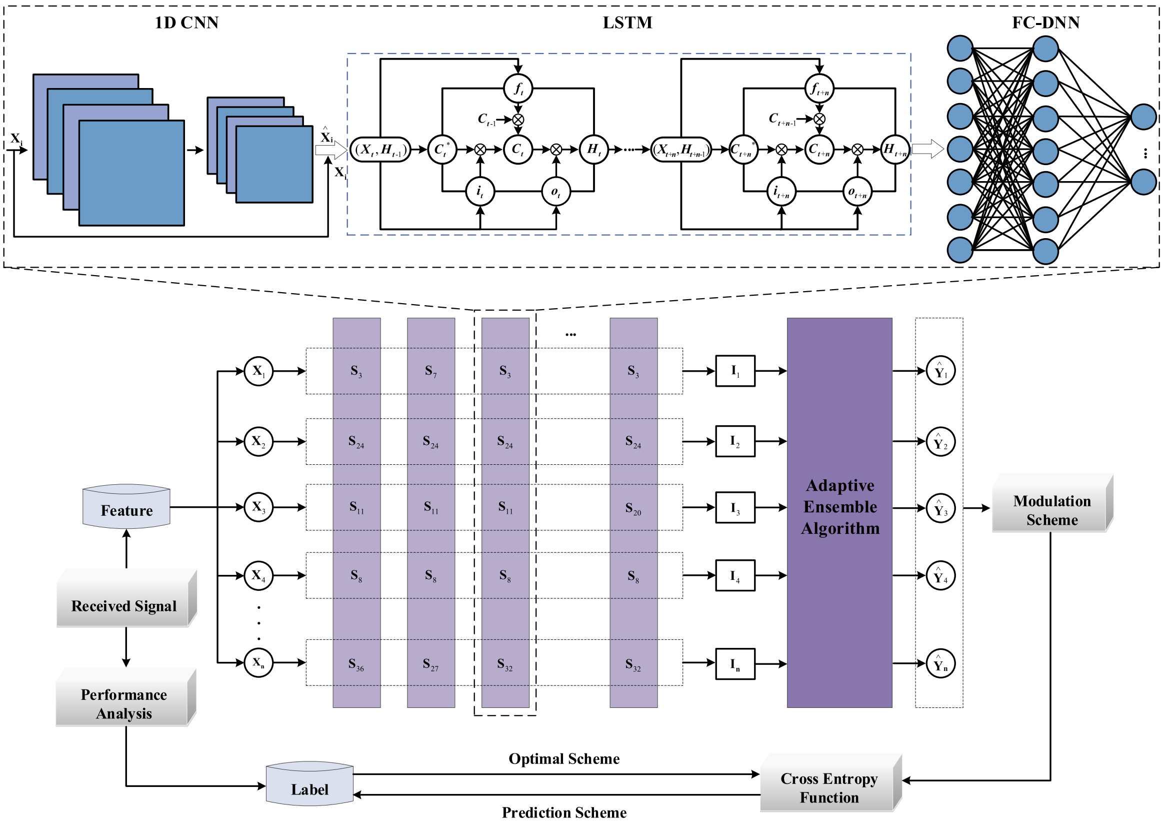

FIGURE 2. AM scheme based on the AMNet deep learning model.

ZF equalization has low computational complexity but does not consider the existence of noise. If the channel fading is extensive, it also amplifies the noise while compensating for the signal. In response to these problems, MMSE equalization considers both noise and MAI. The MMSE equalization matrix corresponding to the k-th frequency-domain sub-channel can be written as

$$G_{MMSE}^{k} = ((H^k)^H H^k + \frac{\sigma_v^2 N_T}{P} I_{N_T})^{-1} (H^k)^H, \tag{6}$$

where σ_v^2 denotes the noise variance, N_T denotes the number of transmitting antennas. Also, P denotes the total power of the transmitted signal. The realization of MMSE equalization requires not only the channel matrix but also the received signal-to-noise ratio (SNR). Besides, MMSE equalization cannot completely eliminate the interference between data streams. After the IFFT, the AMR scheme based on the cyclic spectrum is employed to demodulate the modulated signal, and the original bit information is recovered after parallel-to-serial conversion.

The combination of AT technology and the MIMO-SCFDE system improves the effectiveness of information transmission. However, the traditional rule-based AT scheme ignores the channel correlation between antennas, and sometimes the transmission performance can not be optimized by choosing the pre-defined transmission scheme according to the channel information. Therefore, to meet the 5G communication requirements, it is necessary to develop a more reliable AT plan.

