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A Novel Signal Detection Scheme Based on Adaptive Ensemble Deep Learning Algorithm in SC-FDE Systems

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ABSTRACT Reliable signal detection plays an essential role in enhancing the quality of signal transmission in wireless communication systems. In this paper, we combine signal detection theory with a deep learning model and propose a novel signal detection scheme based on adaptive ensemble long short term memory (AE-LSTM) neural network to handle wireless single carrier frequency domain equalization (SC-FDE) systems in an end-to-end manner. The feature information used for offline training of the deep learning model is extracted from the received signal containing channel state information (CSI) after the multi-path channel and fast Fourier transform (FFT), and the labels are assigned according to the constellation map adopted at the transmitter. To improve the adaptability of the system, we utilize the received power under different delays as the adaptive factor to integrate the output of each sub-network. Then the original data generated by the channel model is recovered by using the trained model instead of channel estimation and frequency domain equalization. Comparative experiments on SC-FDE symbol detection demonstrate that the proposed scheme achieves better performance in terms of reliability than the traditional scheme and the similar deep learning scheme.

INDEX TERMS Deep learning, adaptive ensemble, signal detection, SC-FDE, channel estimation, frequency domain equalization.

I. INTRODUCTION

With the development of mobile Internet, 5G technology has become a hot topic in the communication industry and academia [1]. Since the 5G mobile communication network has the characteristics of high dimensions, high capacity, and high density, how to use massive amounts of data to reduce the complexity of the system and improve the reliability of performance has become the critical point of the physical layer technology [2]. Single carrier frequency domain equalization (SC-FDE) is a new broadband wireless communication technology developed by combining the advantages of traditional single carrier transmission and orthogonal frequency division multiplexing (OFDM) technology, which uses the cyclic prefix (CP) and frequency domain equalization to eliminate the effect of multi-path channels on the signal [3], [4]. However, due to the impact of inter-block interference (IBI) in channel estimation and frequency domain equalization, the system's reliability fluctuates with the change of the channel impulse response(CIR). Although the SC-FDE system's performance has been improved in various ways, it is far from meeting the requirements of 5G communication [5].

Experts from all over the world have done relevant research on signal detection in wireless communication systems. The authors of [6] design a method to mitigate interferences for SC-FDE with insufficient CP symbols, and uses an iterative interference cancellation method to remove the residual interferences. To ensure the integrity of information, [7] proposes a frequency-domain multipacket detection technique for SC-FDE schemes, which can achieve an efficient packet separation in the presence of successive collisions.

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In [8], the relationship between distorted symbols and decision boundaries is explored, and a unique pilot position selection (PPS) scheme is proposed to confine the distorted symbols within their designated decision regions dispenses with a priori knowledge of the channel. For arbitrary signal constellations formulated in the frequency domain with the maximum likelihood detection problem, [9] proposes a multiple-input multiple-output (MIMO) detection algorithm based on the alternating direction method of the multipliers (ADMM) for single-carrier transmissions in time dispersive channels. The authors of [10] utilize the virtual pilot to assist channel estimation and partial minimum-mean-square error (MMSE) equalization to improve the accuracy of the estimation. To solve the problem of lack of information interaction between channel estimation and channel equalization in doubly selection channels, the work in [11] proposes a novel joint channel estimation and equalization (JCEE) algorithm for MIMO-SCFDE systems that combines iterative expectation maximization-based least square (LS) channel estimation, MMSE equalization based on inter-frequency interference (IFI), time-domain IFI cancellation, and data detector. The traditional signal detection scheme effectively improves the system's bit error rate (BER) performance through the optimization of various algorithms. However, the traditional scheme has high computational complexity and is easily affected by external factors, and its reliability is still the next research focus.

Intelligent communication is considered to be an inevitable trend in the development of wireless communications in the future. Especially after 5G, people have higher and higher requirements for communication quality with improved living standards. As one of the latest trends in machine learning and artificial intelligence, deep learning has brought profound changes to computer vision and speech recognition [12], [13]. Deep learning has become a data analysis tool that can be applied to various fields, including wireless communications. In [14], a deep learning scheme for channel estimation and signal detection is exploited to handle wireless OFDM channels in an end-to-end manner. For OFDM systems with noise, the authors of [15] integrate the ensemble deep learning model with the acquired received signals from the multi-path channel to complete channel estimation and compensation, which can get a favorable result in BER performance. Unlike the data-driven deep learning method, [16] combines deep learning with the expert knowledge and proposes a model-driven deep learning approach to replace the existing OFDM receiver, which offers a more accurate channel estimation compared with the linear minimum mean square error method and exhibits higher data recovery accuracy than the existing methods. Aiming at the problem of a high peak-to-average power ratio (PAPR) in OFDM systems, [17] introduces a PAPR reducing network (PRNet) to determine the constellation mapping and demapping of symbols adaptively on each subcarrier through a deep learning technique. In [18], a learning framework based on the combination of convolutional neural network (CNN) and long short term memory (LSTM) network is designed to achieve CSI online prediction of historical data for 5G wireless communication systems. The work in [19] designs a detection network (DetNet) by unfolding the iterations of projected gradient descent algorithm into a network to realize state-of-the-art performance while maintaining low computational requirements. Based on the traditional modulation algorithm, [20] proposes an machine learning-based adaptive modulation model for a MIMO-OFDM system to adjust data rate and reliability according to the channel condition. In [21], a model-driven MIMO detection deep learning network is designed by unfolding the iterative algorithm to improve the detection performance. For large overloaded MIMO systems, [22] presents a trainable projected gradient-detector (TPG-detector), which is a deep learning-aided iterative detection algorithm based on the projected gradient descent method with trainable parameters and can optimize the trainable internal parameters with standard deep learning techniques. Although the above research further improves the accuracy of signal detection by introducing the deep learning model into wireless communications systems, the detection results lack stability, and there is still much room for improvement.

