Deep Neural Network Based Parallel Signal Detection in SM-OFDM System

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***Abstract*—A novel deep neural network based parallel signal detection (DNN-PSD) is proposed for the spatial modulation based orthogonal frequency division multiplexing (SM-OFDM) system. With the purpose to reduce the complexity of the conventional DNN, a uniform small-scale DNN with fewer parameters and less training time is exploited to detect the signals for each subcarrier parallelly. Apart from maximum likelihood (ML) and maximal ratio combining (MRC) detection schemes, the detailed DNN-PSD algorithm and its complexity analysis are presented. Simulation results confirm that the bit error rate (BER) performance of the proposed DNN-PSD is far superior to the MRC detection and similar to the optimal ML detection but with much lower complexity under different scenarios. It has more robustness and achieves a finer compromise between BER performance and complexity.**

***Index Terms*—Deep neural network (DNN), signal detection, spatial modulation based orthogonal frequency division multiplexing (SM-OFDM), bit error rate (BER).**

I. Introduction

Ultra-high data rate and spectral efficiency emerge as urgent requirements of the fifth generation mobile communication [1]. Spatial modulation (SM) as an attractive and efficient transmission technique plays a vital position in multiple-input multiple-output (MIMO) communication. SM conveys the index information by activating a transmit antenna, which achieves high spectral efficiency and is free of inter-channel interference (ICI) [2]. Another aspect, Orthogonal frequency division multiplexing (OFDM) can effectively resist inter symbol interference (ISI) and frequency selective fading, which has been envisioned as a mature and prospective multicarrier technique [3]. SM based OFDM (SM-OFDM) was introduced in [4] to fully exploit the advantages of the SM and OFDM schemes, which is viewed as a crucial technique capable of fulfilling the communication requirements of the future.

Compared to conventional SM or OFDM system, SM-OFDM obtains improved communication performance, however, its detection complexity is also vastly enhanced. The paper [5] demonstrated that conventional detectors like maximum likelihood (ML) and maximal ratio combining (MRC) were incapable of striking a nice compromise between bit error rate (BER) performance and complexity. ML detector collectively estimates the antenna index and the modulated constellation symbol through exhaustive search, which gets the optimal BER performance and the exponentially increased complexity. MRC detector separates the antenna index estimation and the modulated symbol recovery for low complexity, but its BER performance is sacrificed.

Deep learning (DL) technology has shown extraordinary performance in numerous fields such as image and speech, solving cumbersome and sophisticated problems, which is attributed to its robust acquisition and characterization capability [6]. In addition of that, DL has currently been studied in wireless communication to realize intelligent and flexible communication. DL not only becomes a substitute for traditional communication modules, such as channel estimation [7] and signal detection [8], but also helps to realize end-to-end communication of the system. A. Badi *et al*. proposed a machine learning detector to directly demodulate the received symbols in SM-OFDM system, which achieves the similar BER performance to the minimum mean square error (MMSE) detector [9]. Nevertheless, its network structure was very complex and the BER performance was far from the optimal ML detector. With the aim of obtaining improved performance with less complexity, a novel DNN based parallel signal detection algorithm is proposed. Since the proposed DNN-PSD simplifies the common DNN structure, fewer parameters are needed and training time is obviously shortened. Furthermore, the complexity of the ML, MRC, and DNN based detection has been analyzed. Simulation results prove that proposed DNN-PSD algorithm exhibits a better compromise between BER performance and complexity, while with excellent robustness under various scenarios.

The remaining parts of the paper are arranged as follows. Section II describes the SM-OFDM system model and existing detection schemes. The architecture of the proposed DNN-PSD algorithm, the data pre-processing process, the training procedure, and the complexity analysis are demonstrated in Section III. Simulation results and analysis are presented in Section IV. Lastly, conclusion is derived in Section V.

