iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** VII **Month of publication:** July 2026

DOI: https://doi.org/10.22214/ijraset.2026.84202

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Deep Learning-Based Detection Algorithm for the Multi-User MIMO-NOMA System

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Abstract: The increasing demand for high data rates and massive connectivity in next-generation wireless systems has led to the adoption of non-orthogonal multiple access (NOMA) techniques. However, conventional successive interference cancellation (SIC)-based receivers suffer from performance degradation due to error propagation and nonlinear interference effects, particularly in multi-user MIMO environments. To address these limitations, this work proposes a feedback-based deep neural network (FDNN) receiver for signal detection in MIMO-NOMA systems. The proposed model integrates deep learning capabilities with iterative interference cancellation, enabling improved nonlinear signal separation and robustness against noise and inter-user interference. A comprehensive simulation framework is developed using Python to evaluate system performance under varying signal-to-noise ratios (SNR) and power allocation conditions. The results demonstrate that the FDNN-based receiver achieves significantly lower bit error rates (BER) compared to traditional SIC methods, especially in scenarios with small power differences between users. This study highlights the effectiveness of deep learning in enhancing receiver design for future wireless communication systems.
Keywords: MIMO-NOMA, Deep Neural Network, FDNN, Signal Detection, Successive Interference Cancellation, Bit Error Rate (BER), 5G Communication, Machine Learning, Nonlinear Detection

I. INTRODUCTION

The rapid evolution of wireless communication technologies has been driven by the exponential growth in connected devices and the increasing demand for high data rates. Modern applications such as Internet of Things (IoT), smart cities, and real-time multimedia services require efficient utilization of limited spectrum resources. Traditional orthogonal multiple access (OMA) techniques, which allocate distinct time or frequency resources to users, are no longer sufficient to meet these growing requirements.

Non-orthogonal multiple access (NOMA) has emerged as a promising solution for improving spectral efficiency and supporting massive connectivity in next-generation wireless systems. Unlike OMA, NOMA allows multiple users to share the same time and frequency resources by superimposing signals in the power domain. At the receiver side, successive interference cancellation (SIC) is typically employed to separate user signals. Although SIC offers low computational complexity, its performance is highly sensitive to channel conditions and power allocation strategies. In particular, the presence of strong inter-user interference and the near–far effect often leads to error propagation, resulting in degraded detection accuracy.

To further enhance system capacity and reliability, NOMA is often combined with multiple-input multiple-output (MIMO) technology. MIMO systems exploit spatial diversity by using multiple antennas at the transmitter and receiver, significantly improving throughput and energy efficiency. However, the integration of MIMO with NOMA introduces additional challenges in signal detection due to increased interference and higher system complexity.

In recent years, deep learning techniques have gained significant attention in wireless communications due to their ability to model complex nonlinear relationships. Neural networks, particularly deep neural networks (DNNs), can learn mapping functions directly from data without relying on explicit mathematical models. This capability makes them well-suited for signal detection problems in NOMA systems, where traditional linear methods often fail to handle nonlinear interference effectively.

Motivated by these advantages, this work proposes a feedback-based deep neural network (FDNN) receiver for MIMO-NOMA systems. The proposed approach replaces conventional linear detection stages with a neural network-based model capable of performing nonlinear signal estimation. Additionally, a feedback mechanism is incorporated to iteratively refine the received signal by canceling previously detected interference, thereby reducing error propagation.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

The main contributions of this work are summarized as follows:
A novel FDNN-based receiver architecture is developed for multi-user MIMO-NOMA signal detection.
A data-driven detection framework is designed to improve robustness against noise and inter-user interference.
A comparative analysis is performed between the proposed FDNN receiver and the conventional SIC receiver in terms of bit error rate (BER).
The impact of signal-to-noise ratio (SNR) and power allocation differences between users is systematically evaluated.
The remainder of this paper is organized as follows. Section 2 presents the system model and problem formulation. Section 3 describes the proposed FDNN-based detection method. Section 4 provides simulation results and performance analysis. Finally, Section 5 concludes the paper and outlines future research directions.