III. MODEL-DRIVEN DEEP LEARNING SCHEME FOR ADAPTIVE TRANSMISSION

A. ADAPTIVE MODULATION SCHEME

The primary purpose of the AM scheme is to adjust the modulation mode of each antenna according to the channel conditions to improve transmission efficiency. The modulation order varies with the modulation method, which reflects the difference in transmission bit rate. For example, the modulation order of binary phase-shift keying (BPSK), quadrature phase-shift keying (QPSK), 16 quadrature amplitude modulation (16QAM), and 64QAM are 1, 2, 4, and 6 respectively [24]. The channel with good conditions adopts a high-order modulation mode to improve the transmission rate on the premise of ensuring the signal detection quality. On the contrary, the channel with poor conditions takes a low-order modulation mode to ensure reliable communication [25]. For the MIMO-SCFDE system with four transmitting antennas and four receiving antennas, and each antenna has four kinds of modulation options, the modulation schemes are listed in Table 1.

Figure 2 shows the AM scheme based on the AMNet deep learning model. AMNet is an integrated network model, where each sub-network consists of 1D CNN, LSTM, and FC-DNN. The 1D CNN includes a convolutional layer and

TABLE 1. Modulation mode selection and order sum of different modulation schemes.

Modulation Schemes	Modulation Mode				Order Sum
	Antenna 1	Antenna 2	Antenna 3	Antenna 4	
1	BPSK	BPSK	BPSK	BPSK	4
2	BPSK	BPSK	BPSK	QPSK	5
3	BPSK	BPSK	BPSK	16QAM	7
4	BPSK	BPSK	BPSK	64QAM	9
5	BPSK	BPSK	QPSK	BPSK	5
6	BPSK	BPSK	16QAM	BPSK	7
7	BPSK	BPSK	64QAM	BPSK	9
⋮	⋮	⋮	⋮	⋮	⋮
254	64QAM	64QAM	16QAM	16QAM	20
255	64QAM	64QAM	64QAM	16QAM	22
256	64QAM	64QAM	64QAM	64QAM	24

an average pooling layer, which are used to extract the feature parameters of the estimated channel and achieve dimensionality reduction of the data to be processed. The original feature parameters and the reduced dimension feature parameters are used as the input of LSTM to improve the diversity of features. The output of 1D CNN can be expressed as

$$\hat{X}_i = f(w * X_i + b), \tag{7}$$

where $f(\bullet)$ denotes the Relu activation function. Also, X_i, w, and b are the input, weight, and bias value of the network. Each LSTM unit can complete the long-term memory of information and further extract features through the cooperation of the forget gate, input gate, and output gate. After t time steps, the output of LSTM can be obtained as

$$\hat{X}_i{}' = LSTM(X_t, f_t, i_t, o_t), \tag{8}$$

where $LSTM(\bullet)$ is the operation of an LSTM unit, and X_t is the input at the time of t. Also, f_t, i_t, and o_t are the operation of forgetting gate, input gate, and output gate, respectively. The LSTM is followed by a three-layer FC-DNN to make the network's output dimension consistent with the modulation scheme category. The following formula obtains the final predicted modulation scheme

$$\hat{Y}_i = \sigma(w' * \hat{X}_i{}' + b'), \tag{9}$$

where σ denotes the sigmoid activation function, w' and b' are the weight and bias of FC-DNN, respectively.

The number of sub-networks can affect the performance and complexity of AMNet, so we set the number of sub-networks equal to the combined amount of transmitting antennas and receiving antennas. The feature X required for each sub-network training is extracted from the received signal, and the feature information should select the parameters that can reflect the channel condition. Each group of feature information X_i is input into the AMNet in the form of a matrix, which contains the estimated SNR, frequency-domain sub-channel marking information, frequency-domain sub-channel rank information, and channel equalization information. SNR is an indicator for judging signal quality, and the useful signal power and noise power are different under different SNR. The expression can be calculated as

$$SNR(dB) = 10\lg(\frac{P_S}{P_N}), \tag{10}$$

where P_S and P_N denotes the useful signal power and noise power of the received signal, respectively. The frequency-domain sub-channel marking information reflects the number of available frequency-domain sub-channels. The N bits of sub-channel marking information can be expressed as $b_{CSI} = (b_0, b_1, \cdots, b_{N-1})$, where each dimension represents a frequency domain sub-channel, and the selected and forbidden sub-channels are represented by 1 and 0 respectively. The rank information of the frequency-domain sub-channel is determined by the channel capacity criterion, which can be written as $R = (R_k, k = 0, 1, \cdots, N-1)$, where R_k represents the rank of the k-th frequency domain sub-channel. Meanwhile, because the FDE process can resist IBI caused by the channel's time-varying and frequency selectivity, the channel equalization information can also be the embodiment of the channel condition. The modulation scheme is formed by assigning modulation modes to each antenna. However, two cases should be considered to obtain the optimal modulation scheme. One is to select the modulation scheme with the largest sum of modulation orders as much as possible when meeting the required bit error rate (BER) of the system. The formula can be defined as