In this paper, we propose a novel scheme for signal detection based on the adaptive ensemble LSTM (AE-LSTM) neural network, which extracts features from the received signal of the SC-FDE system and assigns label according to the constellation map adopted at the transmitter. Simultaneously, the generated data set is used to train the deep learning model and perform online testing. For the analysis of the results of each sub-network, the received power under different delays is selected as the adaptive factor to integrate the results adaptively. Simulation experiments prove that the proposed scheme is superior to the existing signal detection schemes in BER performance.

The remainder of this paper is organized as follows. Section II describes the structure of the SC-FDE system and the algorithms related to signal detection. Section III introduces the adaptive ensemble deep learning model, where also presents the implementation of the adaptive ensemble algorithm. The BER performance based on the proposed scheme is simulated and discussed in Section IV. Finally, Section V concludes the paper.

II. SC-FDE SYSTEM MODEL

The SC-FDE system model is shown in Fig.1. The data bits are first mapped into symbols through a symbol mapping module at the transmitter, then a CP is inserted as guard interval between the SC-FDE symbols, and the length of the guard interval needs to be higher than the maximum delay spread of the wireless channel to avoid IBI [23], [24]. The transmitted SC-FDE symbol is received through a multi-path fading channel. The received signal can be expressed as

$$y(n) = x(n) * h(n) + v(n) \quad n \in [0, N-1], \tag{1}$$

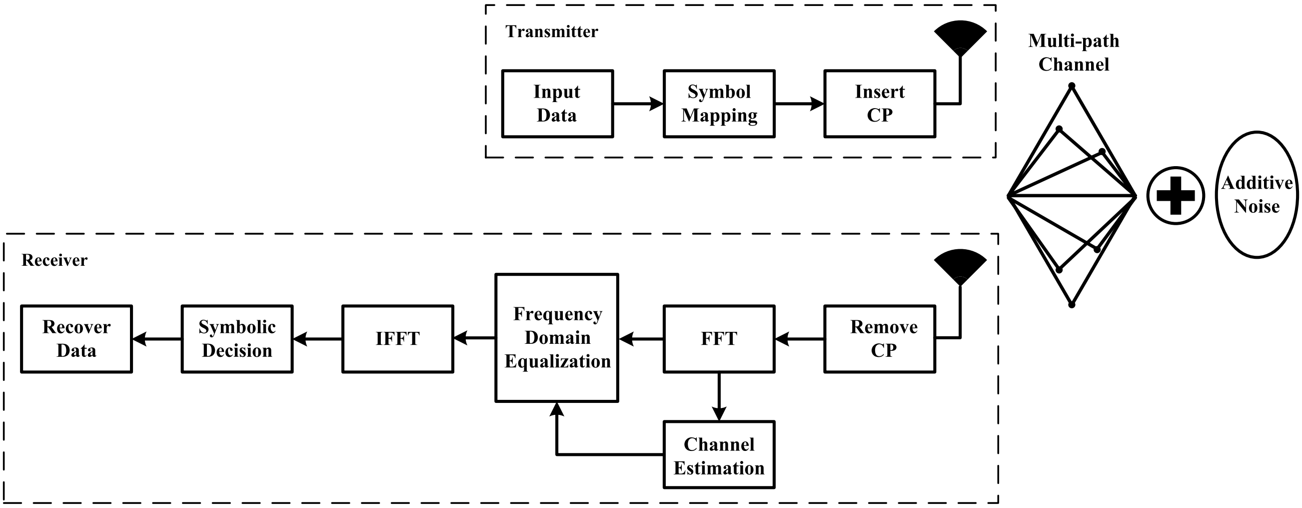

FIGURE 1. SC-FDE system model.

where $x(n)$ denotes the transmitted SC-FDE symbol, and $h(n)$ denotes the CIR. Also, $v(n)$ denotes the additive white Gaussian noise (AWGN), and $*$ denotes the convolution operation. After removing the CP, the received signal is transformed into the frequency domain by fast Fourier transform (FFT) [25], [26], the frequency domain signal is written as

$$Y(k) = X(k)H(k) + V(k) \quad k \in [0, N-1], \tag{2}$$

where $X(k)$, $Y(k)$, $H(k)$ and $V(k)$ denotes the input signal, output signal, channel frequency response (CFR) and AWGN of the k-th sub-channel, respectively.

Channel estimation and frequency domain equalization are the keys to the entire system. After equalization, the receiver can obtain the time domain signal by inverse fast Fourier transform (IFFT), and then the original signal is recovered by symbol decision. The accuracy of channel estimation directly affects the performance of frequency domain equalization. Traditional pilot-based channel estimation algorithms include LS and MMSE. LS is derived based on the least-squares criterion, and its cost function can be written as

$$J_{LS} = (Y(k) - X(k)\hat{H}(k))^H (Y(k) - X(k)\hat{H}(k)), \tag{3}$$

where $\hat{Y}(k)$ denotes the signal after channel estimation. $\hat{H}(k)$ denotes the estimated value of CFR $H(k)$ of the k-th sub-channel. Use Eq. (3) to take the first partial derivative to $\hat{H}(k)$, and obtain the extreme point of J_{LS}. Then the estimated value of the frequency domain channel can be obtained as

$$\hat{H}_{LS} = (X(k)^H X(k))^{-1}(X(k)^H Y(k)) = X(k)^{-1}Y(k), \tag{4}$$

The LS calculation is simple, but the performance deteriorates when the signal to noise ratio (SNR) is low. To avoid the shortcomings of LS, MMSE considers the effect of noise based on LS and reduces the channel estimation error by smoothing the estimation results. The cost function of the MMSE channel estimation algorithm is written as

$$J_{MMSE} = E\{\|H(k) - \hat{H}(k)\|^2\}. \tag{5}$$

To get the optimal value, take the first partial derivative of J_{MMSE}, and the minimum value $\hat{H}_{MMSE}$ is obtained as

$$\hat{H}_{MMSE} = R_{HY}{R_{YY}}^{-1}Y(k), \tag{6}$$

where R_{HY} denotes the cross-correlation matrix of the channel transmission function and the received signal, and R_{YY} denotes the auto-correlation matrix of the received signal. The estimated channel of MMSE can be obtained by combining the above variables and formulas. The expression can be followed as