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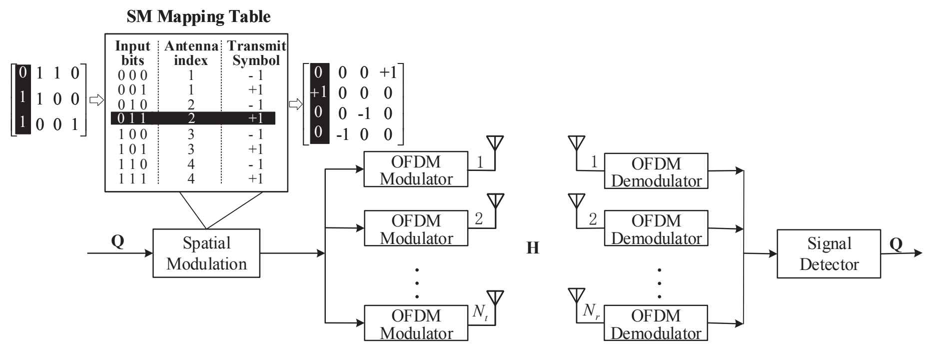

Fig. 1. The framework of SM-OFDM system.

II. System Model and Conventional Detection

A. SM-OFDM System

The SM-OFDM system structure is constituted by one SM module, N_t OFDM modulators, N_t transmit antennas, N_r OFDM demodulators, N_r receive antennas and signal detector, as illustrated in Fig. 1. $\mathbf{Q} = [\mathbf{q}_1, \ldots, \mathbf{q}_n, \ldots, \mathbf{q}_N]$ is a $P \times N$ binary matrix to be transmitted, where P denotes the bits on each subcarrier, N indicates the quantity of subcarriers, and $\mathbf{q}_n$ with $n \in \{1, 2, \ldots, N\}$ refers to the information bit vector of the n-th subcarrier. We illustrate the SM mapping rules by taking the mapping table in Fig. 1 as an example, herein, BPSK modulation and four transmit antennas are considered. The information bits in each column of $\mathbf{Q}$ are split into two portions for the selection of an activation antenna and the constellation mapping with $\log_2 N_t$ bits and $\log_2 M$ bits, respectively. Finally, $\mathbf{Q}$ is mapped to a signal matrix $\mathbf{X}$ with dimension $N_t \times N$, where each row consists of the symbols to be transmitted from the corresponding antenna. The OFDM modulator is taken for each row of the signal matrix and the generated signal vectors are transmitted concurrently from the corresponding antennas over flat Rayleigh fading channels denoted by $\mathbf{H} \in \mathbb{C}^{N_r \times N_t}$ with each element $h_{ij} \sim \mathcal{CN}(0, 1)$.

Thus, the received signal matrix $\mathbf{Y} \in \mathbb{C}^{N_r \times N}$ is formulated by

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{V}, \tag{1}$$

where $\mathbf{V} \in \mathbb{C}^{N_r \times N}$ indicates the additive white Gaussian noise (AWGN) matrix, and each term of $\mathbf{V}$ is a complex Gaussian random variable with zero-mean and variance σ^2. The vector of the received signal $\mathbf{y}_n = \left[y_n^1, y_n^2, \ldots, y_n^{N_r}\right]^T \in \mathbb{C}^{N_r \times 1}$ corresponding to the n-th subcarrier is given by

$$\mathbf{y}_n = \mathbf{H}\mathbf{x}_n + \mathbf{v}_n, \tag{2}$$

where $\mathbf{x}_n = \left[x_n^1, x_n^2, \ldots, x_n^{N_t}\right]^T \in \mathbb{C}^{N_t \times 1}$ and $\mathbf{v}_n = \left[v_n^1, v_n^2, \ldots, v_n^{N_r}\right]^T \in \mathbb{C}^{N_r \times 1}$ are the transmit vector and AWGN vector of the n-th subcarrier, respectively. However, the noise at the receive antennas does not obey independent and identically distributed (i.i.d) Gaussian distribution considering the non-ideal transmission condition in practice. We introduce a noise correlation model derived by Nyquists thermal noise theorem [10], where the noise correlation matrix $\mathbf{N}_c$ is expressed as

$$\mathbf{N}_c = \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{N_t-1} \\ \rho & 1 & \rho & \cdots & \rho^{N_t-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{N_t-1} & \rho^{N_t-2} & \rho^{N_t-3} & \cdots & 1 \end{bmatrix}, \tag{3}$$

where $\rho\,(0 \le \rho \le 1)$ is the correlation coefficient and indicates the degree of correlation. Then, the relationship between the correlated noise and the i.i.d Gaussian noise can be given by $\mathbf{V}_c = \mathbf{N}_c\mathbf{V}$.