$$S_i = \arg\max_i(O_i), \tag{11}$$

where O_i is the sum of modulation orders of the i-th modulation scheme. The other is to select the modulation scheme with the best BER performance if the required BER cannot be met. The optimal modulation scheme obtained by analyzing the comprehensive performance is selected as the label. Accordingly, the AMNet can learn the relationship between the extracted features and the optimal modulation scheme through the nonlinear operation of multiple neural network layers.

Since each sub-network will generate corresponding output S_x after inputting the feature information of different groups into the AMNet, it is necessary to integrate S_x to get the final result $\hat{Y}_i$. As the received signal has a different delay and received power under different transmission paths, the received power under various delays is selected as the adaptive factor to achieve the adaptive ensemble of S_x. The number of sub-channels and feature information in the proposed model is set to m and n, respectively, so the adaptive factor of the j-th sub-channel and the i-th group of feature information can be expressed as

$$A_{ij} = \frac{P_{ij}}{\sum_{j=1}^{m} P_{ij}}, \tag{12}$$

where P_{ij} denotes the received power of the signal component corresponding to the i-th group of features when passing through j-th sub-channel, $i = 1, 2, \cdots, n$, and $j = 1, 2, \cdots, m$.

The index of the modulation scheme predicted by each sub-network is represented by a matrix composed of 0 and 1. For the modulation scheme S_x, the value of the x-th element in the matrix is 1, and the remaining elements are 0. Meanwhile, each sub-network results are combined through the matrix I, where the i-th group of feature information can be expressed as

$$I_i = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ 1 & 0 & 1 & \cdots & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & 0 & \cdots & 0 \end{bmatrix}, \tag{13}$$

where each column of I_i denotes a kind of modulation scheme output by the sub-network. Under the effect of adaptive factors, the integration result of the network can be obtained as

$$\hat{Y}_i = S_{\arg\max_x (\sum_{j=1}^{m} A_{ij} \odot I_{ij})}, \tag{14}$$

where I_{ij} denotes the vector composed of the j-th column elements of I_i. Also, $\arg\max(\bullet)$ denotes the operation of searching the maximum value in $(\bullet)$, $\odot$ represents point multiplication. According to the channel condition, the AM scheme based on DL can adaptively adjust the combination of modulation modes among different transmitting antennas. Consequently, using the trained AMNet to replace the original communication module can obtain a higher data transmission rate under the premise of ensuring the BER.

B. ADAPTIVE MODULATION RECOGNITION SCHEME

In the context of using multiple modulation modes for signal transmission, the ability to correctly identify the modulated signal is the basis for demodulation. Since the cyclic spectrum distribution of the modulated signal presents a cyclostationary discrete characteristic on the cyclic frequency axis, modulation recognition can be achieved by utilizing the modulated signal with a sizeable cyclic spectrum amplitude value at the non-zero cyclic frequency and no amplitude value or small amplitude value of noise [26].

The estimation algorithm of the spectral autocorrelation function is an essential step in obtaining the cyclic spectrogram. The discrete form of cyclic autocorrelation function can be expressed as

$$R_x^{\alpha}(\tau) = \lim_{T \to +\infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x(t+\tau/2)x^*(t-\tau/2)e^{-j2\pi\alpha t}dt, \tag{15}$$

where τ denotes the time interval, and α denotes the cycle frequency. Also, $*$ denotes the complex conjugation, and T denotes the duration of the signal. The FFT form of the cyclic autocorrelation function can be expressed as

$$S_x^{\alpha}(f) = \int_{-\infty}^{+\infty} R_x^{\alpha}(\tau)e^{-j2\pi f\tau}d\tau, \tag{16}$$

where $S_x^{\alpha}(f)$ represents the cyclic spectral density function, and f represents the signal frequency. When α is not 0, the spectral correlation function of stationary noise is equal to 0. In a limited data segment, the cyclic spectral density function with a discrete frequency smoothing method can be estimated as

$$\hat{S}_{x\Delta t}^{\alpha}(t,f)_{\Delta f} = \frac{1}{M} \sum_{v=-(m-1)/2}^{(m-1)/2} \frac{1}{\Delta t} \hat{X}_{\Delta t}(t, f+\alpha/2+vF_s) \bullet \hat{X}_{\Delta t}^{*}(t, f-\alpha/2+vF_s), \tag{17}$$

where $\Delta f = MF_s$, which represents the spectral smoothing interval. M is the number of smoothed points, $F_s = 1/NT_s$, T_s is the sampling time interval, and N is the number of data points. $\Delta t = (N-1)T_s$, which represents the total length of the data.

