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UTILIZATION OF DEEP LEARNING ARCHITECTURES FOR MIMO DETECTION

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Abstract. Applications of deep learning in communications systems are becoming popular today with their powerful solutions to complex problems. This study considers the utilization of deep learning detectors for small-scale multiple-input multiple-output systems. Deep neural network, long short-term memory, and one-dimenisonal convolutional neural network architectures are discussed and the bit error rate performances of these deep learning based detectors are compared with the optimal maximum likelihood and sub-optimal minimum mean square error detectors. Simulation results show that the deep neural network architecture has the best detection performance among the discussed deep learning detectors and may outperform the sub-optimal minimum mean square error detector. For small-scale multiple-input multiple-output systems, the performance of the deep learning based detector is close to that of the optimal detector.

1. Introduction

Unlike the single-input single-output (SISO) systems, in a multiple-input multiple-output (MIMO) system, both the transmitter and the receiver employ more than one antennas to transmit and receive signals at the same time. MIMO technique is a promising technology for the current and next generation systems with the aim of enhancing the spectral efficiency and increasing the reliability. To increase the reliability, in a diversity system the transmitter conveys the same information through multiple antennas, while a MIMO system using spatial multiplexing transmits different signals over a group of transmitter antennas to improve the spectral efficiency.

Keywords. DNN, LSTM, 1DCNN, MIMO, deep learning, detection.
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Traditional MIMO detection techniques have been discussed in the literature [1, 2] for many years. Detection complexity and performance are among the biggest concerns in a typical MIMO system. Among these detection techniques, maximum likelihood (ML) detector has the optimum performance in terms of bit error rate. However, the increasing complexity with the number of antennas makes this technique unfeasible for practical systems. On the other hand, the sub-optimal detection techniques such as the minimum mean square error (MMSE), zero forcing (ZF), Gauss-Seidel, and conjugate-gradient (CG) cause a significant performance degradation while reducing the complexity [3-5].

Deep learning (DL) approaches have brought powerful solutions in many areas such as image and speech recognition, computer vision, and wireless communications for more than two decades [6]. In recent years, DL approaches are also considered as an auspicious solution for MIMO signal detection [7, 8]. DL based MIMO detection is mainly based on two different approaches, model-based and data-driven. Model-based approaches simply unfold the iterations of a well-known detection technique as the layers of a deep learning structure [9,10]. The combination of neural networks with an iterative detection method improves the detection performance and decreases the computation complexity. Also, although the model-based structure is mainly based on DL approaches, it can be trained with much less training data than a traditional data-driven DL algorithm.

In the literature, there are many recent studies that discuss model-based and data-driven approaches. For instance, in [11], a model-based deep learning detection technique for MIMO systems is proposed. Authors state that the proposed technique has a better detection performance than the existing sub-optimal detectors and a lower computational complexity. Another model-based deep learning detection technique, which depends on the orthogonal approximate message passing (OAMP) algorithm, for a MIMO system is discussed in [12]. The proposed technique inserts new parameters to the iterative algorithm to improve the detection performance. The simulation results show that the proposed technique has a superior performance than does the iterative OAMP algorithm under different channel conditions. In [3], instead of adding new parameters to an iterative algorithm, the authors proposed to learn a universal step size value using a model-based DL technique based on conjugate gradient detector. The results show that proposed technique may outperform the performance of the iterative CG detector when the number of antennas is high. On the other hand, purely data-driven MIMO detection solutions are also discussed in the literature for a while. One of the first studies for MIMO detection in the literature is discussed in [13] in which an unsupervised deep learning structure for a MIMO system is proposed by using an autoencoder. Authors claim that DL based solution has a remarkable performance for the MIMO system compared to the existing methods. In [14], two deep neural networks are proposed for MIMO detection and authors state that the proposed DL structures have a high detection accuracy. A recent study [15] discusses DL based MIMO detection for a conventional MIMO system by using deep neural network (DNN) and convolutional neural network (CNN) structures for fixed channel scenarios. The results show that DNN based data-driven structure has a detection performance close to the optimum detection performance for a single-tap channel model, while for multi-tap fixed channel models both CNN and DNN have an acceptable performance at low SNR values. In [16] a DL detection performance for a MIMO system with an erroneous channel information is proposed. Authors state that DNN has a better bit error rate (BER) performance than the CNN structure. Also, authors in [17] discuss a combination of two DNN structures for MIMO detection. They state that the detection performance is close to the optimal maximum likelihood detector. In [18] DL based MIMO detection is studied in an optical transmission system and the results of the proposed structure are compared with traditional detectors.