At the end of the receiver, all the receive signals are first demodulated by traditional OFDM demodulators, and then the information bits are recovered through the signal detector.

B. Conventional Signal Detection

1) ML Detection: The ML algorithms collectively estimate the antenna index and modulated symbol through exhaustive search as

$$\left[\hat{i}_n, \hat{s}_n\right] = \arg\min_{i \in \mathbf{I}, s \in \mathbf{S}} \left\|\mathbf{y}_n - \mathbf{h}_i s\right\|_F^2, \tag{4}$$

where $\hat{i}_n$ and $\hat{s}_n$ denote the demodulated active antenna index and the recovered constellation symbol corresponding to the n-th subcarrier, respectively, $\mathbf{I} = \{1, 2, \ldots, N_t\}$ denotes the antenna index set, $\mathbf{S}$ represents the constellation symbol set, and $\mathbf{h}_i$ represents the i-th column of $\mathbf{H}$. The high reliability of the ML algorithm is attributed to its ergodic nature, unfortunately, its complexity grows explosively as modulation order and the amount of antennas increase.

2) MRC Detection: The MRC scheme makes the antenna index estimation and the modulated symbol recovery seperately, and it can be represented as

$$\hat{i}_n = \arg\max_{i \in \mathbf{I}} \frac{\left|\mathbf{h}_i^{\dagger}\mathbf{y}_n\right|}{\left\|\mathbf{h}_i\right\|}, \tag{5}$$

$$\hat{s}_n = \arg\min_{s \in \mathbf{S}} \left\|\mathbf{y}_n - \mathbf{h}_{\hat{i}_n} s\right\|^2, \tag{6}$$

where † stands for the conjugate transpose. Firstly, the active antenna index is estimated, and then it is further utilized to recover the corresponding modulated signal. Although the MRC detection has low complexity, its BER performance becomes considerably worse than that of the ML detection.

III. Proposed DNN Based Parallel Detection

In this section, we proceed to present the DNN-PSD algorithm for SM-OFDM system in detail, including the data pre-processing process, the DNN structure, and the training procedure. Furthermore, the computational complexity of the ML, MRC, and DNN-PSD schemes is also analyzed.

A. Detection Process

The proposed DNN-PSD algorithm recovers the information bits for each subcarrier parallelly using N identical small-scale DNNs. Fig. 2 exhibits the overall process of the DNN based parallel detection, which has N parallel identical DNN detectors. For the n-th detection, the original data, including $\mathbf{y}_n$ and $\mathbf{H}$, is pre-processed to form feature vector $\mathbf{d}_n$, and then taken as the input of the DNN detector. The relationship between the feature input vector and the network output is equivalent to a nonlinear function, which can be expressed as

$$\hat{\mathbf{q}}_n = f_{\mathrm{DNN}}\left(\mathbf{d}_n\right), \tag{7}$$

where $\hat{\mathbf{q}}_n$ denotes the estimated n-th bit sequence detected by the n-th DNN detector. Finally, the estimated bit matrix $\hat{\mathbf{Q}}$ can be formed as $\hat{\mathbf{Q}} = [\hat{\mathbf{q}}_1, \hat{\mathbf{q}}_2, \ldots, \hat{\mathbf{q}}_N]$.

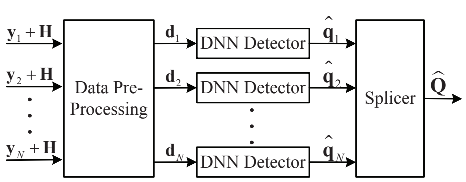

Fig. 2. The overall process of the proposed DNN-PSD algorithm.