Figure 3 shows the AMR scheme based on ADNet. The establishment of ADNet first requires a data set containing the cyclic spectrogram of various modulation methods. To train the model with high classification accuracy, we believe that the size of the data set should be large enough to hold the possible situations. Due to the input parameters required for ADNet training is a 2D image, it is necessary to normalize the 3D cyclic spectrum to the X-Y plane. In CNN-based modulation recognition, the shallow model is fast but low accuracy, while the deep model has high precision but takes a long time. To improve the adaptability of the proposed scheme, we select the CNN model with different network structures and depth to form the adaptive ensemble DL model. Before inputting the cyclic spectrogram into the modulation classification CNN, the complexity classification network based on the color moment, gray level co-occurrence matrix, information entropy, and edge detection parameters are adopted to calculate the complexity of different cyclic spectrograms. Then, the appropriate modulation classification CNN is selected according to the complexity level of the image.

The choice of modulation classification sub-network can also affect the overall recognition performance. On the one hand, if too few CNN layers are used, it is not enough to extract features. On the other hand, if CNN taken has too much depth, the recognition accuracy is not improved, but the efficiency is reduced. According to the adaptability relationship between the complexity of cyclic spectrogram and the depth of CNN after several tests, LeNet-5, AlexNet, VGG-16, and ResNet-50 are used for the cyclic spectrogram with the complexity of 0, 1, 2, and 3 respectively, which can give full play to the inherent characteristics of CNN and improve the classification accuracy.

IV. EXPERIMENT AND ANALYSIS

In this section, we use the trained deep learning model to replace the modulation and modulation recognition modules of the MIMO-SCFDE system in Fig.1 and verify the performance of the proposed AT scheme through comparative experiments. Sub-section A compares the data throughput of

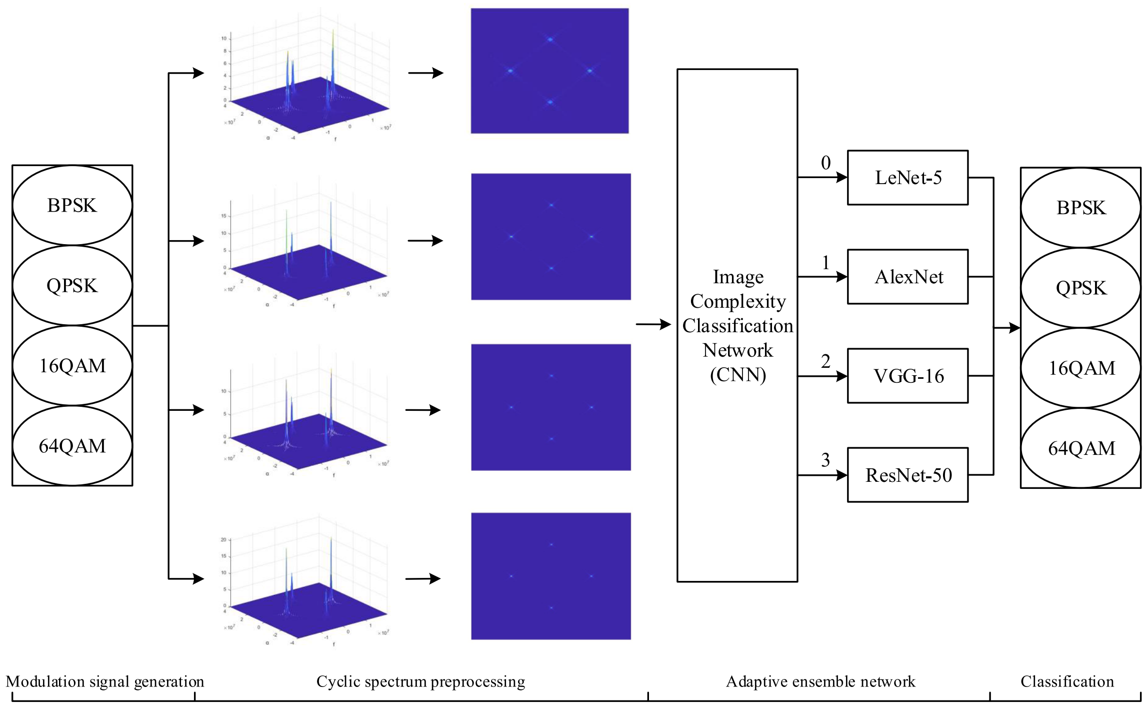

FIGURE 3. AMR scheme based on the ADNet deep learning model.

