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RESEARCH ARTICLE

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A NEW RECEIVER DESIGN FOR SPATIAL MODULATION SYSTEMS*

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ABSTRACT

In this study, spatial modulation (SM), which is an interesting and new approach for 5G and beyond communication systems, and deep neural network (DNN), which have also received great attention recently, are discussed, and a DNN-based receiver architecture for SM systems is proposed. Since the DNN will not be retrained until the channel change after training, it requires less processing, so it will be a potential receiver architecture for next-generation wireless communication and therefore SM systems. In this paper, a new DNN-based SM receiver is proposed to detect the transmitted symbols and the activated antenna index at the same time, and its performance is examined. As can be seen from the computer simulations, the DNN-based receiver offers low error performance with a small number of hidden layers and a low number of neurons in these layers. At the same time, even when the data rate is increased, the same DNN structure (without increasing the processing load) shows better/same performance than the receivers in the literature.

Keywords: *MIMO, Spatial Modulation, Deep Learning, Deep Neural Network.*

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UZAYSAL MODÜLASYON SİSTEMLERİ İÇİN YENİ BİR ALICI TASARIMI

ÖZ

Bu makalede, 5G ve ötesi iletişim sistemleri için ilgi çekici ve yeni bir yaklaşım olan uzaysal modülasyon (Spatial Modulation (SM)) ile yine son zamanlarda büyük ilgi gören derin sinir ağları (Deep Neural Network (DNN)) konuları ele alınmış ve SM sistemleri için DNN tabanlı alıcı mimarisi önerilmiştir. DNN, eğitim sonrası kanal değişene kadar yeniden eğitilmeyeceğinden daha az işlem gerektirir, bu nedenle yeni nesil kablosuz iletişim ve dolayısıyla SM sistemleri için potansiyel bir alıcı mimarisi olacaktır. Bu çalışmada, aktif edilmiş anten indisi ile iletilen sembolleri ortaklaşa algılamak için tam bağlantılı (fully connected) DNN tabanlı yeni bir SM sezici önerilmiş ve performansı analiz edilmiştir. Bilgisayar benzetimlerinden de görüldüğü gibi DNN tabanlı alıcı az sayıda gizli katman ve bu katmanlardaki yine az sayıdaki nöron sayısı ile düşük hata performansı sunmaktadır. Aynı zamanda veri hızı artırıldığında bile aynı DNN yapısı (işlem yükü artmadan) literatürdeki alıcılardan daha iyi/aynı performansı göstermektedir.

Anahtar Kelimeler: *MIMO, Uzaysal Modülasyon, Derin Öğrenme, Derin Sinir Ağları*

1. INTRODUCTION

Today, access to information quickly and accurately has become an indispensable need. Therefore, multiple-input multiple-output (MIMO) systems are currently one of the most effective methods in increasing the reliability of information. MIMO systems aim to increase the capacity of the radio link with the multipath obtained by using multiple transmit and receive antennas (Telatar, 1999). MIMO has been a fundamental element used in new generation communication standards such as IEEE 802.11n (Wi-fi 4), IEEE 802.11ac (Wi-fi 5) (IEEE, 2020), WiMAX, Long Term Evolution (LTE) (IEEE, 2017). The two main MIMO transmission techniques in the literature are space-time block code (STBC) (Tarokh et al., 1999) and spatial multiplexing (SMX) (Tse & Viswanath, 2005). The first of these techniques extends the traditional two-dimensional signal constellation set to space and time dimensions, providing transmission diversity, and increasing signal reliability. However, an orthogonal STBC per channel use provides the full symbol rate for two transmit antennas, while for more than two transmit antennas, it is a maximum of 3/4 symbols. The latter can achieve higher data rates. The best-known applications of SMX are Bell Labs layered space time (BLAST) techniques. In one of the BLAST techniques, Vertical-BLAST (V-BLAST) (Wolniansky et al., 1998), the capacity is increased by sending multiple symbols from multiple transmit antennas. However, since these systems have simultaneous transmission over all antennas, a pricy radio frequency (RF) stage is needed for whole antennas and a high rate of inter-channel interference (ICI) occurs, which adds additional complexity to the receiver.