B. Data Pre-Processing

An essential approach toward improving the efficiency of DL algorithms is data pre-processing. For the purpose of adapting the input characteristics of DNN and improving the detection performance, a feature vector generator (FVG) is introduced to preprocess the original data from the complex-value vector to the real-value vector. Suppose perfect channel state information (CSI) is already aware on the receiver side, we can get the input vector $\mathbf{d}_n$ as

$$\begin{cases} \mathbf{d}_n = [f_{FVG}(\mathbf{y}_n), f_{FVG}(\mathbf{H})]^{\mathrm{T}} \\ f_{FVG}(\mathbf{y}_n) = \left[\mathrm{Re}\left(y_n^1\right), \mathrm{Im}\left(y_n^1\right), \ldots, \mathrm{Re}\left(y_n^{N_r}\right), \mathrm{Im}\left(y_n^{N_r}\right)\right]^{\mathrm{T}} \\ f_{FVG}(\mathbf{H}) = [\mathrm{Re}(h_{11}), \mathrm{Im}(h_{11}), \ldots, \mathrm{Re}(h_{N_r N_t}), \mathrm{Im}(h_{N_r N_t})]^{\mathrm{T}} \end{cases} \tag{8}$$

with $\mathbf{d}_n \in \mathbb{R}^{(2N_r + 2N_r N_t)\times 1}$.

C. DNN Structure and Training Procedure

As shown in Fig. 3, the DNN is a classical multilayer network model that contains an input layer and L fully connected layers.

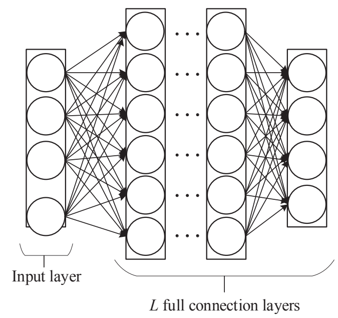

Fig. 3. The structure of DNN.

During the training process, the pre-processed training data is first fed into the network and forward computation is performed layer by layer. The feature input vector is transformed by the common action of weights, bias, and nonlinear activation function to reach the output layer. For the l-th layer, we set the weight matrix and the bias vector as $\mathbf{W}$ and $\mathbf{b}$, respectively, so that the final output is given by

$$\begin{aligned} \mathbf{Z}^L = f^L & \left(\mathbf{W}^L \left(f^{L-1}\left(\mathbf{W}^{L-1}\left(\cdots f^1\left(\mathbf{W}^1 \mathbf{Z}^0 + \mathbf{b}^1\right)\cdots\right)\right.\right.\right. \\ & \left.\left.\left. + \mathbf{b}^{L-1}\right)\right) + \mathbf{b}^L\right), \end{aligned} \tag{9}$$

where $\mathbf{Z}^0$ is the input vector of the DNN detector, and $f(\cdot)$ indicates the activation function that adds nonlinear factors into the model to improve the ability of nonlinear fitting. With the aim to make the model more sparse, so as to better mine the relevant features and fit the training data, the rectified linear unit (ReLU) activation function is adopted in the hidden layers, and is expressed as

$$f_{\mathrm{ReLU}}(x) = \max(0, x). \tag{10}$$

The sigmoid activation function is employed to solve binary classification problem in the output layer, and given by

$$f_{\mathrm{sig}}(x) = \frac{1}{1 + e^{-x}}. \tag{11}$$

The binary cross-entropy can be utilized as the loss function to measure the DNN performance and formulated as

$$Loss = -\frac{1}{P}\sum_{i=1}^{P} z_i \log\left(p\left(z_i\right)\right) + \left(1 - z_i\right)\log\left(1 - p\left(z_i\right)\right), \tag{12}$$

where P denotes total bits, z_i identifies binary bit 0 or 1, and $p\left(z_i\right)$ is the prediction probability. We can add ℓ_2-norm to the loss function to optimize the objective function. Therefore, a smooth solution is obtained to prevent the model overfitting.