rule-based and AMNet-based modulation schemes under different numbers of transmitting antennas and receiving antennas. Sub-section B shows the advantages of the proposed ADNet compared to existing methods in recognition accuracy. The data generation and signal preprocessing required for the experiment are completed through MATLAB2019a.

A. PERFORMANCE COMPARISON ANALYSIS OF AM SCHEME

The performance of the AM scheme is analyzed by adopting the MMSE signal detection algorithm at the receiver. The number of antennas adopted in the experiment ranges from 1 to 4, and the signals on each antenna can be modulated by BPSK, QPSK, 16QAM, and 64QAM. The wireless channel environment is based on the SUI-4 channel model, in which the sampling rate is 10M, the frame length of SC-FDE is 256, and the CP length of 64 is considered. The experiment is performed under the average classification accuracy of AMNet. The detailed simulation parameters of AMNet are shown in Table 2.

Figure 4 shows the throughput performance of different modulation schemes. The throughput can be calculated as

$$Throughput = (1 - BLER) \times M \times CR, \tag{18}$$

where $BLER$, M, and CR denotes the block error rate, modulation order, and code rate, respectively. The number of antennas will affect the throughput of the system. As shown in Fig. 4, when N=1, due to poor channel conditions at low SNR, a low-order modulation method is first adopted to increase the reliability. As the SNR increases, the channel conditions gradually get better, so the modulation method is adjusted to a higher-order. Under the same SNR, the throughput when the target BER is less than 10^{-2} is higher than that of 10^{-4}, and the proposed AMNet scheme has more system throughput than the comparison work in both cases. Besides, the FC-DNN scheme is better than the rule-based project by about 0.52bit/s and 0.4bit/s, respectively, at an SNR of 10dB under these two BERs. When N=2, N=3, and N=4, the increase in the number of antennas improves the throughput of the system, and the maximum throughput of these three cases are 12bit/s, 18bit/s, and 24bit/s,

TABLE 2. Simulation parameters of AMNet.

Parameter	Value
Loss Function	Cross Entropy
Activation Function	Relu, Tanh, Sigmoid
Optimizer	Adam
Initial Learning Rate	0.005
Learn Rate Drop Factor	0.1
Dropout	0.4
Gradient Threshold	1
Number of Layers	7
Maximum Epochs	900
Minimum Batch Size	200
Number of Training Sets	10000
Number of Validation Sets	2000
Number of Test Sets	3000