To sum up, both model-based and data-driven DL based MIMO detection structures have been discussed for the past few years as mentioned above. This study discusses the MIMO detection in terms of various data-driven DL networks such as DNN, long short-term memory (LSTM), and one-dimensional convolutional neural network (1DCNN) architectures. Several MIMO systems with different number of transmitter and receiver antennas are considered to compare the performance of the proposed detectors. Besides, binary phase-shift keying (BPSK), quadrature phase-shift keying (QPSK), and 16-quadrature amplitude modulation (16-QAM) schemes are utilized. Simulation results show that DL based MIMO detectors have a remarkable detection performance and may surpass the detection performance of the sub-optimal detectors.

Organization of this study is as follows. Section 2 describes the system model of the discussion. In Section 3, we will give the details of the proposed structures. Simulation parameters and results are given in Section 4. Finally, a brief conclusion is discussed in Section 5.

2. MIMO System Model

In this study, we discuss a conventional N_rxN_t MIMO system, given in Figure 1, using spatial multiplexing on the transmitter side. Thus, multiple symbols, x_{N_t} are transmitted at the same time with the N_t transmitting antennas. The received symbols, y_{N_r} at the N_r receiver antenna can be given as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{N_r} \end{bmatrix} = \begin{bmatrix} h_{1,1} & \dots & h_{1,N_t} \\ \vdots & \dots & \vdots \\ h_{N_r,1} & \dots & h_{N_r,N_t} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{N_t} \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_{N_r} \end{bmatrix} \tag{1}$$

where h_{N_r,N_t} is the entries of the channel matrix between the N_t-th transmitter antenna and N_r-th receiver antenna, n_{N_r}-th is the additive white Gaussian noise (AWGN), having zero mean and σ^2 variance, in the N_r-th receiver antenna. x_{N_t}, y_{N_r}, n_{N_r}, and h_{N_r,N_t} are complex-valued numbers and the channel represents a flat Rayleigh fading. The channel entries, h_{N_r,N_t} are assumed to be independent and identically distributed (i.i.d) with zero mean and unit variance.

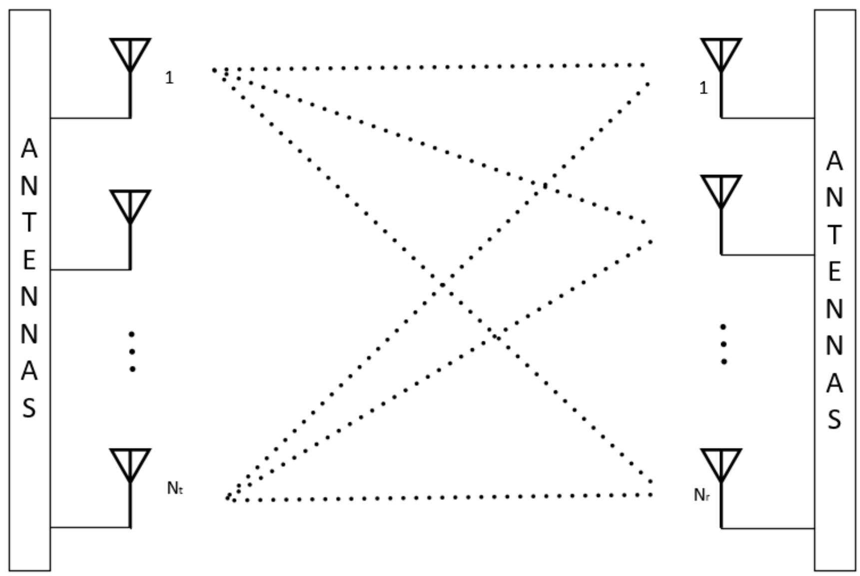


FIGURE 1. Simplified block diagram of a MIMO system.