In addition, an efficient adaptive momentum (Adam) optimization algorithm is applied for accelerating convergence by adaptively adjusting different learning rate for each different parameter and realize lightweight DNN design. The objective of the training process of the proposed DNN-PSD algorithm is by minimizing the loss function to search for the most optimum parameter set.

D. Complexity Analysis

From the perspective of measuring the merit of an algorithm, the complexity is a key metric. The computational complexity of the proposed DNN-PSD algorithm and the typical detection schemes, ML and MRC, is presented in Table I. For the ML and MRC detectors, their complexity is immensely affected by the transmit-receive antennas and modulation constellation size. Nevertheless, for the proposed DNN-PSD algorithm, the primary factor that affects its complexity is δ_l, the nodes in the l-th layer. Any change in the transmit-receive antennas and modulation order has little impact on the complexity of the proposed DNN-PSD, unlike the other typical detectors.

TABLE I
COMPUTATIONAL COMPLEXITY OF VARIOUS DETECTORS

Detector	Complexity
ML	$6N_rN_tMN$
MRC	$((6N_r+3)\,N_t+6N_rM)\,N$
DNN-PSD	$\left((2N_r+2N_rN_t)\,\delta_1+\sum_{k=1}^{L-1}\delta_k\delta_{k+1}\right)N$

IV. SIMULATION RESULTS AND ANALYSIS

The BER performance of the proposed DNN-PSD algorithm, ML and MRC detection schemes is presented under different scenarios in this section. Herein, we consider a 2×2 SM-OFDM system with $N=128$ and BPSK/QAM modulation, where flat Rayleigh fading channel is employed. In such a system configuration, the parameters and the corresponding values of the DNN detection scheme are exhibited in Table II. The training data is generated by simulation, and its total number is 2×10^5, of which 70% is used for training and 30% is taken for validation. In the training phase, the training epochs and learning rate are set with values of 100 and 0.001, respectively. We assume that the noise follows i.i.d Gaussian distribution and the perfect CSI is aware on the receiver side.

TABLE II
DNN PARAMETERS AND VALUES OF PROPOSED DETECTOR

Parameters	Value	Parameters	Value
Input nodes	$2(N_r+N_rN_t)$	Optimizer	Adam
Output nodes	P	Loss function	Binary cross entropy
Hidden layers	2	Hidden nodes	64-32
Hidden layer activation function	ReLU	Number of training set	140000
Output layer activation function	Sigmoid	Number of validation set	60000
Learning rate	0.001	ℓ_2	0.0001
Epoch	100	Training SNR	20dB

Fig. 4 exhibits the BER performance of the DNN-PSD under different training signal to noise ratios (SNRs) with BPSK. We can notice that BER performance improves as the training SNR increases, but with limited improvement. Therefore, we should select the appropriate training SNR to effectively improve the detection performance. In order to get the satisfied performance, the training SNR is set to be 20dB in the subsequent simulation.

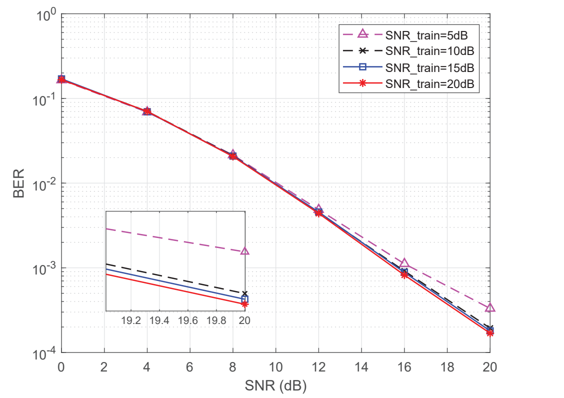

Fig. 4. BER of the proposed DNN-PSD with BPSK and different training SNRs.