Spatial modulation (SM) (Mesleh et al., 2008), which carries information in both antenna domain and classical symbol set, has started to attract increasing attention in recent years and has become a new alternative to STBC and SMX. In an SM system where N_t is the number of transmit antennas and M is the size of the constellation set for conventional phase shift keying (PSK)/quadrature amplitude modulation (QAM) modulations, $\log_2(N_t M)$ information bits are assigned to an SM symbol. The first $\log_2(N_t)$ bit of the total $\log_2(N_t M)$ bit defines the transmit antenna, while the remaining bits are reserved for M-PSK/QAM modulation. Since a single transmit antenna is activated during each symbol transmission, a single RF stage is adequate in SM systems and ICI is eliminated.

As a result of the popularity of SM, special cases of SM such as space shift keying (SSK) (Jeganathan et al., 2009), generalized spatial modulation (GSM) (Younis et al., 2010), quadrature SM (QSM) (Mesleh, Ikki & Aggoune, 2015), receive SM (RSM) (Yang, 2011), etc. has been proposed. In SSK, information is carried only in antenna domain where symbol domain is not used. In the GSM system, multiple transmit antennas are enabled rather than a single antenna for increasing the data rate. In QSM, on the other hand, PSK/QAM symbols are divided into real and imaginary parts and sent over activated antennas. In RSM, the receive antenna indices convey messages with the help of precoding in the transmitter. An extensive study of SM systems can be found at (Wen et al., 2019).

Artificial neural networks (ANNs) are parallel and distributed computing structures that are designed with inspiration from the human brain, and are formed with interconnecting nodes, each of which operates with weighting and biasing (Hassoun, 2003). In other words, they are computer programs that emulate biological neural networks. Deep neural networks (DNN) are defined as versions of ANNs that are structurally "deep" by increasing the number of hidden layers and neurons in these layers. In recent years, DNN has been used in many fields from health to medicine, engineering applications to architecture, finance to weather forecasts, biology to chemistry, etc. Three main techniques are generally used in DNN applications, namely: Fully connected neural network (FCNN), convolutional neural network (CNN) and recurrent neural network (RNN). Detailed information on these techniques can be found in (Hassoun, 2003), (Bishop, 2006).

The use of ANNs in wireless communication has attracted great interest and there has been a great increase in studies on the subject in recent years. Studies on the use of DNN in wireless communication can be found in (Dai et al., 2020) and its references. This interest in DNN has started to be seen in SM and other variants (SSK, GSM, etc.) and various studies have emerged. Transmit antenna selection and power allocation for SM systems using machine learning methods are investigated in (Yang et al., 2019). A GSM system in which the transmitted symbols and antenna indices are determined by separate DNN structures is given in (Shamasundar & Chockhalingam, 2020). Unlike (Shamasundar & Chockhalingam, 2020), the GSM system, which uses a Block-DNN structure that decodes both active antenna indices and modulated symbols together, is studied in (Albinsaid et al. 2020). In (Luong et al., 2019), the OFDM frames are decoded by FCNN technique in index modulated OFDM (OFDM-IM) structure. In (Kim, Ro & Park, 2021), an architecture that decodes active antenna indices with CNN and transmitted PSK/QAM symbols with FCNN is proposed for dual-mode OFDM-IM. (Altın, 2022) develops a new detection technique for MIMO-OFDM-IM using deep learning (DL) methods.

To the best of the authors' knowledge, a receiver design using the DNN method for the SM system (only for SM, not for other variants of SM) has never been considered. In this study, a new SM receiver using FCNN is constituted to decode SM symbols. The main contributions of this article are listed below:

- Since the complexness of the optimum receiver for SM systems increases exponentially due to the number of transmit and receive antennas, and constellation size, using a DNN-based receiver will be a more convenient solution due to its near-optimal performance and lower complexity.