$$R_{HY} = E\{H(k)Y(k)^H\} = R_{HH}X(k)^H, \tag{7}$$

$$R_{YY} = E\{Y(k)Y(k)^H\} = X(k)R_{HH}X(k)^H + \sigma^2 I, \tag{8}$$

$$\hat{H}_{MMSE} = R_{HH}(R_{HH} + \sigma_w^2(X(k)X(k)^H)^{-1})^{-1}\hat{H}_{LS}, \tag{9}$$

where R_{HH} denotes the autocorrelation matrix of the channel, σ_w^2 denotes the power of additive white Gaussian noise in the channel, and I denotes the identity matrix. MMSE algorithm achieves better channel estimation performance by eliminating part of the noise. However, MMSE requires complex calculations to obtain the channel autocorrelation characteristics in continuous time, and the power of the noise cannot be directly obtained in the actual receiver. Besides, the received noise amplified by the channel compensation process also affects the performance of the system.

III. SIGNAL DETECTION SCHEME BASED ON DEEP LEARNING ALGORITHM

A. LSTM DEEP LEARNING ALGORITHM

Figure 2 shows the signal detection scheme based on the LSTM deep learning model. LSTM neural network is an

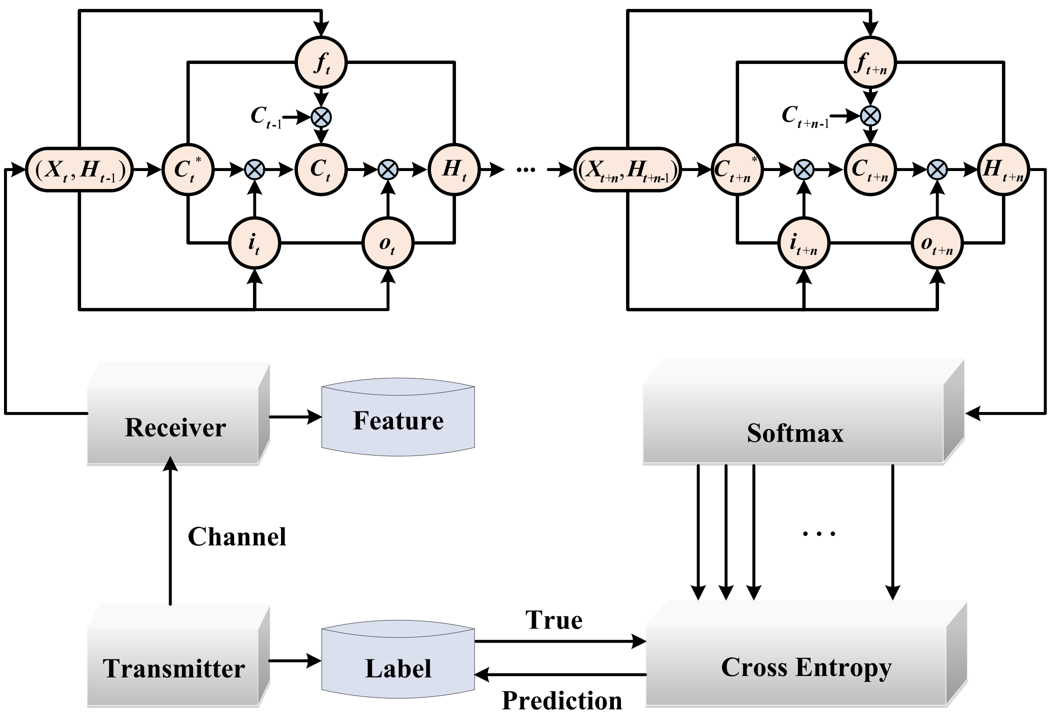

FIGURE 2. Signal detection based on LSTM deep learning model.

evolved form of the recurrent neural networks (RNN) [27]. By adding a memory cell, it solves the long-term dependence problem in the neural network and has an excellent ability to process time-series information [28]. Since the input is a series of sequence data with inner-relationship of channel information, it is better to use LSTM to learn the relationship between the extracted features and the classification of constellation points and utilize the trained model to replace a specific module or multiple modules of the communication system. Besides, the realization of LSTM learning ability is to control the forgetting and remembering of information through various types of gates. The input of the gate is a vector, and the output is a real vector between 0 and 1 obtained by a sigmoid function and a point multiplication operation [29]. A memory block is mainly composed of forgetting gate, input gate, and output gate [30].

The input of the forgetting gate includes the output H_{t-1} of the previous cell and the input X_t of the current cell. Values between 0 and 1 are generated by sigmoid function to control the retention of information in the previous cell state. The expression can be calculated as

$$f_t = \sigma(W_f \cdot [H_{t-1}, X_t] + b_f), \tag{10}$$

where W_f and b_f denotes the weight matrix and bias term of forgetting gate, respectively. $[H_{t-1}, X_t]$ denotes the input vector connected by vector H_{t-1} and vector X_t. Also, $\sigma(\cdot)$ denotes the sigmoid activation function.

The cooperation of the input gate layer and tanh function determines how much new information is added to the cell state. This process is mainly achieved in two steps. First, the input gate layer determines how much information from $[H_{t-1}, X_t]$ is updated, and obtain a new candidate cell information C_t^* through the tanh layer. Then, combining the output f_t of forgetting gate and the output i_t of input gate layer to update the old cell state C_{t-1} to C_t. The formula can be expressed as

$$i_t = \sigma(W_i \cdot [H_{t-1}, X_t] + b_i), \tag{11}$$
$$C_t^* = tanh(W_c \cdot [H_{t-1}, X_t] + b_c), \tag{12}$$
$$C_t = f_t * C_{t-1} + i_t * C_t^*, \tag{13}$$

where W_i and b_i denotes the weight matrix and bias term of the input gate, respectively. Also, W_c and b_c denote the weight matrix and bias term of cell state, respectively.

