Enhancing Signal Detection in 6G Networks through LSTM-based MIMO Technology

Bibin Babu
School of Computing
Ulster University
Belfast, UK
babu-b2@ulster.ac.uk

Muhammad Yunis Daha
School of Engineering
Ulster University
Belfast, UK
Student Member IEEE
daha-my@ulster.ac.uk

Muhammad Usman Hadi
School of Engineering
Ulster University
Belfast, UK
Member IEEE
m.hadi@ulster.ac.uk

***Abstract*—Artificial intelligence (AI) transforms the multiple input multiple output (MIMO) technology into a promising candidate for beyond-fifth-generation (B5G) and upcoming sixth-generation (6G) networks. However, due to the large number of antennas in the MIMO systems, the detection process becomes very complex and also shows high computational complexity. To address this issue, this paper introduces an optimized AI-based signal detection method based on Long short-term memory (LSTM) called LSTM-based signal detection for MIMO systems. The proposed model works more efficiently in signal detection as compared to the conventional signal detection methods in terms of symbol error rate (SER) at different signal-to-noise ratios (SNR). The optimized simple LSTM architecture provides significant advantages in detecting patterns from input data. This paper goes through the various aspects of signal detection using LSTM, such as system architecture design, data preparation and training process of the neural network, performance evaluation, and future scope. Overall, this paper provides a comprehensive resource for the deployment of an LSTM neural network for signal detection in the upcoming 6G wireless networks.**

***Index Terms*—beyond 5G networks, B5G, AI, Machine learning, signal detection, 6G, LSTM**

I. INTRODUCTION

Currently, we are living in the era of beyond 5G also known as 6G networks where millions of internet devices are competing for connectivity on a daily basis and this number is continuously growing. This overloading puts a huge pressure on network resources specifically energy efficiency, reliability, power consumption, and network latency. Now it has become a very challenging job to meet their ever-increasing network demands [1]. In order to meet these requirements, MIMO technology along with Artificial Intelligence (AI) is playing a vital role in the development of B5G and 6G networks. Multiple input multiple outputs (MIMO) technologies have brought about notable advancements in wireless communication, particularly in comparison to previous generation technologies such as Multiple-input single-output (MISO), Single-input Multiple-output (SIMO) and Single-input single-output (SISO) in terms of channel selection, spectral efficiency, throughput, and spatial diversity [2]. When the quantity of transmitting and receiving antennas is substantial, typically ranging from tens to hundreds, MIMO systems are referred to as Massive Multiple Input Multiple Output (Ma-MIMO) systems.

Combining AI with regular networking methods creates a big change in how we manage and improve networks. AI can quickly analyze lots of data, predict how the network will behave, and change settings as needed. This has huge potential to make networks more reliable and faster. AI methods have been increasingly recognized as valuable tools for addressing complex and challenging problems characterized by expansive search spaces [3],[4]. With AI, network operators can spot and fix problems before they affect users. AI can also smartly use network resources based on how they are being used, making things more efficient and reducing traffic jams. AI systems can keep learning and changing their weights and biases to match what the network needs as it evolves. This paper takes a journey to develop an AI-based signal detection for MIMO systems. To meet the increased wireless network needs and to become a solution to the computational overhead of signal detection methods in MIMO systems, the integration of AI could be the best solution. Given the substantial data load carried by our MIMO system, LSTM has been selected due to its capability to effectively capture long-term dependencies and its provision for sequential data input [5]. The rest of the paper is organized as follows. Section II presents the related work based on signal detection in MIMO systems. The system model and problem formulation are presented in Section III. Section IV discusses the proposed deep learning model for signal detection in the MIMO system. The simulation results, along with the discussion are given in Section V. Finally, the conclusions of the paper are presented in Section VI.