We discuss two fundamental detection techniques within this section. The optimal maximum likelihood (ML) detector compares all the transmitted symbols and proceeds a likelihood test; therefore, the estimated symbol, $\hat{x}_{ML}$ can be given as follows:

$$\hat{x}_{ML} = \arg min \|y - Hx\|^2 \qquad (2)$$

where y, H, and x are the received symbol, perfectly known channel matrix, and transmitted symbol, respectively.

Sub-optimal detection methods are also available for conventional MIMO systems. For instance, well-known MMSE detector attempts to minimize the mean square error between the transmitted symbol and the received symbol. The estimated symbol, $\hat{x}_{MMSE}$ can be given as follows:

$$\hat{x}_{MMSE} = W_{MMSE}^{H} y = (H^H H + \sigma^2 I_{N_T})^{-1} H^H y \tag{3}$$

where W_{MMSE}^{H} represents the Gramian matrix and the superscript H denotes the Hermitian transpose operator. Besides, σ^2 and I_{N_T} are the noise variance and the identity matrix, respectively.

Basically, both methods rely on the perfectly known channel matrix, while the MMSE detector has a lower complexity than the ML detector but causes degradation in detection performance in a conventional MIMO system.

3. Data-Driven Deep Learning Architectures for MIMO Detection

In this section, we will briefly present the utilization of DNN, LSTM, and 1DCNN architectures for MIMO detection. All of these DL architectures employ a supervised learning using a mapping function between the input and output variables.

Typically, a DNN structure, shown in Figure 2, consists of the input layer, a series of hidden layers, and the output layer. The number of hidden layers and the number of hidden units of each layer vary depending on the complexity of the problem and the performance requirements. Hidden layers mainly provide both a linear and nonlinear relation between the input and output of each layer. This dependency consists of a multiplication matrix w, a bias vector b, and a nonlinear activation function, f. Therefore, depending on the previous layer, the n-th layer output, y_n can be given as follows [19]:

$$y_n = f(w_n . y_{n-1} + b_n) \tag{4}$$

Although different activation functions such as hyperbolic tangent (tanh) or sigmoid can be employed to ensure the nonlinearity of this dependency, nowadays many DNN structure use rectified linear unit (ReLU) activation function, given in (5), which is also a powerful solution for the vanishing gradient problem:

$$ReLU(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{5}$$

The output layer of a typical DNN architecture generally employs a softmax function to obtain the predicted output. Adam optimizer is usually employed to minimize the loss function based on cross-entropy.

Hyper parameters also play a crucial role in deep learning algorithms during the training process. Learning rate, batch size, number of epochs, and normalization of data will definitely affect the performance of the network [15].

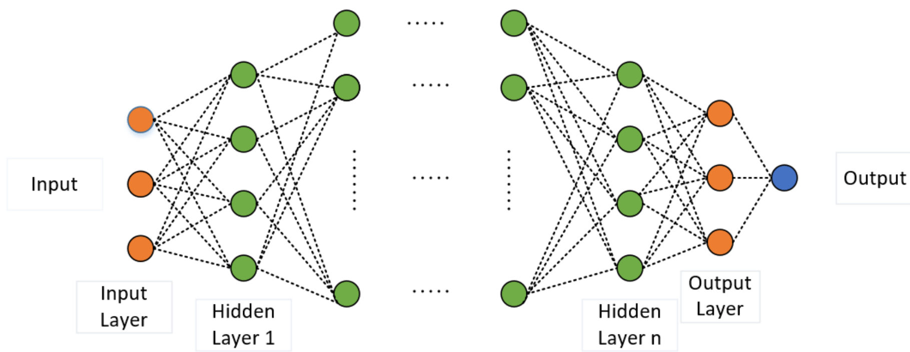


FIGURE 2. Simplified deep neural network (DNN) architecture.