The BER contrast for the three detection schemes in the SM-OFDM system is depicted in Fig. 5, with BPSK and QAM, respectively. As an illustration in Fig. 5(a), the BER performance of the DNN-PSD algorithm is pretty identical to the ML detection and vastly superior to the MRC detection. At the BER of 10^{-2} for BPSK modulation, the proposed DNN-PSD gets about 8.7dB gains over MRC detection, but ML detection only has about 0.3dB gains over DNN-PSD. This is due to the powerful nonlinear fitting and learning capabilities of DNN, which can achieve near optimal BER performance. When using high order modulation, the same conclusion can be clearly viewed in the Fig. 5(b). The BER performance of the DNN-PSD is quite similar to the ML detection and considerably outperforms the MRC detection.

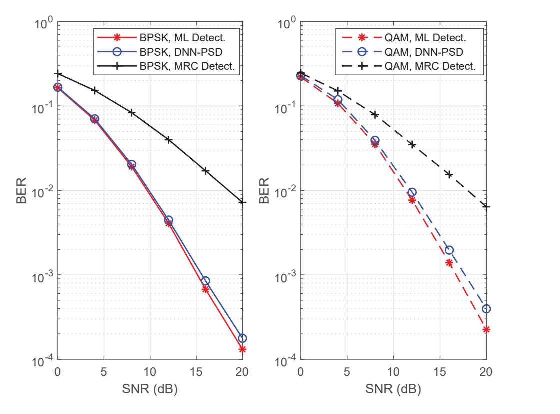

Fig. 5. BER of the DNN-PSD and the typical detection with two modulation schemes (a) BPSK (b) QAM.

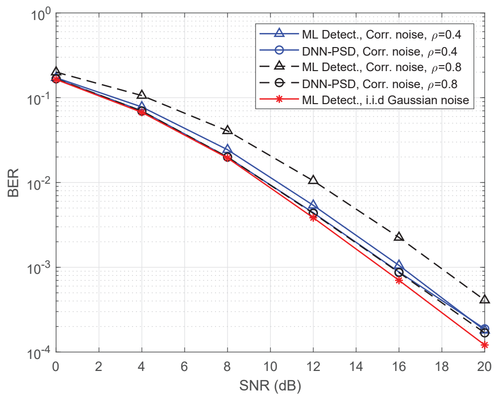

Fig. 6. BER of the DNN-PSD and the ML detection under correlated noise with ρ = 0.4, 0.8 and BPSK.

Fig. 6 demonstrates the BER comparison of the DNN-PSD and the ML detection under correlated noise with $\rho = 0.4$ and 0.8, and BPSK. We can see that the BER performance of the DNN-PSD is superior to the ML detection with $\rho = 0.4$ and $\rho = 0.8$, and is almost as good as the ML detection under i.i.d Gaussian noise. There exists a certain BER performance gap for the ML detection as ρ turns larger. A bigger ρ means a higher noise correlation, which may hamper the signal detection procedure. Nevertheless, the BER performance of the DNN-PSD is better under the case of higher noise correlation. Since the DNN can make more effective learning with high correlation, the proposed DNN-PSD can achieve comparable optimal BER performance.

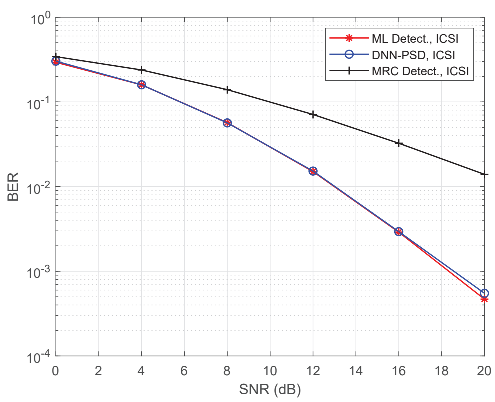

Fig. 7. BER of the proposed DNN-PSD and the typical detection under imperfect CSI.