II. SIGNAL DETECTION IN MIMO SYSTEMS

MIMO, short for multiple-input multiple-output, is a technology in wireless network communication where base stations have an extensive array of antenna elements to enhance

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both energy and spectral efficiency [6]. MIMO enhances coverage at the cell edge by directing transmissions spatially toward users, resulting in stronger signals even as they move away from the base station. Through spatial multiplexing, this technology enables simultaneous communication with multiple user equipment, significantly improving overall throughput and spectral efficiency. Additionally, the utilization of millimeter-wave frequencies in conjunction with MIMO amplifies signal power [7]. In the signal detection process of wireless communication networks, MIMO maintains a high signal-to-noise ratio (SNR) without necessitating adjustments to bandwidth, unlike traditional methods. Despite MIMO's considerable success in addressing this issue, the proliferation of connected devices is giving rise to significant challenges, including signal loss, interference, and fading within networks. Several conventional techniques exist for signal detection, including the widely utilized Zero-Forcing algorithm (ZF), Minimum Mean Square Error (MMSE) algorithm, and Maximum Likelihood (ML) solution [8].

A. Zero-Forcing Algorithm

The Zero-Forcing Algorithm is proficient at reducing interference and noise in the received signal by the receiver. It achieves this by creating a linear filter that cancels out interference from other users in the network, essentially eliminating the received signal's presence at those frequencies of interference. This enables the receiver to separate the desired signal from the interference, consequently enhancing the precision of channel estimation [8]. The ZF algorithm uses the following equations to estimate the transmitted signal $\hat{x}$.

$$\mathbf{z} = \mathbf{H}^{\dagger}\mathbf{y} = \mathbf{H}^{\mathrm{T}}(\mathbf{H}\mathbf{H}^{\mathrm{T}})^{-1}\mathbf{H}^{\mathrm{T}}\mathbf{y} \tag{1}$$

where $\mathbf{H}$ is the channel matrix and *y* is the received signal matrix. $\mathbf{H}^{\dagger}$ is the pseudo inverse of *H*. Then for each symbol, it will independently find the closest point from the set of finite symbols [8].

$$\hat{x_i} = \operatorname*{argmin}_{a \in \mathcal{A}} (z_i - a) \tag{2}$$

B. Minimum Mean Square Error Algorithm

The Minimum Mean Square Error (MMSE) Algorithm is employed in wireless communication systems to estimate channels. Its goal is to minimize the mean square error between the estimated channel and the actual channel response, thereby diminishing the impact of noise and interference on the received signal. Unlike the ZF Algorithm, which eliminates interference at particular frequencies, the MMSE algorithm adopts a statistical approach to estimating channel parameters, taking into account the noise and interference within the system [9]. The algorithm uses the following equations to estimate $\hat{x}$.

$$\mathbf{E}[\mathbf{x}|\mathbf{y}] = \mathbf{H}^{\mathrm{T}}\mathbf{H} + \sigma^2\mathbf{E}_s^{-1}\mathbf{H}^{\mathrm{T}}\mathbf{y} \tag{3}$$

where $\mathbf{H}$ is the channel matrix, *x* is the transmitted signal matrix and *y* is the received signal matrix. *E* is the mean of symbol energy. Then for each symbol, it will independently find the closest point from the set of finite symbols using the following equations [8].

$$\hat{x_i} = \operatorname*{argmin}_{a \in \mathcal{A}} \mathbb{E}[\mathbf{x}|\mathbf{y}_i] - a \tag{4}$$

C. Maximum Likelihood Solution

The Maximum Likelihood Solution is a method employed in wireless communication systems to estimate parameters. Its objective is to find parameter values that maximize the likelihood of observing the received signal given the estimated parameters, thereby identifying the most probable parameter set that generated the observed data. In the context of channel estimation, this approach is utilized to estimate channel characteristics that best account for the received signal. In contrast to methods like the Zero-Forcing Algorithm or the Minimum Mean Square Error Algorithm, which concentrates on mitigating interference and noise, the Maximum Likelihood Solution aims to determine the most probable parameters describing the channel, based on the observed data [10].

$$\mathbf{x} = \operatorname*{argmin}_{\mathbf{x} \in A^N} ||\mathbf{y} - \mathbf{H}\mathbf{x}||^2 \tag{5}$$

where $\mathbf{H}$ is the channel matrix, *x* is the transmitted signal matrix and *y* is the received signal matrix. $A^N$is a finite set of all possible symbols in a 4-quadrature Amplitude Modulation (QAM) constellation [8].