- As far as is known, DNN-based receiver structures have been studied for other types of SM in the literature, but no study has been done in this direction for SM. In these studies, antenna indices and modulated symbols is determined separately. However, since the correct decoding of both dimensions at the same time in SM is very important for performance, a DNN receiver is designed in this paper that jointly detects both the antenna index and the transmitted symbol.

- In order to increase the performance, some studies in the literature process the received signal in another layer and give it to the DNN input. However, this complicates the receiver even more and brings extra costs. In our study, there is no preprocessing before DNN.

The remainder of the paper is composed as follows. The classical SM scheme and optimal decoding for the SM are re-examined in Section 2. In Section 3, the architecture, training and testing phases of the DNN for the

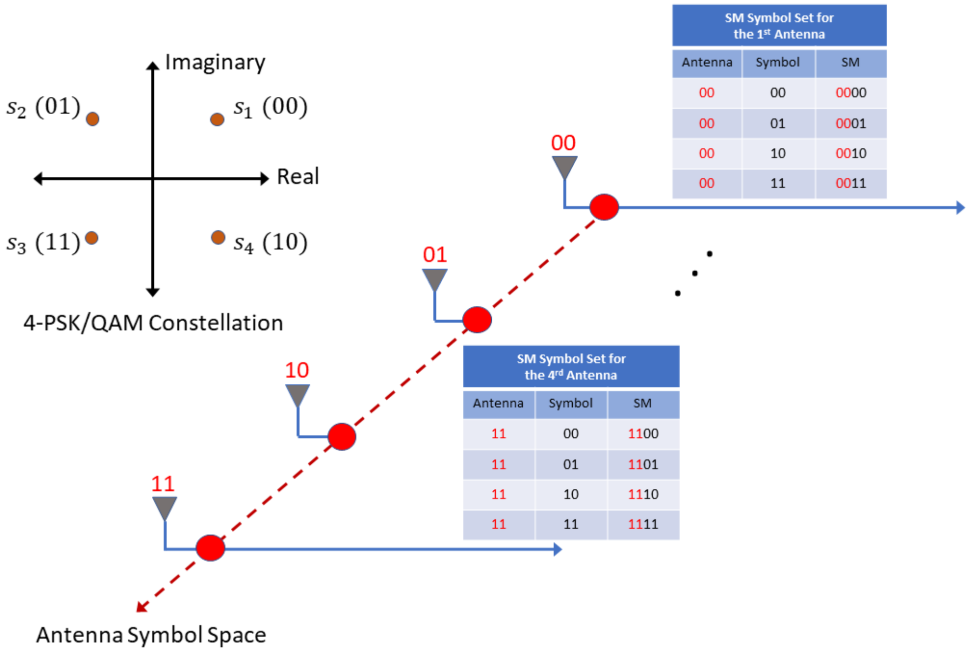

Figure 1. SM constellation for $N_t = 4$ and 4-PSK/QAM modulation.

SM receiver are proposed in Section 3. The computer simulations for the proposed scheme are given in Section 4 and Section 5 concludes the work.

Notation: A scalar is represented by lowercase and uppercase italics. A vector is in bold, lowercase and a matrix is in bold, uppercase letters. $(.)^T$ and $(.)^H$ denote transpose and Hermitian transpose, respectively. $\|.\|$ corresponds to the Euclidean/Frobenius. $\mathbf{I}_N$, is the $N \times N$ unitary matrix. $diag(.)$ shows the diagonal of a matrix and $vek(\mathbf{A})$ is the vectorization operator by writing consecutive columns of matrix $\mathbf{A}$. $\mathbb{C}^{n \times m}$ shows the dimensions of a complex matrix. Expectation operation is denoted by $E\{.\}$. $\mathcal{CN}(0, \sigma^2)$ describes a circularly symmetric, zero-mean complex Gaussian distribution with σ^2 variance. Binomial coefficient and floor operator can be given as $\binom{.}{.}$ and $\lfloor . \rfloor$, respectively. $\Re\{.\}$ is the real part and $\Im\{.\}$ is the imaginary part of a complex number.