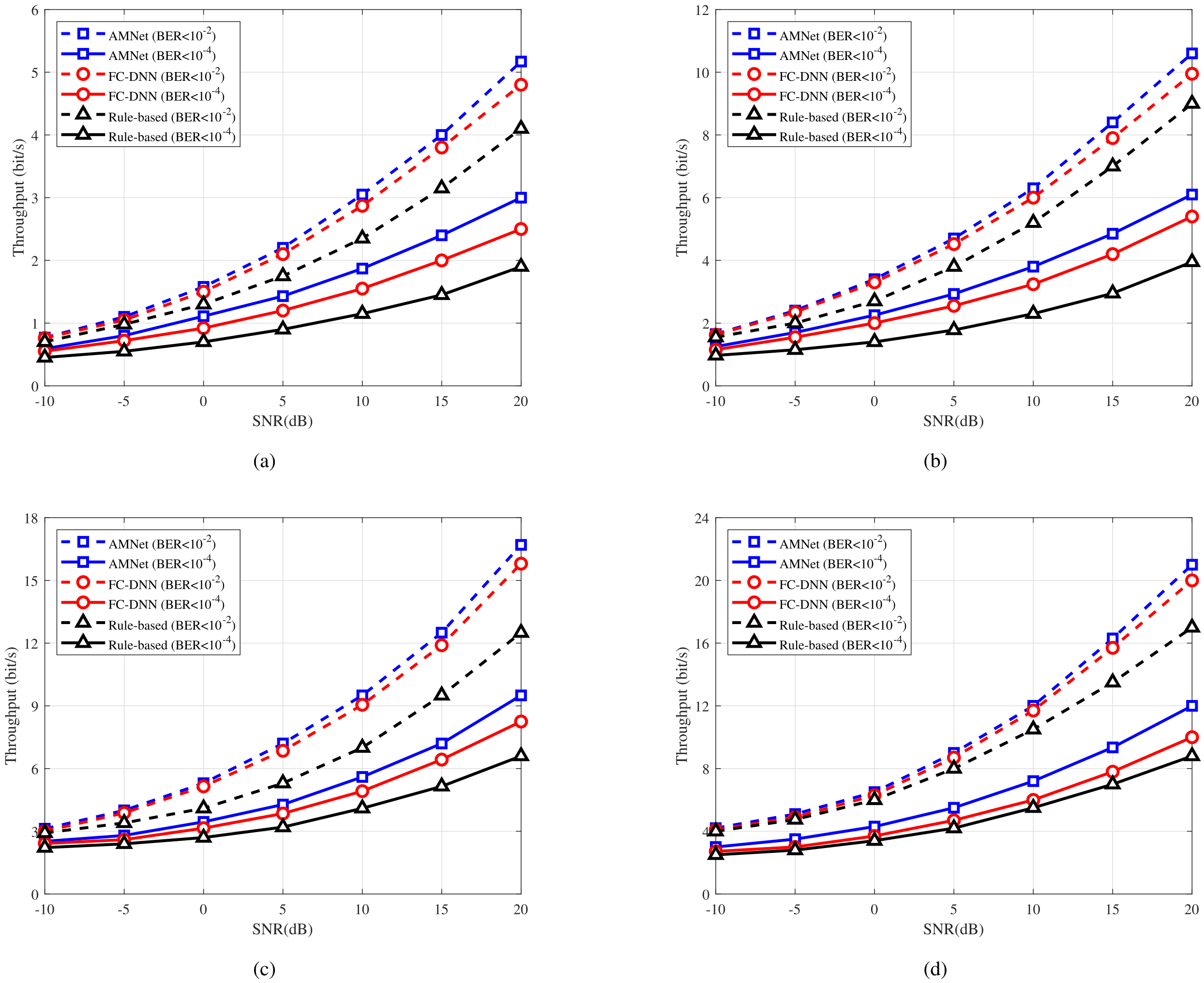

FIGURE 4. Throughput of different modulation schemes, (a) N D 1. (b) N D 2. (c) N D 3. (d) N D 4.

TABLE 3. Throughput (T) of AMNet and comparison scheme under 20dB.

N	Scheme	T (BER<10^{-2})	T (BER<10^{-4})
1	AMNet	5.1 bit/s	3.0 bit/s
	FC-DNN	4.8 bit/s	2.5 bit/s
	Rule-based	4.1 bit/s	1.9 bit/s
2	AMNet	10.6 bit/s	6.1 bit/s
	FC-DNN	9.9 bit/s	5.4 bit/s
	Rule-based	9.0 bit/s	3.9 bit/s
3	AMNet	16.7 bit/s	9.5 bit/s
	FC-DNN	15.8 bit/s	8.2 bit/s
	Rule-based	12.5 bit/s	6.6 bit/s
4	AMNet	21.1 bit/s	12.0 bit/s
	FC-DNN	20.0 bit/s	10.1 bit/s
	Rule-based	17.0 bit/s	8.8 bit/s

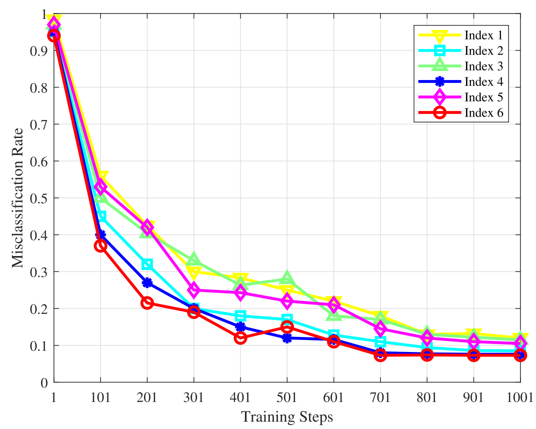

FIGURE 5. Misclassification rate curve under different training parameters.

respectively. Also, the selectivity of the modulation method increases exponentially. Table 3 compares the throughput of the proposed scheme with the FC-DNN scheme and the rule-based scheme under 20dB. In the case of four types of antenna numbers, the throughput of the proposed work is 0.5bit/s, 0.7bit/s, 1.3bit/s, and 1.9bit/s higher than the FC-DNN program at a BER of 10^{-4}, respectively, indicating that the AM scheme can adaptively adjust the transmission strategy to improve the throughput performance.