II. SYSTEM MODEL

A. NOMA System

In this section, the fundamental model of a power-domain non-orthogonal multiple access (NOMA) system is presented. Unlike conventional multiple access techniques, NOMA enables multiple users to transmit simultaneously over the same time–frequency resource by utilizing different power levels. This superposition of signals improves spectral efficiency and supports a higher number of connected users.
Consider an uplink NOMA system consisting of (N) users communicating with a base station (BS). Each user transmits its signal with a specific power allocation, and the signals are combined over the wireless channel. Let (s_i) denote the transmitted symbol of the (i)-th user, and (h_i) represent the corresponding channel coefficient. The received signal at the base station can be expressed as the superposition of all user signals along with additive noise.

B. Received Signal

$$y = \sum_{i=1}^{N} \sqrt{P_i}\, h_i\, s_i + w$$

Here, (P_i) is the transmit power assigned to the (i)-th user, and (w) represents additive white Gaussian noise (AWGN). In practice, users are typically ordered based on their channel conditions such that users with stronger channel gains are assigned higher transmission power. This ordering facilitates efficient signal separation at the receiver.
At the base station, signal detection is performed using successive interference cancellation (SIC). In this process, signals are decoded sequentially, starting from the user with the highest received power. While decoding a particular user's signal, the remaining users' signals are treated as interference.
The signal-to-interference-plus-noise ratio (SINR) for the (i)-th user can be expressed as:

C. SINR of -th User

$$\mathrm{SINR}_i = \frac{P_i \mid h_i \mid^2}{\sum_{k=i+1}^{N} P_k \mid h_k \mid^2 + N_0}$$

where (N_0) denotes the noise power. Based on this SINR, the achievable data rate for each user can be derived using Shannon's capacity formula:

D. Achievable Rate

$$R_i = B\log\left(1 + \frac{P_i \mid h_i \mid^2}{\sum_{k=i+1}^{N} P_k \mid h_k \mid^2 + N_0}\right)$$

Although NOMA significantly improves spectral efficiency, its performance largely depends on proper power allocation and accurate signal detection. In practical scenarios, factors such as channel fading, noise, and interference make signal separation challenging. Additionally, the reliance on SIC introduces the risk of error propagation, where incorrect detection of one user affects subsequent users.
These limitations motivate the use of advanced detection techniques, such as deep learning-based receivers, to enhance performance in complex multi-user communication Environment

E. SIC Receiver

The successive interference cancellation (SIC) receiver is a widely used detection technique in power-domain NOMA systems due to its relatively low computational complexity and practical feasibility. The fundamental principle of SIC is to decode user signals sequentially based on their received power levels, starting from the strongest signal and proceeding toward the weakest.

In an uplink NOMA system, the base station first detects the signal of the user with the highest effective received power. Once the signal is estimated, it is reconstructed and subtracted from the total received signal. This process reduces interference for the remaining users and is repeated iteratively until all user signals are detected.

Let (y) denote the received signal at the base station. During the (n)-th stage of SIC detection, the residual signal can be expressed as:

F. Residual Signal (SIC Stage)

$$\boldsymbol{y}^{(n)} = \boldsymbol{y} - \sum_{i=1}^{n-1} \sqrt{\boldsymbol{P}_i}\, \boldsymbol{h}_i\, \hat{\boldsymbol{s}}_i$$

At each stage, the receiver applies a detection rule to estimate the transmitted symbol. In many practical implementations, linear detection methods such as zero-forcing (ZF) or minimum mean square error (MMSE) are employed.

For example, using a linear detection model, the estimated transmitted signal vector can be written as:

G. Linear Detection (Zero-Forcing)

$$\hat{\mathbf{x}} = (\mathbf{H}^{H}\mathbf{H})^{-1}\mathbf{H}^{H}\mathbf{y}$$

H. Symbol Detection

$$\hat{s}_{\boldsymbol{n}} = \mathcal{D}(\boldsymbol{y}^{(n)})$$

I. Signal Reconstruction & Cancellation

$$\boldsymbol{y}^{(\boldsymbol{n}+\mathbf{1})} = \overline{\boldsymbol{y}^{(\boldsymbol{n})}} - \sqrt{\boldsymbol{P}_{\boldsymbol{n}}}\, \boldsymbol{h}_{\boldsymbol{n}}\, \hat{s}_{\boldsymbol{n}}$$

After estimating the strongest user's signal, it is reconstructed and subtracted from the received signal, and the process continues for the next user. This iterative interference cancellation improves detection performance compared to direct linear detection.