MIMO channel model discussed in (1) is utilized for the DL network. Therefore, the complex-valued system model needs to be converted to an equivalent real domain representation, as shown in (6), to be processed by the deep learning functions. In this equation $Re\{.\}$ and $Im\{.\}$ represents the real and imaginary parts of the complex-valued number, respectively [12, 20]:

$$\begin{bmatrix} Re\{y\} \\ Im\{y\} \end{bmatrix} = \begin{bmatrix} Re\{H\} & -Im\{H\} \\ Im\{H\} & Re\{H\} \end{bmatrix} \begin{bmatrix} Re\{x\} \\ Im\{x\} \end{bmatrix} + \begin{bmatrix} Re\{n\} \\ Im\{n\} \end{bmatrix} \tag{6}$$

A classification of deep networks can be made by the direction of the data flow from the input layer to the output layer. In a feed-forward neural network (FFFN), input data can only move in the forward direction whereas a feedback loop exists in a recurrent neural network (RNN) [21]. In addition to the discussed DNN structure above, CNN is another subclass of FFFN, while LSTM is a typical example of RNN.

While two-dimensional CNN (2DCNN) architecture is a powerful solution for image processing, in this study for MIMO signal detection, we implement the 1DCNN architecture, which is an influential technique for times series and vector data. In a typical CNN structure, in addition to the fully connected layer a convolutional layer is employed to filter the input data by the linear convolution operation. Besides, a pooling layer, which separates the data into sub-blocks to get the maximum or average of each block, is often utilized in a CNN structure. In 1DCNN architecture, both convolutional filter and pooling layers are employed to the one dimensional inputs. A typical activation function such as ReLU and a fully connected layer are also required to construct the 1DCNN structure.

As an RNN structure, LSTM can also be utilized for problems involving correlated samples or time series [20, 21]. Unlike DNN or CNN as examples of FFFN, LSTM allow both forward and reverse flow of data. In an LSTM network architecture, an LSTM layer consists of input, forget, and output gates. Depending on these gates, LSTM architecture decides which information will be passed to other layers, whether it is important to remember, and how this information will affect the dependency in the input data. Although LSTM architecture is considered as a suitable solution for time series and correlated samples, it can also be employed in MIMO signal detection [15, 20]. An LSTM architecture basically consists of LSTM layers with different number of hidden units and a fully connected layer.

In general, DL based algorithms require a large amount of training data for the architecture to learn variables and provide high performance, which increase the computational complexity. In addition, number of layers, number of filters, filter sizes, type of activation function also affect both the complexity and the learning performance of the network. However, in many practical deep learning applications, training is an offline process and the computational complexity of learning algorithms is not considered as a major burden for the feasibility of these approaches.

4. Simulation Parameters and Results

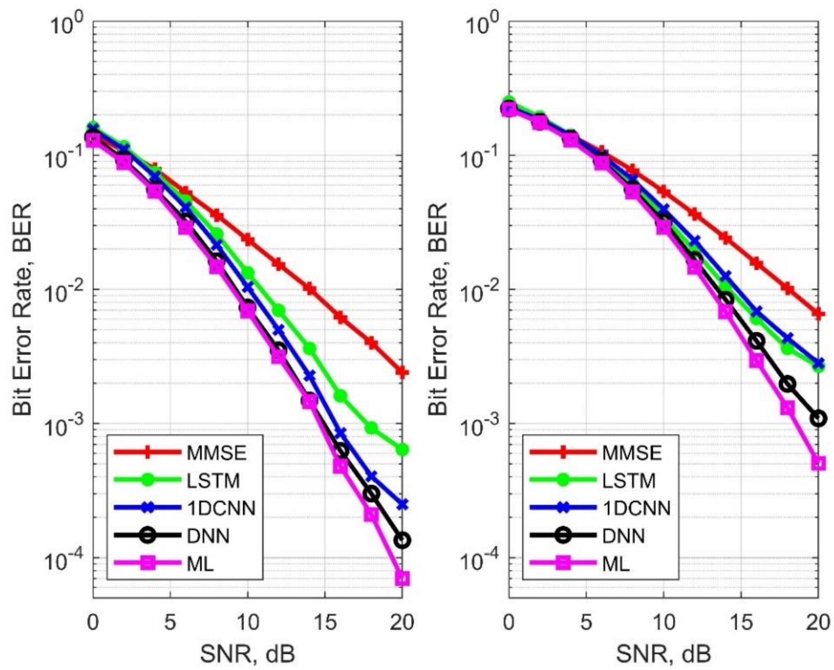
In this study, we utilized three different deep learning network architectures of similar complexity, DNN, 1DCNN, and LSTM, to discuss the detection performance of a conventional MIMO system with different modulation levels and number of antennas. Besides, ML and MMSE detectors were implemented to compare the detection performance of the proposed DL based architectures with optimal and sub-optimal detectors, respectively. Main simulation parameters used for DL based detectors are given in Table 1.