The output gate can determine the value of the next hidden state. o_t is obtained by passing the previous hidden state H_{t-1} and the current input X_t to sigmoid function. Meanwhile, C_t is passed to the tanh activation function, and that result is multiplied with o_t to determine the information that the hidden state should carry. The formula can be expressed as

$$o_t = \sigma(W_o \cdot [H_{t-1}, X_t] + b_o), \tag{14}$$
$$H_t = o_t * tanh(C_t), \tag{15}$$

where W_o and b_o denotes the weight matrix and bias term of cell state, respectively. In the signal detection model, a fully connected layer with softmax as the activation function is connected behind the LSTM network for classification of constellation points, the formula of the softmax activation function is expressed as

$$Softmax(z_x) = \frac{e^{z_x}}{\sum_{c=1}^{t} e^{z_c}}, \tag{16}$$

where t denotes the number of categories, x denotes a category in c ($c = 1, 2, \cdots, t$), and z_x denotes the output value of the x-th category. The softmax function can convert the output value of multiple classifications into a probability distribution with a range of [0, 1] and a sum of 1.

Two stages of offline training and online testing are required to build the LSTM deep learning model for channel estimation and signal detection. In the offline training stage, the SC-FDE system generates the training set under different SNRs, where the features are extracted from the FFT-processed received signal, and the labels are assigned according to the constellation map adopted at the transmitter. The purpose of model training is to learn the channel characteristic information and convert the values of neurons in the output layer to constellation points by continually updating the network parameters. In the experiment, adaptive moment estimation (Adam) is selected as the optimizer to update the weight and bias of the network. We choose the cross-entropy function as the loss function. The loss function is calculated as

$$L = -\sum_{i=1}^{n} C_i \log(\hat{C}_i), \tag{17}$$

where C_i denotes the label of constellation points, and $\hat{C}_i$ denotes the model's prediction value. In the online test stage, using the trained deep learning model instead of channel estimation and frequency domain equalization process to achieve signal detection.

B. ADAPTIVE ENSEMBLE ALGORITHM

Figure 3 shows the signal detection scheme based on the AE-LSTM deep learning model. The LSTM-based signal detection model takes the extracted features from the received signal after removing the CP and FFT as the input of a single neural network. However, the ensemble-based model assigns the received SC-FDE symbol to the input layer of each sub-network. Meanwhile, the number of sub-networks is equal to the number of multi-path channels. Figure 4 shows the receive power characteristic under different delays. For m independent parallel channels with Gaussian additive noise, the receive power P_m varies with different delay ($t_1 \sim t_m$). More precisely, the power value gradually decreases with the increase of delay time. To improve the performance of the ensemble model, we select the received power under different delays as the adaptive factor. The adaptive coefficient can be obtained according to the proportion of a certain received power in the total power. The final result is calculated by combining the output of the sub-network. The specific algorithm implementation is expanded below.

The number of multi-path channels and sub-carriers in the AE-LSTM scheme is set to m and n, respectively, so the received power of n sub-carriers of m channels can be expressed as

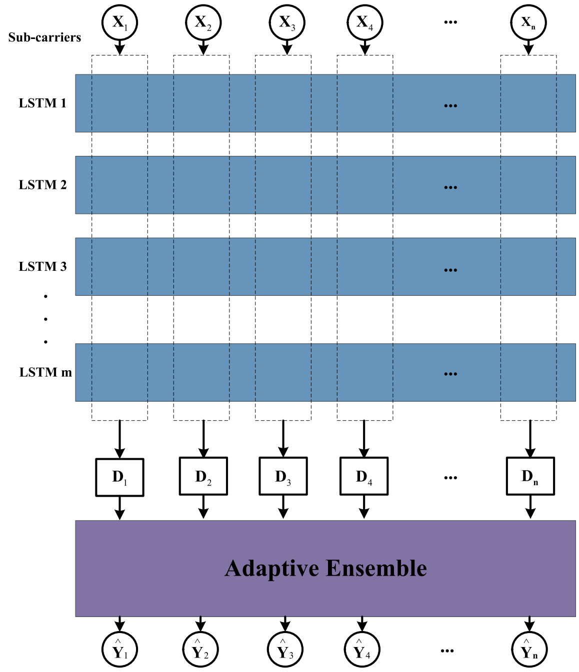

FIGURE 3. Signal detection based on AE-LSTM deep learning model.

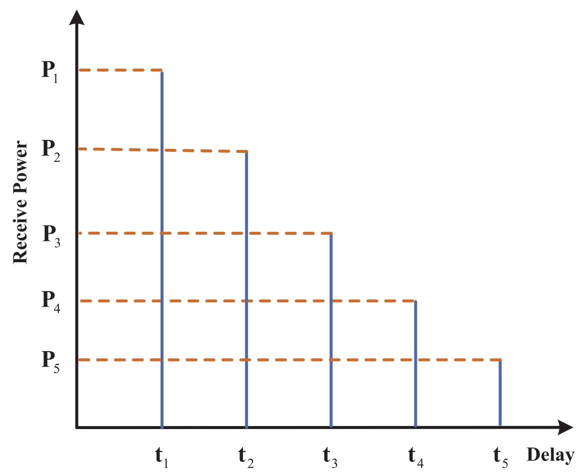

FIGURE 4. Receive power characteristics under different delays.