III. SYSTEM MODEL AND PROBLEM FORMULATION

This section presents a discussion about the MIMO system model and problem formulation of the MIMO system.

A. System model

We consider a system with *N* number of transmitting antennas and *M* number of receiving antennas. Each antenna on either side is capable of communicating with each other. So there will be *N*M* communication or channels. There will be noises in the transmission and it is considered from each receiving antenna side. QAM of constellation size 4 is used for the generation of the transmitting symbols [15]. The performance evaluation of the system is in the SNR range of 0 to 20dB in a step size of 5. Fig. 1 depicts the general system model for a MIMO system consisting of transmitted signal *x*, received signal *y*, and channel matrix $\mathbf{H}$ and AWGN noise *n*. While Eq. (5) shows the general mathematical formulation of the MIMO system [4]. The development of the proposed system will be based on the following equation,

$$y = Hx + n \tag{6}$$

where *y* is the received signal, *H* is the channel matrix, *x* is the transmitted signal and *n* is the Additive White Gaussian Noise(AWGN) vector[13]. The developed model estimates the transmitted signal in terms of $\hat{x}$ from equation 6. It can be expressed in the form of a matrix equation [14]:

$$\begin{bmatrix} H_{11} & H_{12} & . & H_{1N} \\ H_{21} & H_{22} & . & H_{2N} \\ . & . & . & . \\ . & . & . & . \\ H_{M1} & H_{M2} & . & H_{MN} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ . \\ . \\ x_M \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ . \\ . \\ n_M \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ . \\ . \\ y_M \end{bmatrix} \tag{7}$$

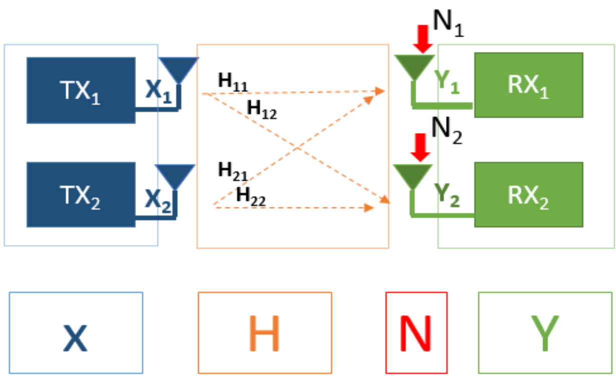

Fig. 1. Mathematical architecture of MIMO system model.

B. Problem formulation

Mathematical model-based algorithms suffer from several drawbacks, such as elevated complexity and limited scalability [11]. To overcome present limitations and increase the utilization of MIMO technology in wireless communication in networks, incorporating detection methods with artificial intelligence like machine learning (ML) offers a promising solution. By leveraging ML algorithms, signal detection can be more adaptive and dynamic, leading to the realization of ultra-reliable low-latency wireless networks [12]. AI's ability to learn from former experiences aids it in making intelligent decisions and adapting effectively to changing conditions. Through the optimized allocation of channels based on traffic patterns, AI can enhance the overall network performance and spectral efficiency significantly. The ultimate objective here is to develop an AI model for signal detection in MIMO systems. We needed to design a neural network method to estimate the transmitted signal instead of the conventional detection methods. After developing the neural network we trained the network using several transmitted symbols and after that, we tested the performance of the system using several symbols. The performance of the developed system should be compared with the performance of the traditional methods.

C. Data preparation

Initially, input symbols are generated according to the constellation size and modulation scheme. The indices of the *ntrain* symbols are randomly generated and using these indices, the transmitted symbol vector x is generated. Also the channel coefficient vector H is generated and normalized to ensure that the magnitude of the vector elements follows the Rayleigh distribution with a scaling parameter 1. The Rayleigh distribution is a mathematical representation used to describe the likelihood of various values of a measurement when influenced by multiple random factors [16]. The received signal vector y is generated from the previously generated vectors for a chosen signal-to-noise ratio (SNR) range, resulting in a received symbol vector y several times the size of vector x. Feature extraction is done by extracting the features of vectors y and H i.e. taking the real and imaginary parts from vectors y and H. Targets corresponding to the feature data are as generated.