Table 1. Main simulation parameters.

Parameter	**Value**
Number of Transmitter Antennas	2, 4
Number of Receiver Antennas	2, 4, 8, 16
Modulation Types	BPSK, QPSK, 16-QAM
Detector Types	ML, MMSE, DNN, LSTM, 1DCNN
Activation Function	ReLU
Mini Batch Size	10000
Maximum Number of Epochs	1000
Optimizer	Adam
Learning Rate	0.001
Number of Training Trials	500,000
Number of Test Trials	100,000

Within this section, we will present the bit error rate performance of the mentioned detectors over several signal-to-noise ratio (SNR) values. In all simulations, we assume that the channel is perfectly known at the receiver for conventional detectors and for DL based detectors the channel matrix is given to the DL input layer along with the received signal. In each trial a new channel was randomly generated and used to transmit the symbols simultaneously. A MIMO simulator in Python was implemented to generate and transmit symbols over a Rayleigh fading channel with additive white Gaussian noise, having different noise variances.

DNN architectures employed five fully connected layers with different number of hidden units to perform the detection of the symbols, while LSTM architecture used three LSTM layers and one fully connected layer. 1DCNN architecture has two one-dimensional convolutional layers and one fully connected layer. In all simulations, number of hidden parameters, filter sizes, and number of filters were set the same regardless of the difficulty of the detection problem. During the training process, ReLU activation function and Adam optimizer were used with a fixed learning rate.



a) BPSK b) QPSK

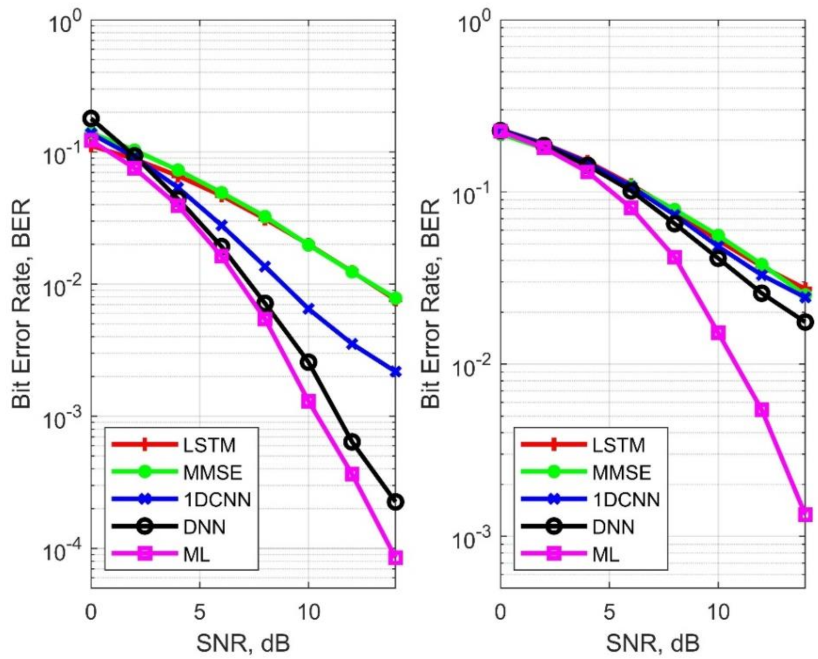
FIGURE 3. Bit error rate performance of detectors over 2x2 MIMO system.