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mn} \end{bmatrix}. \tag{18}$$

where P_{ij} denotes the entry of the power matrix P, $i = 1, 2, \cdots, m$, $j = 1, 2, \cdots, n$. Therefore, the adaptive coefficient A_{ij} of the j-th sub-carrier of the i-th channel can be obtained as

$$A_{ij} = \frac{P_{ij}}{\sum_{i=1}^{m} P_{ij}}, \tag{19}$$

where $\sum_{i=1}^{m} P_{ij}$ denotes the sum of power value for the j-th sub-carrier of received SC-FDE symbol through each multi-path. The detection result of the j-th sub-carrier through the i-th sub-network is represented by a matrix with N_P rows and 1 column, which consists of 0 and 1. N_P represents the maximum value of the constellation point. If the detected constellation point is C_x, the value of the x-th element in the matrix is 1, and the other elements are 0. The detection results C_x of each sub-network corresponding to the sub-carrier is combined by matrix D, and A_{ij} is used as the coefficient of D_{ij}. After adding the adaptative factor, the detected constellation points of the j-th sub-carrier can be expressed as

$$W_x = \arg\max_x \Big(\sum_{i=1}^{m} A_{ij} \bigodot D_{ij}\Big), \tag{20}$$

where arg max() denotes the operation of searching the maximum value in (), $\bigodot$ represents point multiplication. Therefore, the estimation symbols of the j-th sub-carrier based on the ensemble model are shown as

$$\hat{Y}_j = C_{W_x}, \tag{21}$$

In the adaptive ensemble model, the network continuously adjusts the value of adaptive coefficient according to the amount of the received power in different multi-paths and realizes the adaptive ensemble of detection results of sub-networks through comprehensive analysis, which not only enhances the reliability of signal detection effectively but also the adaptability of SC-FDE system. Although the complexity of the network increases with the number of sub-carriers and the constellation size, this conclusion is only valid in the offline training stage, such as the extension of training time, which has little impact on the online testing stage.

IV. EXPERIMENT AND ANALYSIS

In this section, we verify the performance of signal detection based on deep learning scheme through several different sets of comparative experiments. Experimental data is generated by MATLAB2019a simulation based on the WINNER II channel model, which uses a carrier frequency of 2.6 GHz and the number of paths of 7 is considered. The SC-FDE system contains 64 sub-carriers, and the length of the inserted CP is 16. The channel autocorrelation matrix used in the simulation is represented by a matrix of 64 rows and 64 columns, which is calculated in advance according to the selected channel model. Meanwhile, the input dimension and output dimension of the LSTM deep learning model are equal to the number of sub-carriers and constellation points, respectively. The number of samples of the training set, verification set, and test set used in the offline training process is 10000, 2000, and 1000, respectively. The detailed simulation parameters of the LSTM deep learning model are shown in Table 1.

TABLE 1. Simulation parameters of LSTM deep learning model.

Parameter	Value
Optimizer	Adam
Loss Function	Cross Entropy
State Activation Function	Tanh
Gate Activation Function	Sigmoid
Initial Learning Rate	0.005
Learn Rate Drop Factor	0.2
Dropout	0.5
Gradient Threshold	1
Number of Layers	3
Time Step	64
Maximum Epochs	800
Minimum Batch Size	100

A. PERFORMANCE COMPARISON ANALYSIS OF LSTM DEEP LEARNING SCHEME

The performance of signal detection is affected by different modulation methods selected at the transmitter. Generally speaking, the BER performance of signal detection decline with the increase of constellation points. Conventional modulation methods include orthogonal phase-shift keying (QPSK), 8PSK, 16 quadrature amplitude modulation (16QAM), and 64QAM. Also, each modulation method has a corresponding constellation map. Since the BER performance comparison of different modulation methods needs to be in the same power state, the constellation maps are normalized. The comparison of BER performance under different modulation methods is shown in Fig. 5. It can be seen from Fig. 5 that the SNR of MMSE scheme based on QPSK, 8PSK, 16QAM, and 64QAM is more than 35dB at a BER of 10^{-4}, while that of LSTM scheme is about 23.0dB, 28.3dB, 34.1dB, and 35dB+, respectively. Besides, the fewer the constellation points, the higher the detection accuracy.

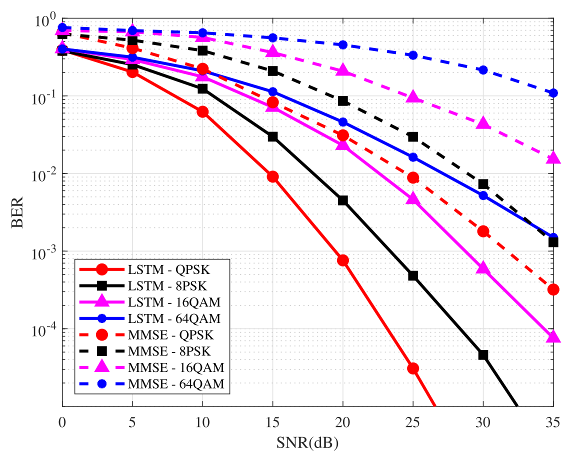

FIGURE 5. BER performance under different modulation methods.

To study the impact of the pilot number on signal detection, QPSK is selected as the modulation mode of the signal to be sent, and the signal detection performance when the number of pilots is 8 and 64 is detected under the same conditions. As shown in Fig. 6, when inserting 64 pilots into SC-FDE symbols, the MMSE scheme has better signal detection performance than the LS-based method, because it utilizes the known channel statistical characteristics. Still, the LSTM based deep learning scheme has almost the same performance as an MMSE scheme with lower computational complexity. When the pilot number is 8, the signal detection performance of LS and MMSE is obviously affected by the decrease in channel information. As shown in Table 2, except for the LSTM-based scheme, which has an SNR of 23.3dB at a BER of 10^{-4}, the SNR of the other two traditional methods exceeds 35dB under the same situation, indicating that the deep learning scheme is less affected by the number of pilots and has stronger robustness.

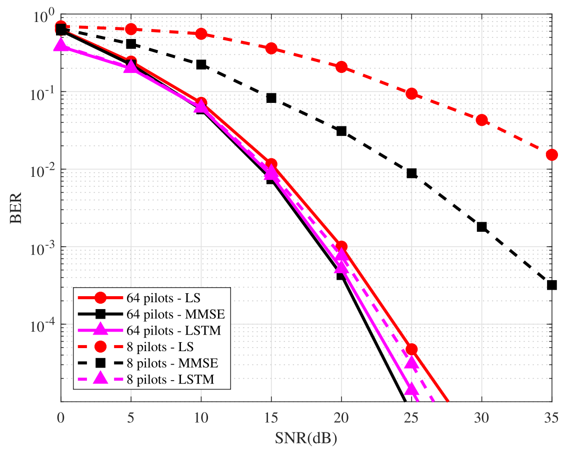

FIGURE 6. BER performance under different pilot number.