To further validate whether DNN-PSD has highly adaptive and highly robust characteristics, we consider the simulation under imperfect CSI. Here, we exploit the MMSE based different CSI uncertainty model in [11]. Let us denote CSI error variance by $\epsilon^2 = (1 + \bar{\gamma})^{-1}$, where $\bar{\gamma}$ represents the average SNR. Fig. 7 illustrates the BER performance of the DNN-PSD, the ML detection and the MRC detection under imperfect CSI. It is clearly seen that the BER performance of the DNN-PSD is supremely analogous to the ML detection and outperforms the MRC detection significantly. The DNN trained with perfect CSI can also achieve excellent detection performance under imperfect CSI. The reason is that the DNN schemes are capable of acquiring and remembering the characteristics of the authentic channel and may achieve better signal detection in the SM-OFDM system.

V. Conclusion

In this paper, a novel DNN-PSD algorithm has been proposed in the SM-OFDM system to recover the information bits for each subcarrier parallelly using the uniform small-scale DNN, which considerably reduces the detection complexity. The detailed data pre-processing process, the DNN structure, the training procedure, and the computational complexity have been presented. Simulation results and analysis reveal that the proposed DNN-PSD gets the near optimal BER performance, strikes a brilliant compromise between the system BER performance and detection complexity, and has high adaptability and robustness. In the future, we will extend the algorithm based on DL to cooperative SM-OFDM systems, and optimize the network design to adapt to higher dimensional systems.

References

[1] Y. Li, J. C. Dai, Z. W. Si, K. Niu et al., "Unsourced multiple access for 6G massive machine type communications," *China Commun.*, vol. 19, no. 3, pp. 70-87, March 2022.

[2] Y. Li, X. Lei, Y. Xiao, M. Xiao and X. Zhou, "Performance Evaluation of Offset Spatial Modulation Systems With Practical Channel Estimation," *IEEE Syst. J.*, vol. 16, no. 1, pp. 1334-1344, Mar. 2022.

[3] Y. Xie, X. Liu, K. C. Teh and Y. L. Guan, "Robust Deep Learning-Based End-to-End Receiver for OFDM System With Non-Linear Distortion," *IEEE Commun. Lett.*, vol. 26, no. 2, pp. 340-344, Feb. 2022.

[4] K. Jiang, P. Yang, Y. Xiao, Z. Liu, Y. L. Guan and M. D. Renzo, "Power Allocation-Aided Enhanced SM-OFDM: Closed-Form Solutions and Experimental Results," *IEEE Trans. on Veh. Technol.*, vol. 71, no. 2, pp. 2146-2151, Feb. 2022.

[5] I. Al-Nahhal, O. A. Dobre and S. Tkki, "Reliable Detection for Spatial Modulation Systems," *2020 IEEE 92nd Veh. Technol. Conf.*, pp. 1-5, 2020.

[6] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Netw.*, vol. 61, pp. 85-117, Jan. 2015.

[7] L. Ge, Y. Guo et al., "Deep Neural Network Based Channel Estimation for Massive MIMO-OFDM Systems With Imperfect Channel State Information," *IEEE Syst. J.*, vol. 8, no. 4, pp. 1228-1231, Aug. 2019.

[8] N. Farsad and A. Goldsmith, "Neural Network Detection of Data Sequences in Communication Systems," *IEEE Trans. on Signal Process.*, vol. 66, no. 21, pp. 5663-5678, Nov. 2018.

[9] A. M. Badi, T. Y. Elganimi, O. A. S. Alkishriwo and N. Adem, "Channel Estimation Based on Machine Learning Paradigm for Spatial Modulation OFDM," *IEEE MI-STA*, 2021, pp. 752-755.

[10] B. Shamasundar and A. Chockalingam, "A DNN Architecture for the Detection of Generalized Spatial Modulation Signals," *IEEE Commun. Lett.*, vol. 24, no. 12, pp. 2770-2774, Dec. 2020.

[11] T. Van Luong and Y. Ko, "Impact of CSI Uncertainty on MCIK-OFDM: Tight Closed-Form Symbol Error Probability Analysis," *IEEE Trans. on Veh. Technol.*, vol. 67, no. 2, pp. 1272-1279, Feb. 2018.