In the AM scheme, due to changes in the external environment, the interference factors increase in the extracted

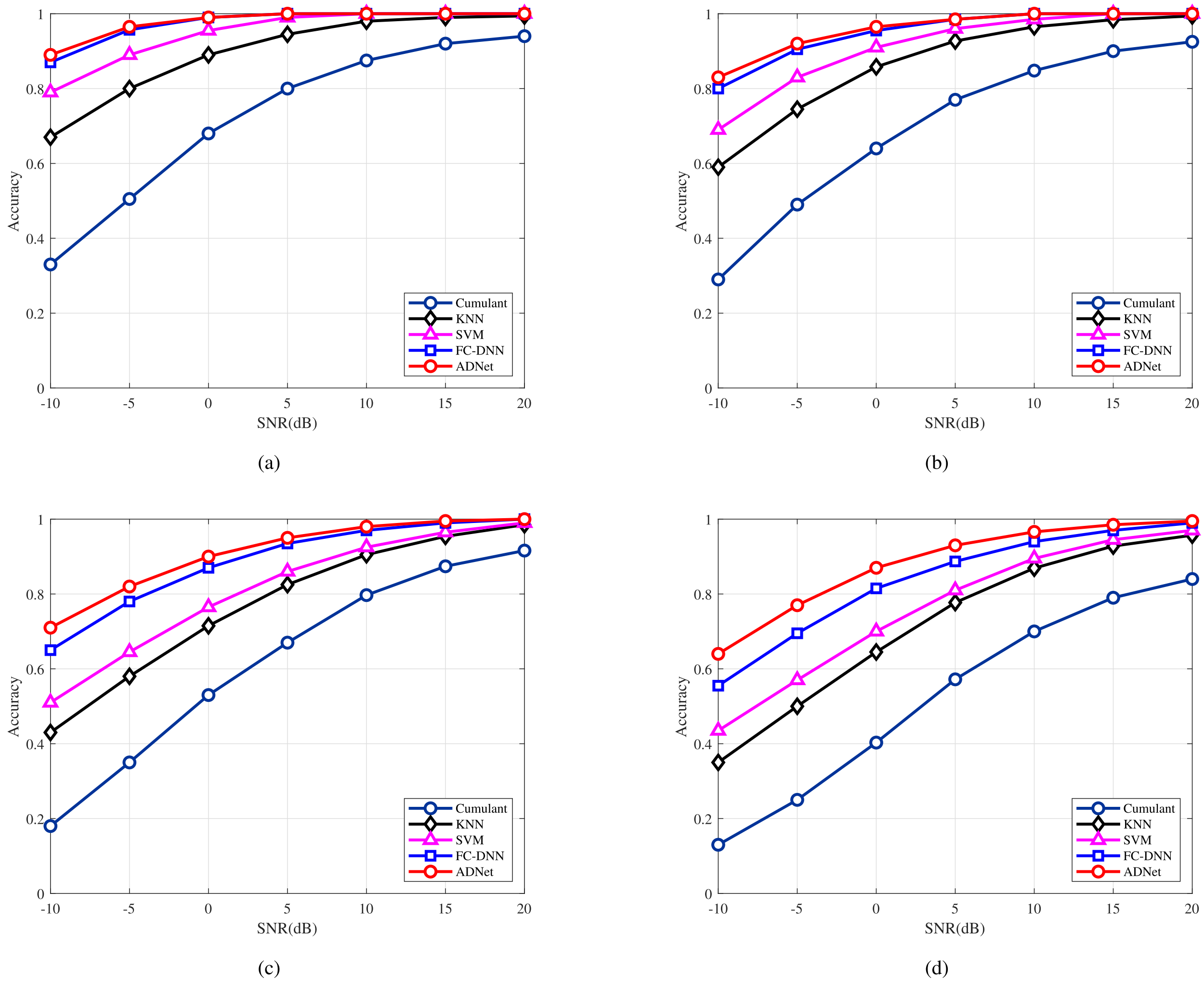

FIGURE 6. Accuracy of different modulation recognition schemes, (a) BPSK. (b) QPSK. (c) 16QAM. (d) 64QAM.

features, and the classification accuracy of the offline trained AMNet model in the online test stage may be affected. The classification precision reflects the throughput of the system, and as the number of antennas or modulation schemes increases, the classification accuracy of the model will gradually decrease. But what needs to be explained is that the AM scheme selects the optimal modulation scheme by choosing the highest information transmission rate under the target BER, so the classification accuracy of the model does not affect the system's signal detection performance.