2. CLASSICAL SM SCHEME

As mentioned before, it can be thought that the antenna index is added as a third dimension to the two-dimensional signal set to transmit information in the SM method. Thus, the SM symbol is selected from the set of symbols, an example of which is shown in Figure 1. So, an SM symbol with unit energy, $E\{\mathbf{s}^H\mathbf{s}\} = 1$, can be given as $\mathbf{s} = \left[\underbrace{0 \;\; \dots \;\; 0}_{i-1} \quad s_q \quad \underbrace{0 \;\; \dots \;\; 0}_{N_t-i}\right]^T$ where i is the activated antenna index and s_q is the M-PSK/QAM symbol. For the channel matrix $\mathbf{H}$, which consists of independent and identically distributed (i.i.d.) random variables with $\mathcal{CN}(0,1)$ distribution, and the noise vector $\mathbf{n}$, which consists of i.i.d. random variables with double-sided noise spectral density N_0 and $\mathcal{CN}(0, N_0)$ distribution, the received signal vector will be

$$\begin{aligned} \mathbf{r} &= \mathbf{Hs} + \mathbf{n} \\ &= \mathbf{h}_i s_q + \mathbf{n}. \end{aligned} \qquad (1)$$

Here, $\mathbf{h}_i$ represents the i^{th} column of the matrix **H.**

Under the assumption that the channel state information (CSI) is known at the receiver, when the maximum likelihood (ML) method, which is the optimum detection technique, is used, the antenna index and the transmitted signal is decided with

$$\left[\hat{\imath}, s_{\hat{q}}\right] = \arg\min_{i,q} \left\| \mathbf{r} - \mathbf{h}_i s_q \right\|^{\mathbf{2}} \qquad (2)$$

(Jeganathan et al., 2008). The receiver complexity of the ML method given in (2) increases with the size of the symbol set, *M,* and the number of transmit and receive antennas. For this reason, many studies have been carried out in the literature to reduce the complexity of ML. Some of these works are presented in (Al Nahhal et al., 2019; Liu et al., 2019; Jiang et al., 2015; Men & Jin, 2014; Rajashekar et al., 2014; Tang et al., 2013; Wang, Jia & Song, 2012; Pillay & Xu, 2013; Zhang & Yin, 2014). However, these studies have generally been developed by arranging and applying known algorithms, and as far as we know, heuristic methods have never been applied for the SM technique.

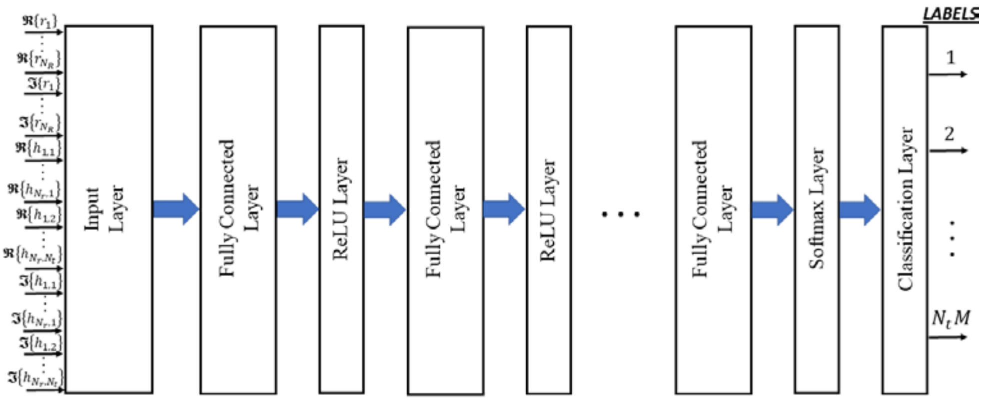

Figure 2. Proposed DNN-based SM receiver.