TABLE 2. BER performance under different pilot number.

Scheme	Pilot Number	SNR(BER=10^{-2})	SNR(BER=10^{-4})
LS	8	35dB+	35dB+
	64	15.6dB	23.8dB
MMSE	8	24.2dB	35dB+
	64	13.9dB	21.8dB
LSTM	8	14.5dB	23.3dB
	64	14.4dB	22.1dB

CP can eliminate IBI, but the addition of CP also leads to a decrease in spectrum utilization. Figure. 7 shows the impact of CP on BER performance. It can be seen from Fig. 7 that in the case of CP removal, the SNR of the traditional channel estimation method is more than 35dB when satisfies the BER of 10^{-4}, while that of the LSTM deep learning scheme is about 25.8dB under the same conditions. After adding CP, the LSTM scheme has better performance, which is about 2.5dB lower than the model without CP. It is indicated that the deep learning scheme can reduce IBI by analyzing channel characteristics.

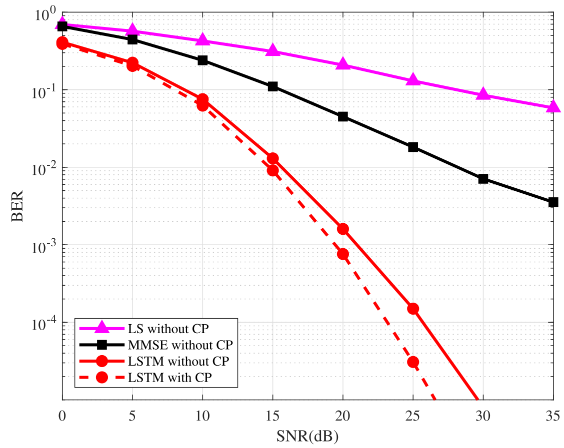

FIGURE 7. Impact of CP on BER performance.

Due to the interference of various environmental factors in the real signal transmission, the number of paths in the offline training stage and online testing stage may be different. For this reason, the number of paths used in the offline training stage is 7, and that used to detect signals in the online testing stage is 4, 7, 10, respectively. As shown in Fig. 8, the BER performance under the different number of paths is approximately the same, indicating that the change of path number has no noticeable impact on the performance of SC-FDE symbol detection. Therefore, the different number of paths only lead to a change in computational complexity and has no significant effect on system performance. The same applies to the setting of the number of sub-carriers.

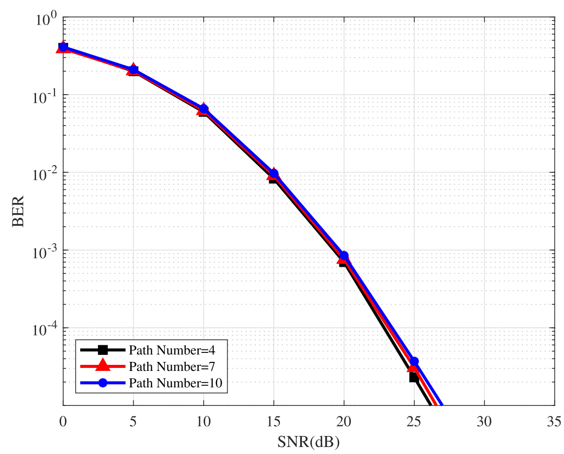

FIGURE 8. BER performance under number of paths.

B. PERFORMANCE COMPARISON ANALYSIS OF ADAPTIVE ENSEMBLE SCHEME

The AE-LSTM deep learning scheme improves the adaptability of signal detection by adding the received power with different delays as the adaptive factor to each LSTM sub-network. As shown in Fig. 9, the BER performance of signal detection based on the LSTM model is better than that of

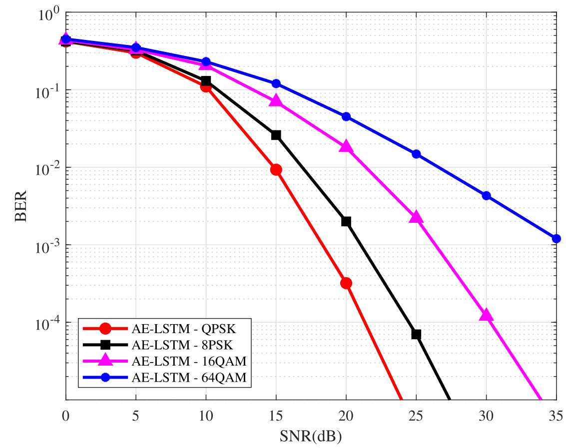

FIGURE 9. BER performance of AE-LSTM scheme.

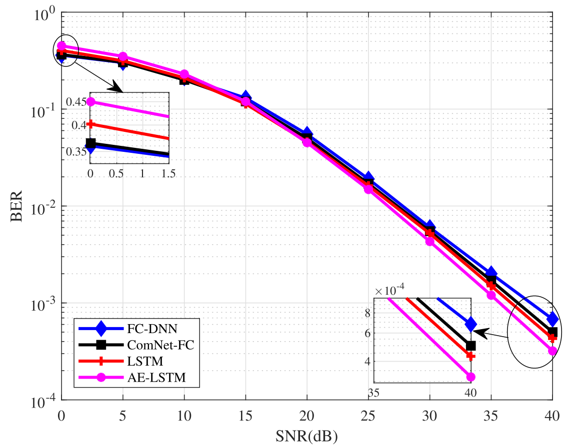

FIGURE 10. BER performance of different deep learning scheme.

the AE-LSTM model when SNR is less than 15dB. But the performance at this time is more than 10^{-2}, which is far from meeting the requirements of 5G communication since 5G communication needs to achieve high rates and low BER. The reason for the poor performance of the AE-LSTM scheme at low SNR is that the proposed scheme can work effectively only when each sub-network meets a certain performance level. Table 3 shows the BER performance comparison under different modulation methods. When BER is 10^{-4}, the SNR of the AE-LSTM scheme is about 1.7dB, 4.1dB, 3.8dB and 2.0dB+ lower than that of the scheme based on LSTM for QPSK, 8PSK, 16QAM, and 64QAM, respectively, and with the increase of SNR, the BER curve still has a significant downward trend.