B. PERFORMANCE COMPARISON ANALYSIS OF AD SCHEME

To verify the performance of the proposed AMR scheme, we generate 3D cyclic spectrograms of modulation signals with BPSK, QPSK, 16QAM, and 64QAM under different SNRs, and take the preprocessed 2D image as the input of ADNet. The cyclic spectrum is estimated by the discrete frequency smoothing algorithm with 20 smoothing points. The cyclic spectrogram data set contains three parts: training set, validation set, and test set, the numbers are 8000, 1000, and 2000 respectively.

Owing to the reason that the selection of training parameters determines the network's recognition accuracy, we define different settings according to the activation function, optimizer, and loss function in Table 4 to compare the network performance. The experiment was performed with QPSK and SNR of -5dB. As shown in Fig. 5, for all networks with different parameters, the network's misclassification rate gradually declines with the increase of the training step and finally tends to be stable. Moreover, the model of Index 6 has the optimal performance with a misclassification rate of 0.073 after 1000 iterations. Therefore, We conduct the following comparative experiments based on the model under Index 6 parameters.

Figure 6 compares the modulation recognition performance of the proposed scheme with those based on high-order cumulant, K nearest neighbor (KNN), support vector machine (SVM), and FC-DNN at different

TABLE 4. ADNet under different training parameters.

Index	Activation Function	Optimizer	Loss Function
1	Sigmoid	SGD	MSE
2	Sigmoid	Adam	Cross Entropy
3	Tanh	SGD	MSE
4	Tanh	Adam	Cross Entropy
5	Relu	SGD	MSE
6	Relu	Adam	Cross Entropy

SNRs. It can be seen from the figure that under different modulation modes, the accuracy of all modulation recognition schemes improves with the increase of SNR, and the recognition accuracy of BPSK is the highest. Among the five schemes, the proposed ADNet scheme has the best performance, and its SNR is 2dB, 8dB, 15dB, and 19dB, respectively, when the accuracy reaches saturation. Although the FC-DNN scheme and the ADNet scheme have similar performance when they tend to stabilize, the recognition precision of FC-DNN is significantly lower than the proposed work under low SNR or high-order modulation. The reason is that FC-DNN can classify general features through nonlinear operations, while ADNet can extract deep-level feature information by convolution kernel and weight sharing. When the SNR is -10dB, the recognition accuracy of the ADNet scheme is higher than the FC-DNN scheme by 0.02, 0.03, 0.06, and 0.09 under the modulation modes of BPSK, QPSK, 16QAM, and 64QAM. Besides, SVM, KNN, and higher-order cumulant schemes are lower than the former two schemes.

According to the cyclic spectrum of different modulation methods, the AD scheme realizes AMR of the received signal by combining deep learning technology and cyclic spectrum features. Since ADNet adopts CNN with an integrated network structure to realize the adaptive selection of the modulation recognition scheme, the model needs a long training time to comply with the expected classification accuracy. As the data set increases, the training time of the network will also rise, but at the same time, the prediction precision of the system will be improved.

V. CONCLUSION

To improve the throughput of the MIMO-SCFDE system and obtain a more reliable signal transmission capability, we propose a model-driven AT scheme based on the combination of deep learning and expert knowledge. The AT plan takes AMNet and ADNet to replace the signal modulation and modulation recognition process of the communication system. The AM scheme is achieved by an integrated neural network model with a combined network of 1D CNN, LSTM, and FC-DNN as sub-networks. The feature information extracted from each sub-channel is input into different sub-networks, and the conversion between features and the optimal modulation scheme is performed according to the network parameters obtained by training. Meanwhile, the received power under various delays is selected as the adaptive factor to realize the adaptive ensemble of the result of each sub-network. Since the cyclic spectrum's advantages to accurately detect the signal type under low SNR, the AD scheme completes the adaptive selection of the modulation recognition scheme based on the complexity of the cyclic spectrogram. When the target BER is 10^{-4}, the simulation results show that the proposed scheme can achieve a throughput of 12bit/s and a modulation recognition average accuracy of 0.927 at the SNR of 20dB and -5dB, respectively, which improves the effectiveness of signal transmission. However, with the increase in the number of modulation modes and antennas, the model's computational complexity will also increase. Therefore, a more advantageous neural network optimization algorithm is required.

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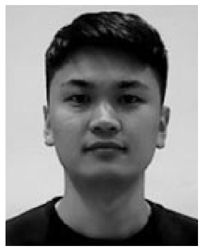

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