3. A NEW RECEIVER DESIGN FOR SM SYSTEMS

3.1. DNN-based Receiver Architecture

SM receiver architecture with a single DNN-based decoder is presented in Figure 2. This architecture has no preprocessing, which further increases the receiver's processing load, so the received signal and channel parameters are given to the input of the proposed DNN, as they are, assuming that CSI is present at the receiver (as in ML). At the same time, since the DNN method is inspired by the human brain, generally the input information is real numbers. Therefore, in our study, the inputs are expressed in real terms as well. As a result, the input (feature) vector for the receiver can be written as

$$\mathbf{v} = \left[\left(\Re(\mathbf{r})\right)^T \left(\Im(\mathbf{r})\right)^T \left(\Re(vek(\mathbf{H}))\right)^T \quad \left(\Im(vek(\mathbf{H}))\right)^T\right]^T. \tag{3}$$

As seen in Figure 2, the proposed DNN receiver consists of multiple fully connected (FC) layers and a classification layer. FC layers transmit the output of the previous layer to the next layer by multiplying it with a weighting matrix and summing it with a bias vector. Furthermore, the rectified linear unit (ReLU) function, which makes the negative input 0 and determines the positive input as itself, is used to activate the neurons, i.e. $f(z) = \max\,(0, z)$. The softmax function, which shows the probabilities of the results, is selected for the output layer as $\sigma(\mathbf{x})_i = \frac{e^{x_i}}{\sum_{j=1}^{Z} e^{x_j}}, i = 1,2, \dots, Z$

for an arbitrary vector $\mathbf{x} = [x_1 \ x_2 \ldots x_Z] \in \mathbb{R}^{\boldsymbol{Z}}$. Therefore, the most probable outcome will correspond to the index of that symbol inside the SM symbol set. Since there are possible $N_t M$ SM symbols to be classified, the number of neurons for the classification layer will also be $N_t M$.

3.2. Training and Testing Phases

The received signal and the channel parameters are needed to train the DNN. At this phase, no channel estimation is needed since the DNN will be trained offline, and the received signal, **r,** and the corresponding channel parameters, **H**, which are artificially generated using (1), help to train the DNN. The noise vector in (1) can be randomly generated based on a given SNR value.

At the training stage, labels are given to each of the SM symbols produced in the transmitter and known in the receiver, and the DNN is expected to make the right decision on these labels at the end of the training process. The labels that will correspond to the SM symbols to be formed for the proposed DNN is given in Table 1.

Table 1. Labelling for training sequence.

SM Symbol	Label
$[s_1 \quad 0 \quad \ldots \quad 0 \quad 0]^T$	1
$[s_2 \quad 0 \quad \ldots \quad 0 \quad 0]^T$	2
$\vdots$	$\vdots$
$\left[0 \quad \ldots \quad 0 \quad \underbrace{s_q}_{i} \quad 0 \quad \ldots \quad 0\right]^T$	i_q
$\vdots$	$\vdots$
$[0 \quad 0 \quad \ldots \quad 0 \quad s_M]^T$	$N_t M$

For a good performance in the training phase, the number of dataset is selected at least 10^7. In addition, 20% of the produced data is reserved for testing/validating of the proposed network. Dataset generation at the training stage is given in Algorithm 1. If the dataset is very large, it can be divided into smaller sets, which is called mini batches, to increase processing speed.

Algorithm 1. Data generation for DNN.

Input: $N_t, N_r, M,$

Initialization: Number of Dataset, SNR

for i ⟵Number of Dataset **do**

Generate randomly $N_r \times N_t$ channel matrix, **H**, and $N_r \times 1$ AWGN noise vector, **n**, based on fixed SNR value.