TABLE 3. BER performance under different modulation methods.

Scheme	Modulation	SNR(BER=10^{-2})	SNR(BER=10^{-4})
MMSE	QPSK	24.2dB	35.0dB+
	8PSK	28.9dB	35.0dB+
	16QAM	35.0dB+	35.0dB+
	64QAM	35.0dB+	35.0dB+
LSTM	QPSK	14.5dB	23.0dB
	8PSK	17.7dB	28.3dB
	16QAM	22.4dB	34.1dB
	64QAM	27.2dB	35.0dB+
AE-LSTM	QPSK	14.7dB	21.3dB
	8PSK	16.9dB	24.2dB
	16QAM	21.3dB	30.3dB
	64QAM	26.5dB	35.0dB+

Figure 10 compares the BER performance of the proposed scheme with the deep learning scheme based on the full connection deep neural network (FC-DNN) in [14] and the ComNet-FC in [16]. The comparison experiment is carried out under 64QAM modulation, so we modify the number of output neurons of FC-DNN in [14] to 48 to make it suitable for the data transmission rate of 64QAM. From Fig. 10, it can be found that the performance curves of the four signal detection schemes are very close when the SNR is less than 20dB. As the SNR increases, the curve decline trend of the proposed scheme is higher than that of the compared scheme. When the BER is 10^{-3}, the SNR of the LSTM-based method is 1.5dB and 0.5dB lower than FC-DNN and ComNet-FC, respectively, but there is still a 1dB gap with the AE-LSTM scheme. In the same situation, the SNR of the AE-LSTM is 35.5dB, which is 2.5dB and 1.5dB lower than FC-DNN and ComNet-FC, respectively. Meanwhile, the experimental results show that the higher the SNR, the advantages of the AE-LSTM-based scheme more evident than the other two schemes.

As analyzed by PartA, CP affects the performance of signal detection scheme based on deep learning technology. Figure 11 compares the BER performance of the proposed scheme and the competing scheme with CP removed. From the figure, the BER curve of the LSTM scheme and the ComNet-FC scheme almost overlap, while the LSTM scheme is slightly lower and the BER when the curve tends to be stable is about 0.01 lower than that of the FC-DNN. Although the BER performance of all signal detection schemes is worse than the case with CP, the AE-LSTM scheme is still the most advantageous. When the SNR exceeds 30dB, AE-LSTM has

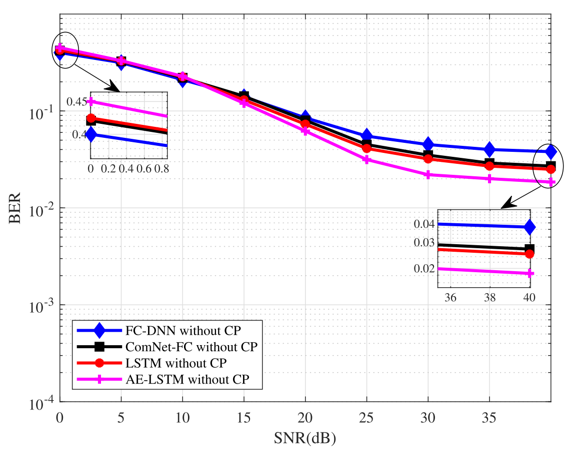

FIGURE 11. BER performance of different deep learning schemes without CP.

about 0.35 BER and 0.5 BER of FC-DNN and ComNet-FC, respectively, indicating that AE-LSTM has better ability to resist IBI than the competition scheme when CP is removed.

V. CONCLUSION

To reduce the complexity and obtain a more reliable signal detection performance, we propose a novel signal detection scheme based on AE-LSTM deep learning model in the SC-FDE system. This scheme combines wireless communication theory with a deep learning model and generates data through simulation of a channel model for neural network training. In the offline training stage, different sub-carriers of SC-FDE symbols are introduced into multiple LSTM sub-networks for self-learning, and the output of each sub-network is adaptively ensemble by using the received power as the adaptive factor. In the online test stage, the trained deep learning model is adopted instead of channel estimation and frequency domain equalization to achieve signal detection. The simulation results show that the AE-LSTM model has better ability of long-term memory and analysis for the characteristics of the channel with a small number of pilots and CP removal. Compared with traditional schemes and similar deep learning schemes, the proposed signal detection scheme has strong adaptability and reliability. However, since the deep learning model used in the proposed signal detection scheme takes a long time to train, a novel feature information processing method or an improved deep learning algorithm is required on the premise of ensuring the detection performance.

REFERENCES

[1] J. An, K. Yang, J. Wu, N. Ye, S. Guo, and Z. Liao, "Achieving sustainable ultra-dense heterogeneous networks for 5G," *IEEE Commun. Mag.*, vol. 55, no. 12, pp. 84–90, Dec. 2017.

[2] A. Aissioui, A. Ksentini, A. M. Gueroui, and T. Taleb, "Toward elastic distributed SDN/NFV controller for 5G mobile cloud management systems," *IEEE Access*, vol. 3, pp. 2055–2064, 2015.

[3] N. Benvenuto, R. Dinis, D. Falconer, and S. Tomasin, "Single carrier modulation with nonlinear frequency domain equalization: An idea whose time has come again," *Proc. IEEE*, vol. 98, no. 1, pp. 69–96, Oct. 2009.

[4] M. Morelli and U. Mengali, "A comparison of pilot-aided channel estimation methods for OFDM systems," *IEEE Trans. Signal Process.*, vol. 49, no. 12, pp. 3065–3073, May 2001.

[5] C. Zhang, Z. Wang, C. Pan, S. Chen, and L. Hanzo, "Low-complexity iterative frequency domain decision feedback equalization," *IEEE Trans. Veh. Technol.*, vol. 60, no. 3, pp. 1295–1301, Mar. 2011.

[6] H. Lee, Y. Lee, and H. Park, "An efficient CP compensation for SC-FDE with insufficient CP symbols," *IEEE Commun. Lett.*, vol. 14, no. 6, pp. 548–550, Jun. 2010.