IV. PROPOSED DEEP LEARNING MODEL

The Long short-term memory (LSTM) is a deep learning recurrent neural network (RNN) that is designed to learn dependencies in the long term, from sequence data [17]. LSTM networks are designed to address the vanishing gradient problem in RNNs. It mainly consists of three gates and memory cells. The memory cells are responsible for the cell state and gates update. The first gate is known as the forget gate which determines which information should be deleted or retained from the previous cell state. The second gate is the input gate which will decide which information should be added to the cell state and the last one is the output gate which determines the output of the LSTM model. The input to the cell state will be the outputs of the input gate and forget gate [18]. The above four components of the LSTM layer enable them to selectively retain and update information over time. Fig. 2, presents the systematic block diagram of the LSTM-based signal detection in the MIMO system.

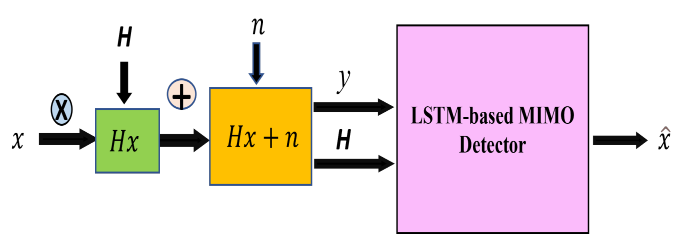

Fig. 2. Block diagram for LSTM-based signal detection in MIMO system

Fig 3. shows the operation of the LSTM layer and the architecture of a cell in the LSTM layer. At each time stamp, the output is generated for the input, and according to the outputs, the weights and biases of the neural network are adjusted. This operation is carried out by the LSTM cells. K_t is the input and H_t is the output of gates inside LSTM cell at time stamp t and C_t is the channel state inside LSTM cell at time instant t [17].

The main layers in the LSTM network are the LSTM layer to find the dependencies over the long term and the sequence input layer to take inputs as sequences [19]. In light of our utilization for classification purposes, the employed model

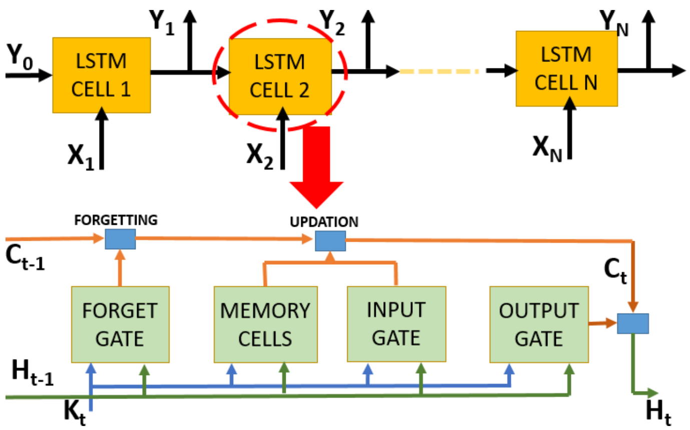

Fig. 3. Block diagram LSTM layer operation and LSTM cell architecture

incorporates classification, softmax, and fully connected layers within its architecture [17]. In the LSTM neural network design for our system, several features in the data are specified in the sequence input layer [20]. The number of hidden units and output mode are specified in the LSTM layer. Also, the number of unique categories in the target data is specified in the fully connected layer. We used the training function 'adam' for the optimization algorithm, a maximum number of epochs set to 1000, the minibatch size to 256, and 'Gradient-Threshold' to 1. Learning rate scheduled *piecewise* with an initial rate of 0.01 with a drop period of 125 and drop factor of 0.2.

V. SIMULATION SETUP

To emulate the suggested approach, a proprietary MATLAB-based simulator has been created. This simulator operates on an Intel i9-10900K CPU, @ 3.70GHz processor with 128 GB RAM. Additionally, it utilizes a 32GB GPU processor for enhanced computational performance. Table 1 summarizes the parameters utilized in the simulation framework.