Generate known GSM symbols corresponding to the $\log_2(N_t M)$ bit and give each a label according to Table 1.
$\mathbf{l} = \left[l^{(1)}, l^{(2)}, \dots, l^{(i)}\right]^T, \qquad l \in \{1,2,\dots,N_t M\}$

$\mathbf{r} = \mathbf{h}_i s_q + \mathbf{n}$

$\mathbf{v}^{(i)} = \left[\left(\Re(\mathbf{r})\right)^T \left(\Im(\mathbf{r})\right)^T \left(\Re(vek(\mathbf{H}))\right)^T \quad \left(\Im(vek(\mathbf{H}))\right)^T\right]^T$

end

Allocate 20% of the generated dataset for validation of the network (test).

Output: $\mathbf{v}^{(training)}, \mathbf{v}^{(test)}, \mathbf{l}^{(training)}, \mathbf{l}^{(test)}$

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4. SIMULATION RESULTS

In this section, computer simulations are depicted for the proposed DNN-based SM receiver on a standalone PC with an AMD Ryzen 5 3600 @3.60 GHz CPU, NVIDIA GeForce GTX 1650 GPU, and 16 GB RAM. These computer simulations include finding the best SNR value and BER results made accordingly. At the same time, the comparisons of the proposed structure according to the BER results with other studies (Wang, Jia & Song, 2012), (Pillay & Xu, 2013) and (Mesleh et al., 2006) are also presented. For DNN simulations, the mini batch size is set as 4096, and step-based learning schedule is selected to scan the first steps quickly and to investigate the next steps in more detail. In here, the initial learning rate is chosen as 0.01 and is reduced by 10% in every 2 epochs.

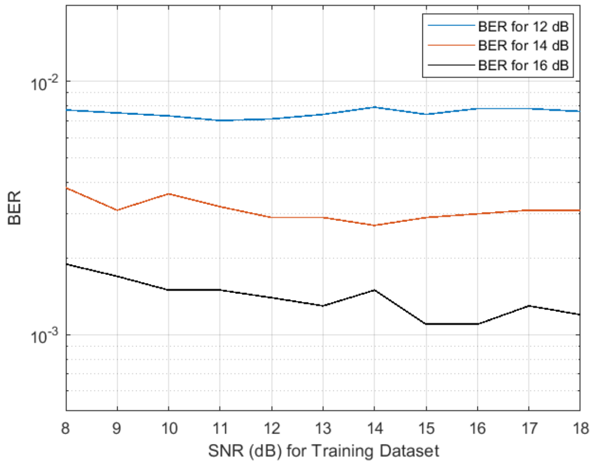

Figure 3. Bit error probabilities for $N_t = 2$, $N_r = 4$ and 16-QAM according to SNR values to be used to determine noise levels in training dataset.

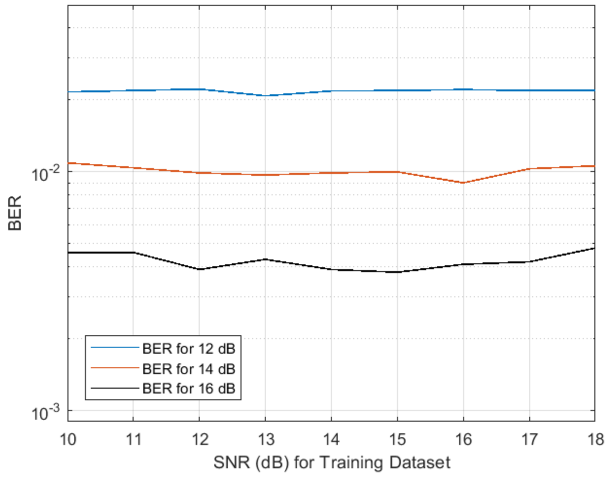

Figure 4. Bit error probabilities for $N_t = 2$, $N_r = 4$ and 32-QAM according to SNR values to be used to determine noise levels in training dataset.