For all DL based detectors, the input consists of the channel matrix and received symbols and is expressed as a one-dimensional vector of real and imaginary parts of these values. Besides, softmax layer and one-hot encoding were employed to perform the classification at the output layer, in which the number of labels depend on the number of modulation order and the number of antennas at the transmitter.

Figure 3 shows the BER performance of the discussed detectors over a 2x2 MIMO system with BPSK and QPSK modulations.

As shown in Figure 3, all three DL based detectors have a high detection performance in terms of bit error rate. Performance of the DNN and 1DCNN is close to that of the optimal ML detector for BPSK modulation, while for QPSK modulation DNN outperforms the 1DCNN detector. In both cases, DL based detectors have a better detection performance than the MMSE detector. Simulation results show that DNN has the best detection performance among these three DL based detectors for both BPSK and QPSK modulation over a 2x2 MIMO system.

In Figure 4, we now compare the detection performance of the mentioned detectors for a 4x4 MIMO system both with BPSK and QPSK modulations.

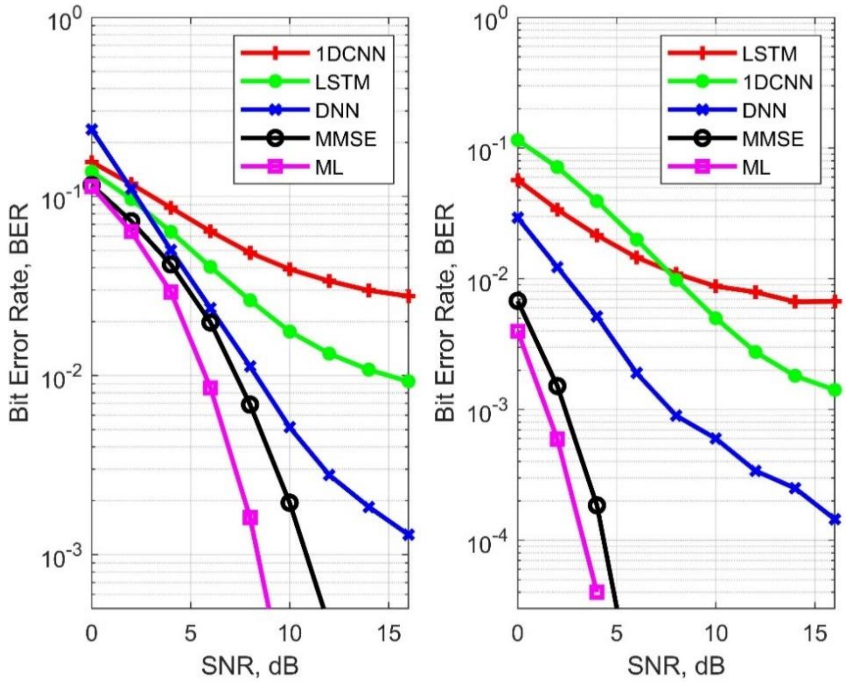


a) BPSK b) QPSK

FIGURE 4. Bit error rate performance of detectors over 4x4 MIMO system.

As shown in Figure 4, performance of the DNN detector has a reasonable BER performance compared to the ML detector for BPSK modulation. For QPSK modulation DNN detector has still a higher detection performance than all other detectors except the ML detector. Nevertheless, DNN performance is not as high for QPSK as for BPSK modulation. The degradation of DNN performance for QPSK modulation depends on the increasing number of one-hot encoding labels which is related with the number of antennas and modulation order. We consider that by increasing the number of hidden layers and the number of layers in the DNN architecture, the degradation in the detection performance will vanish for the high order modulation case. Still, DNN has the best detection performance among the other DL based detectors for both BPSK and QPSK modulations and outperforms the MMSE detector.

In Figure 5, the bit error rate performances of the DNN, LSTM, 1DCNN, MMSE, and ML detectors for BPSK and QPSK modulations are given when the number of transmitter and receiver antennas are not equal to each other.



a) 8x4 MIMO with QPSK b) 16x4 MIMO with BPSK

FIGURE 5. Bit error rate performance of detectors when the number of antennas is not equal.