Despite its advantages, the SIC receiver has several limitations. The performance of SIC is highly dependent on accurate detection in the early stages. Any error in detecting a strong user propagates to subsequent stages, leading to error accumulation. Additionally, SIC relies on linear detection techniques, which may not effectively handle nonlinear interference present in practical communication channels. These limitations motivate the need for more advanced detection approaches, such as deep learning-based receivers, which can better model nonlinear relationships and improve detection accuracy in complex MIMO-NOMA systems.

J. DNN Network

To overcome the limitations of conventional SIC receivers, a feedback-based deep neural network (FDNN) model is introduced for signal detection in MIMO-NOMA systems. Unlike traditional linear detection methods, the FDNN model leverages nonlinear mapping capabilities of neural networks to improve detection accuracy in the presence of interference and noise.

The FDNN architecture consists of three main components: an input layer, multiple hidden layers, and an output layer. The input to the network includes the received signal along with relevant channel parameters. These inputs are processed through a series of fully connected layers, where nonlinear activation functions enable the network to learn complex relationships between transmitted and received signals.

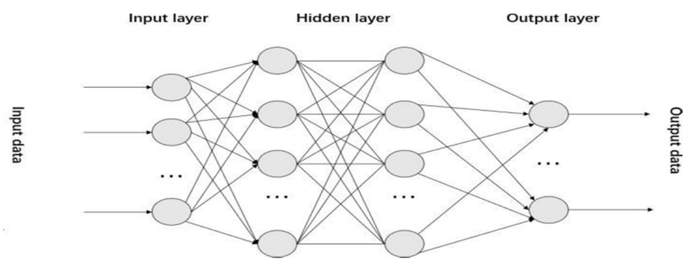

Figure 1. Structure of the DNN model.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

By introducing a DNN algorithm, its nonlinear activation function and hidden layer structure can enable the receivers to have the ability of nonlinear detection, enhancing detection accuracy and reducing errors.

III. PROPOSED METHOD

This section presents the proposed feedback deep neural network (FDNN)-based detection framework for MIMO-NOMA systems. The objective of the proposed method is to improve signal detection accuracy by combining the iterative structure of successive interference cancellation (SIC) with the nonlinear learning capability of deep neural networks.

A. System Overview

In the considered uplink MIMO-NOMA system, multiple users simultaneously transmit their signals to a base station over the same time–frequency resource. The received signal is a superposition of all user signals affected by channel fading and noise. The goal of the receiver is to accurately estimate each user's transmitted symbol from the combined signal.

The FDNN-based receiver processes the received signal in a sequential manner, similar to SIC, but replaces conventional linear detection with a neural network-based nonlinear estimator.

B. Input Representation

At each detection stage, the input to the FDNN consists of the residual received signal along with channel-related parameters. The input vector for the (i)-th user can be expressed as:

Input Feature Vector

$$I_i = [\, y_i^{\mathrm{Re}},\ y_i^{\mathrm{Im}},\ g_i,\ \phi_i \,]$$

Effective Channel Gain

$$g_i = \sqrt{P_i}\, |\, h_i \,|$$

Channel Phase

$$\phi_i = \tan^{-1}\left(\frac{\mathrm{Im}(h_i)}{\mathrm{Re}(h_i)}\right)$$

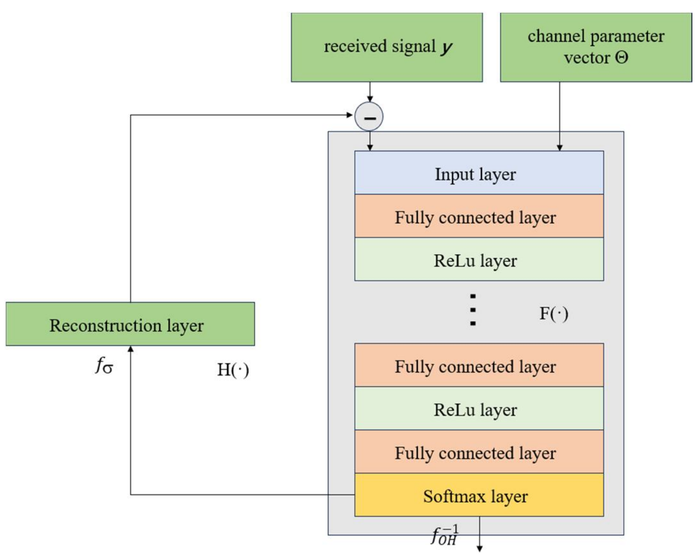

Figure 2. FDNN receiver model.