On the other hand, the signal-to-noise ratio (SNR) is applied as the received SNR seen at the receiver front end. The performance of a DNN receiver is closely related to how well it is trained. For this reason, the noise level to be used in the dataset gains importance. Thus, a trained DNN according to an appropriate SNR will give optimal error performance at all SNR levels. In Figures 3 and 4, bit error probabilities (BER) are given according to the SNR values to be used in determining the noise level in the training dataset for the data rate *R=5 bits/second/Hz* and *R=6 bits/second/Hz*, respectively. In Figure 3, the BER performances of the SM system at 12 dB, 14 dB, and 16 dB show that they jointly perform at the lowest when the training is realized at an SNR of 13 dB. Again, with the same method, if the DNN structure suggested for *R=6 bits/second/Hz* is trained with a 15 dB SNR level, the BER performance of the whole system will be at the optimum level as in Figure 4.

Figure 5 shows the accuracy level during training of the proposed DNN structure with 128 and 96 neurons in the first and second hidden layers, respectively ([128 96]) and the reduction of the loss function according to each iteration. As can be seen from the figure, the proposed DNN architecture reaches a very high level of accuracy in the first iterations and reaches its highest level in the 3rd epoch. This shows that there is no need for long epochs to train the DNN. Likewise, the loss function reaches its minimum value in low iteration numbers.
Figure 6 shows the error performance curves of DNN structures in various configurations and MRC and SVD detectors in the literature for a data rate of *R=5 bits/second/Hz.*

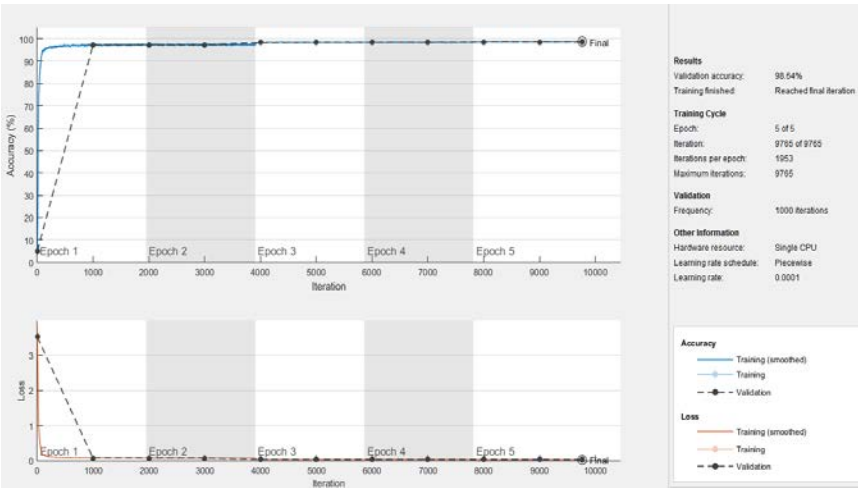

Figure 5. Accuracy level and loss function during training of [128 96] DNN.