In Figure 5, simulation results show that in the 8x4 MIMO system with QPSK modulation, the bit error rate performance of the DNN for low SNR values is close to that of the MMSE and ML detectors, while for high SNR values the performance of the DNN detector degrades. Moreover, performance of the DNN detector is not satisfactory for 16x4 MIMO system with BPSK modulation. On the other hand, DNN still has the best performance over 1DCNN and LSTM detectors for both systems.

Finally, in Figure 6 we consider a 2x2 MIMO system with 16-quadrature amplitude modulation (16-QAM) to compare the performance of the discussed detectors.

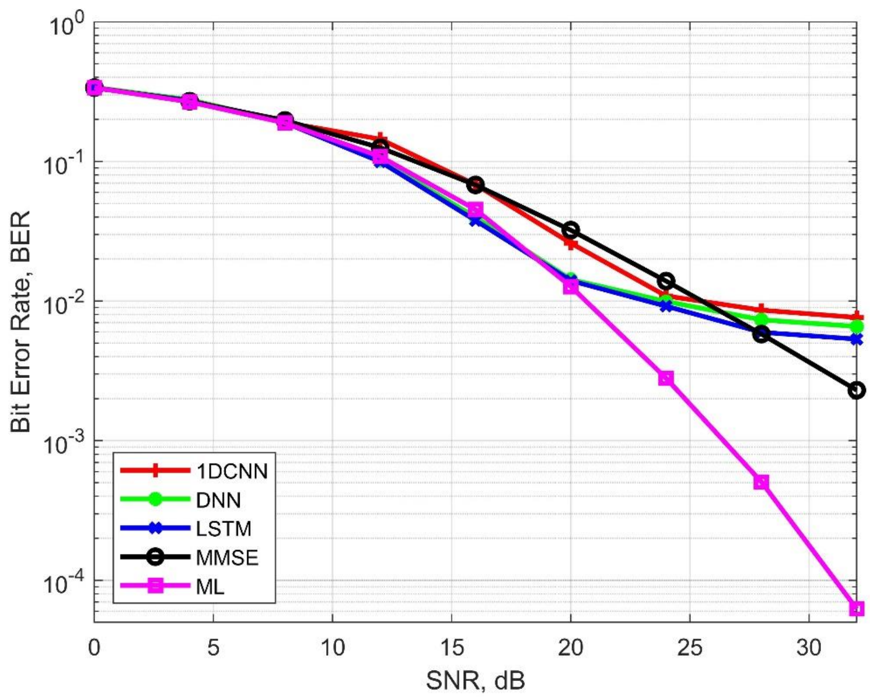


FIGURE 6. Bit error rate performance of detectors over 2x2 MIMO with 16-QAM.

The results in Figure 6 show significant differences from the results in the previous figures. As shown in Figure 6, although DNN, LSTM, and 1DCNN architectures give results close to optimal detector performance at low SNR, for high SNR values performance of the all DL based detectors decreases but still better than the MMSE detector for a limited range. The degradation of the detection performance of the DL based detectors can be explained by the increasing number of labels and complexity of the higher order modulation.

5. Conclusion

In this study, a conventional MIMO system is considered to show the detection performance of the different types of DL based detectors. In addition to a fully connected DNN architecture, performances of the LSTM and 1DCNN structures are discussed. Besides, well-known ML and MMSE detectors are utilized to compare the DL based detectors for different MIMO systems with various modulation types.

Simulation results show that DL based detectors have a detection performance close to the optimal ML detector and outperform the MMSE detector when the number of antennas and the modulation order is low. DNN architecture has the best detection performance compared to the performance of the LSTM and 1DCNN architectures. On the other hand, when the number of antennas and the modulation order are high, the detection performance of the DL based detectors may degrade.

The same parameters were employed in all simulations regardless of the difficulty of the problem to ensure the similar complexity of DL architectures. Therefore, the performance of the detectors can be improved by determining the appropriate network setting for each discussed scenario.

As a future study, the performance of the DNN detectors with different inputs for the input layer can be analyzed to improve the detection performance; however, the ultimate goal is to develop a deep learning detector based solely on the received signal.

Author Contribution Statements Authors are equally contributed to the paper. All authors read and approved the final copy of the manuscript.

Declaration of Competing Interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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