C. FDNN-Based Detection Process

The detection process follows an iterative structure. At each stage, the FDNN estimates the transmitted symbol of one user, reconstructs its signal, and subtracts it from the received signal.

Step 1: Neural Detection

where $\boldsymbol{F}$ (·) represents the FDNN model.

Step 2: Signal Reconstruction

$$\hat{s_i} = F(I_i)$$

$$\hat{y_i} = \sqrt{P_i}\, h_i\, \hat{s_i}$$

Step 3: Interference Cancellation

$$y^{(i+1)} = y^{(i)} - \hat{y_i}$$

This updated signal is then used for detecting the next user.

IV. RESULTS

A. Simulation Setup

The simulation is carried out using a Python-based framework. A two-user uplink NOMA system is considered, where both users transmit QPSK-modulated signals over a shared channel. The key simulation parameters are summarized as follows:
Modulation scheme: QPSK Number of users: 2 Channel model: AWGN SNR range: 0 dB to 20 dB
Power allocation: (P_1 = 0.8), (P_2 = 0.2)
Neural network structure: 2 hidden layers (16 and 32 neurons) Activation function: ReLU
Output function: Softmax Training samples: 200,000
The FDNN model is trained using cross-entropy loss and optimized using gradient descent.

B. BER Performance Analysis

The BER performance of both FDNN and SIC receivers is evaluated across varying SNR values. The results indicate that the BER decreases as the SNR increases for both methods. However, the FDNN-based receiver consistently achieves lower BER compared to the SIC receiver. At lower SNR values (0–5 dB), both receivers exhibit relatively high error rates due to noise dominance. As the SNR increases beyond 10 dB, the FDNN model demonstrates a significant improvement in detection accuracy, while the SIC receiver shows slower convergence. At an SNR of 20 dB, the FDNN receiver achieves a BER on the order of (10^{-3}), whereas the SIC receiver remains around (10^{-2}). This highlights the superior performance of FDNN in high-SNR conditions.

C. Impact of Power Difference (ΔSNR)

The effect of power allocation between users is also analyzed by varying the difference in received SNR (ΔSNR). When the power difference between users is small (e.g., 1–3 dB), the SIC receiver struggles to separate signals effectively, leading to higher BER. In contrast, the FDNN model maintains stable performance even under low ΔSNR conditions due to its ability to learn nonlinear decision boundaries. As ΔSNR increases (e.g., 5–7 dB), both receivers improve, but FDNN continues to outperform SIC. However, when the power difference becomes excessively large, the weaker user experiences performance degradation due to insufficient received power.

D. Training Convergence

The convergence behavior of the FDNN model is analyzed by observing the training loss over multiple epochs. The loss decreases rapidly during the initial training phase and stabilizes after a few iterations, indicating efficient learning.
A moderate batch size provides a balance between convergence speed and stability. Extremely large batch sizes result in slower convergence, while very small batch sizes increase training noise.

E. Comparative Analysis

A comparison between SIC and FDNN receivers is summarized below:

- FDNN achieves significantly lower BER across all SNR values
- FDNN reduces error propagation effects present in SIC
- FDNN performs better under low power differences between users
- SIC remains computationally simpler but less accurate

Overall, the FDNN-based receiver demonstrates superior performance in terms of reliability and robustness, making it a suitable candidate for next-generation wireless communication systems.