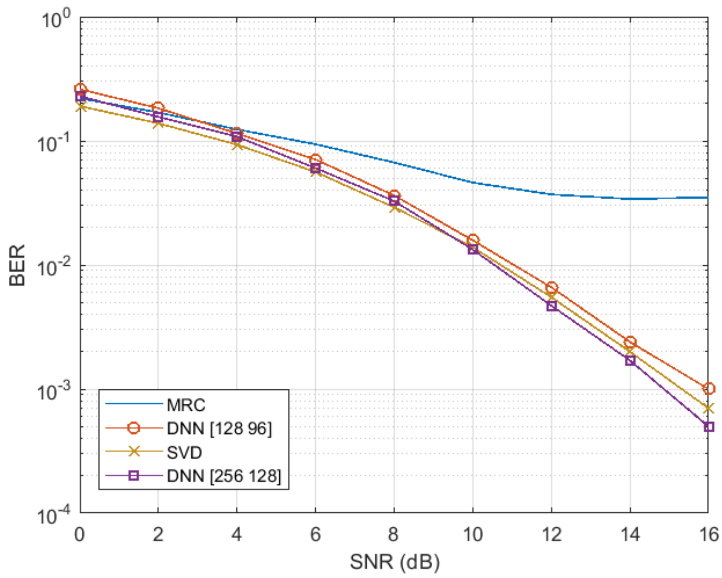

Figure 6. BER performance comparison for R=5 bits/second/Hz.

For the training dataset in DNN, SNR = 13 dB and the number of epochs is chosen as 5. As can be seen from the BER curves presented for the MIMO system structure with $N_t = 2$, $N_r = 4$ and 16-QAM, the [256, 128] DNN receiver gives much better results than the MRC detector, and it provides 0.5 dB SNR gain at 10^{-3} error probability with respect to SVD detector. Moreover, if it is desired to train the DNN faster and reduce the processing load, the number of neurons in the FC layers can be reduced. As can be seen from Figure 6, although the [128, 96] DNN receiver has lower neuron numbers, it gives better results than the MRC algorithm and offers similar performance to the SVD algorithm.

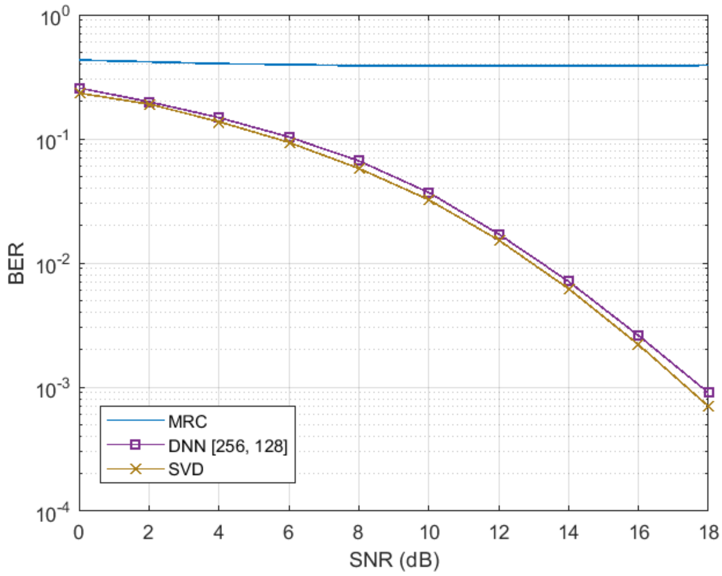

Figure 7. BER performance comparison for R=6 bits/second/Hz.

Figure 7 shows the BER performance curves of SM receivers for a data rate of *R=6 bits/second/Hz*. MIMO system structure is determined as $N_t = 2$, $N_r = 4$ and 32-QAM. Here, it shows almost the same BER performance as the SVD algorithm, even though the same DNN structure is used and the data rate and signal set size are increased compared to the MIMO configuration in Figure 6. It should be noted that although the computational load of the MRC and SVD algorithms grows with the constellation size, *M*, there isn't any increase for the DNN.

5. CONCLUSION

SM is a new and interesting transmission technique for MIMO systems that will be a candidate for 5G and beyond communications with its features such as high data rate, using a single RF chain in the transmitter, and completely eliminating ICI. Simultaneously, DNN-based solution methods have begun to be used in today's technologies due to the many advantages it offers. In this paper, the use of DNN-based detector in the receiver structure of SM is examined. As can be seen from the computer simulations, DNN-based SM receiver offers high performance without the need for many hidden (FC) layers and number of neurons. At the same time, even when the data rate is increased, the same DNN structure (without increasing the processing load) shows better/same performance than the detectors in the literature.

CONFLICT OF INTEREST STATEMENT

The author declares no conflict of interest.

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