[7] R. Dinis, P. Montezuma, L. Bernardo, R. Oliveira, M. Pereira, and P. Pinto, "Frequency-domain multipacket detection: A high throughput technique for SC-FDE systems," *IEEE Trans. Wireless Commun.*, vol. 8, no. 7, pp. 3798–3807, Jul. 2009.

[8] B. Zheng, F. Chen, Q. Guan, M. Wen, H. Yu, and F. Ji, "Novel pilot design and signal detection for SC-FDE systems with frequency-domain pilot multiplexing technique," *IEEE Commun. Lett.*, vol. 19, no. 8, pp. 1466–1469, Aug. 2015.

[9] N. Souto and R. Dinis, "MIMO detection and equalization for single-carrier systems using the alternating direction method of multipliers," *IEEE Signal Process. Lett.*, vol. 23, no. 12, pp. 1751–1755, Dec. 2016.

[10] Z. Xie, X. Chen, and X. Liu, "A virtual pilot-assisted channel estimation algorithm for MIMO-SCFDE systems over fast time-varying multipath channels," *IEEE Trans. Veh. Technol.*, vol. 67, no. 6, pp. 4901–4909, Jun. 2018.

[11] Z. Xie, X. Chen, and C. Li, "A novel joint channel estimation and equalization algorithm for MIMO-SCFDE systems over doubly selective channels," *Digit. Signal Process.*, vol. 75, pp. 202–209, Apr. 2018.

[12] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Proc. Adv. Neural Inf. Process. Syst.*, 2012, pp. 1097–1105.

[13] D. Chen and B. K.-W. Mak, "Multitask learning of deep neural networks for low-resource speech recognition," *IEEE/ACM Trans. Audio, Speech, Language Process.*, vol. 23, no. 7, pp. 1172–1183, Jul. 2015.

[14] H. Ye, G. Y. Li, and B.-H. Juang, "Power of deep learning for channel estimation and signal detection in OFDM systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 114–117, Feb. 2018.

[15] C.-B. Ha and H.-K. Song, "Signal detection scheme based on adaptive ensemble deep learning model," *IEEE Access*, vol. 6, pp. 21342–21349, 2018.

[16] X. Gao, S. Jin, C.-K. Wen, and G. Y. Li, "ComNet: Combination of deep learning and expert knowledge in OFDM receivers," *IEEE Commun. Lett.*, vol. 22, no. 12, pp. 2627–2630, Dec. 2018.

[17] M. Kim, W. Lee, and D.-H. Cho, "A novel PAPR reduction scheme for OFDM system based on deep learning," *IEEE Commun. Lett.*, vol. 22, no. 3, pp. 510–513, Mar. 2018.

[18] C. Luo, J. Ji, Q. Wang, X. Chen, and P. Li, "Channel state information prediction for 5G wireless communications: A deep learning approach," *IEEE Trans. Netw. Sci. Eng.*, vol. 7, no. 1, pp. 227–236, Jan. 2020.

[19] N. Samuel, T. Diskin, and A. Wiesel, "Learning to detect," *IEEE Trans. Signal Process.*, vol. 67, no. 10, pp. 2554–2564, May 2019.

[20] C.-B. Ha, Y.-H. You, and H.-K. Song, "Machine learning model for adaptive modulation of multi-stream in MIMO-OFDM system," *IEEE Access*, vol. 7, pp. 5141–5152, 2019.

[21] H. He, C. Wen, S. Jin, and G. Y. Li, "A model-driven deep learning network for mimo detection," in *Proc. IEEE Global Conf. Signal and Inf. Process.*, Nov. 2018, pp. 584–588.

[22] S. Takabe, M. Imanishi, T. Wadayama, R. Hayakawa, and K. Hayashi, "Trainable projected gradient detector for massive overloaded MIMO channels: Data-driven tuning approach," *IEEE Access*, vol. 7, pp. 93326–93338, 2019.

[23] B. Ng, C.-T. Lam, and D. Falco, "Turbo frequency domain equalization for single-carrier broadband wireless systems," *IEEE Trans. Wireless Commun.*, vol. 6, no. 2, pp. 759–767, Feb. 2007.

[24] D. Darsena, G. Gelli, L. Paura, and F. Verde, "Blind channel shortening for asynchronous SC-IFDMA systems with CFOs," *IEEE Trans. Wireless Commun.*, vol. 12, no. 11, pp. 5529–5543, Nov. 2013.

[25] M. Nassiri and G. Baghersalimi, "Comparative performance assessment between FFT-based and FRFT-based MIMO-OFDM systems in underwater acoustic communications," *IET Commun.*, vol. 12, no. 6, pp. 719–726, Apr. 2018.

[26] Y. Zhu and K. Letaief, "Single carrier frequency domain equalization with time domain noise prediction for wideband wireless communications," *IEEE Trans. Wireless Commun.*, vol. 5, no. 12, pp. 3548–3557, Dec. 2006.

[27] H. Zhao, S. Sun, and B. Jin, "Sequential fault diagnosis based on lstm neural network," *IEEE Access*, vol. 6, pp. 12929–12939, 2018.

[28] N. Srivastava, E. Mansimov, and R. Salakhudinov, "Unsupervised learning of video representations using lstms," in *Proc. Int. Conf. Mach. Learn.*, 2015, pp. 843–852.

[29] J. Y. Choi and B. Lee, "Combining LSTM network ensemble via adaptive weighting for improved time series forecasting," *Math. Problems Eng.*, vol. 2018, Aug. 2018, Art. no. 2470171.

[30] N. Kourentzes, D. K. Barrow, and S. F. Crone, "Neural network ensemble operators for time series forecasting," *Expert Syst. Appl.*, vol. 41, no. 9, pp. 4235–4244, Jul. 2014.

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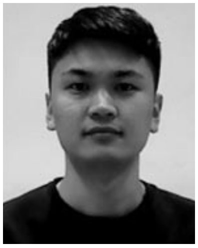

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