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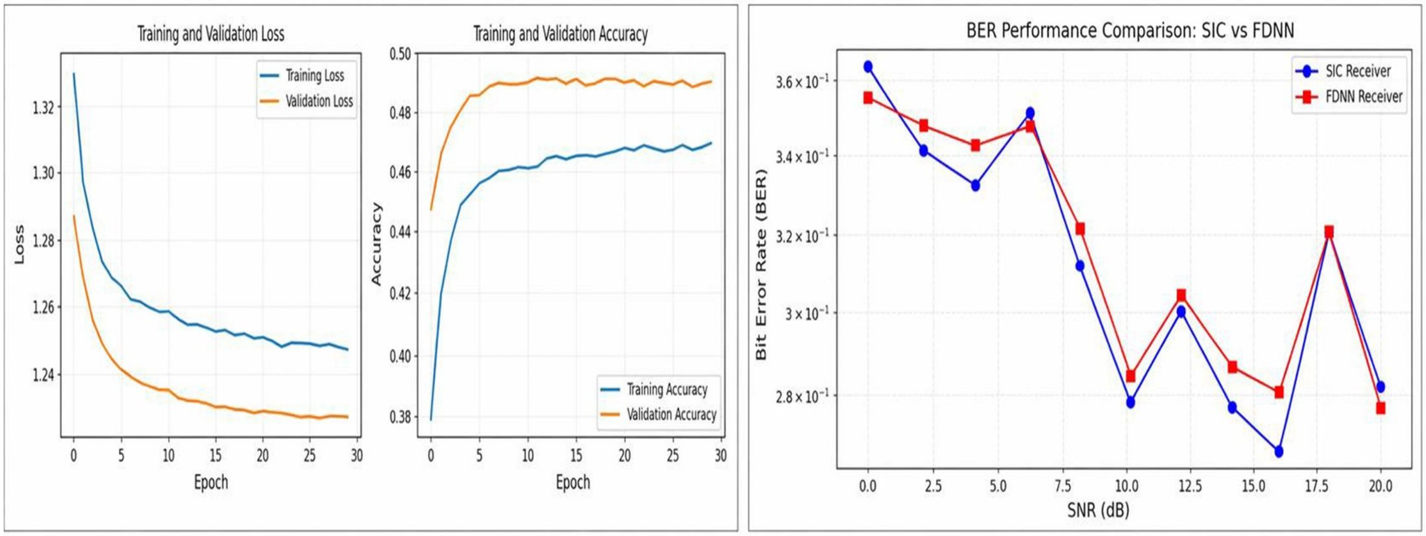
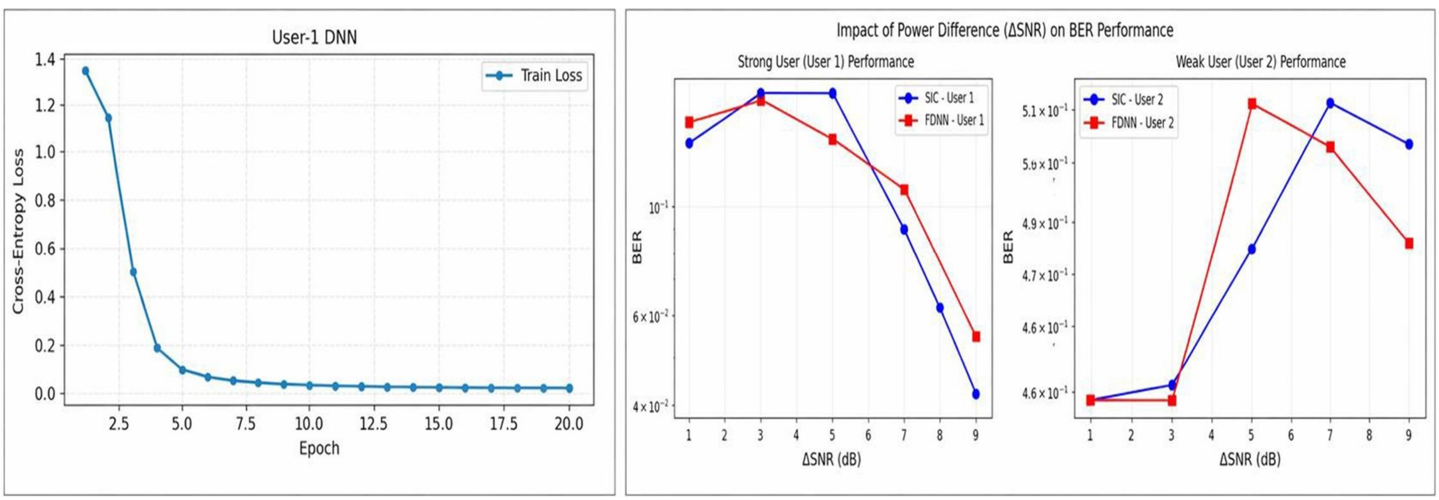


Figure 3. Comparative Analysis



F. Discussion

The results confirm that integrating deep learning into the receiver design enhances detection performance in MIMO-NOMA systems. The nonlinear mapping capability of FDNN allows it to effectively handle interference and noise, which are major limitations in conventional SIC-based methods.

These findings suggest that deep learning-based receivers can play a crucial role in improving the efficiency and reliability of future wireless networks, particularly in scenarios with dense user deployment and limited spectral resources.

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