TABLE I
SIMULATION PARAMETERS

Number of transmitters	2
Number of receivers	2
Modulation	QAM
Constellation size	4
Test data size	1 Million
Train data size	1 Million
SNR Range	0:5:20 dB
Training Function	Adam
Number of neurons	40
Maximum epochs	1000
Mini Batch Size	256
Gradient Threshold	1
Initial Learn Rate	0.01
Learn Rate Schedule	piecewise
Learn Rate Drop Period	125
Learn Rate Drop Factor	0.2

To analyze the performance of the proposed deep learning model we have done the simulation for *ntrain* and *ntest* on 1 million data size, where QAM modulation of constellation size 4 has been used over the range of SNR 0 to 20 dB with a step size 5. Then the performance of the system is plotted as Symbol error rate(SER) vs SNR.

VI. DISCUSSION OF RESULTS

SER vs SNR is compared with the performance of conventional methods like MMSE and ML for the 2x2 system, which is depicted in Fig. 4. At SNR 0dB the SER of the proposed model is 0.108 whereas for the other models, it is in the range of 0.22 to 0.27. At 5, 10, and 15 dB the SER of the LSTM model is 0.022, 0.003, and 0.0006 and for the conventional methods, it is in the range of 0.11 to 0.17, 0.03 to 0.07, and 0.006 to 0.02 respectively. At 20 dB LSTM model shows 0.0002, but at the same time ML, ZF, and MMSE show a bit error rate of 0.0009, 0.006, and 0.004 respectively. The LSTM model outperforms the other methods across various SNR levels and it is more robust to noise.

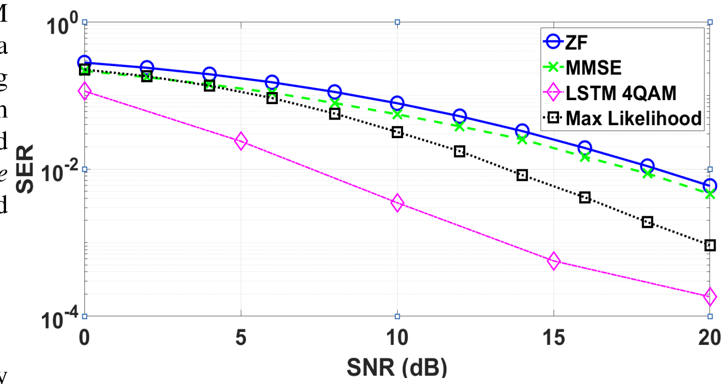

Fig. 4. Comparison between outputs of conventional methods and LSTM model

Using neural networks to estimate transmitted signals has shown great promise, performing better than traditional methods like MMSE, ZF, and ML algorithms from the previous works as reported in [12, 13, 21]. Neural networks offer a flexible and powerful way to estimate signals by understanding complex data relationships. Compared to traditional methods, neural networks have some clear advantages. They are good at finding complicated patterns and relationships in data, which can be tough for traditional methods. This means neural networks can give more accurate and reliable estimates of signals, especially in situations where the signal might change a lot or there's a lot of interference.

VII. CONCLUSIONS AND FUTURE DISCUSSION

MIMO, along with AI advancements, is a crucial technology for networks beyond 5G. It brings big improvements like super-fast data speeds and better use of spectrum beyond 5G networks. However, the estimation of signals is a rigorous task. This paper suggests a simple AI-based detector that works better than regular detectors in MIMO and Ma-MIMO systems compared to basic detectors. The utilization of neural networks, especially LSTM, for transmitted signal estimation, has showcased remarkable efficacy, surpassing conventional methods such as MMSE, ZF, and ML algorithms. Neural networks, with their ability to learn intricate patterns and nonlinear relationships from data, offer a versatile and robust approach to signal estimation tasks. In addition to leveraging standalone neural network architectures like LSTM, exploring hybrid neural network models may present a promising avenue for further advancement in signal estimation tasks. Hybrid models combine the strengths of different types of neural networks to achieve enhanced performance and flexibility. One possible approach could involve combining LSTM networks with convolutional neural networks (CNNs) or RNNs to create a hybrid architecture tailored for signal estimation tasks. By leveraging the spatial and temporal features captured by CNNs or RNNs alongside the memory capabilities of LSTM networks, hybrid models can offer improved accuracy and robustness in estimating transmitted signals.

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