

Energy-Efficient Power Allocation In Mimo-Noma Systems Using Cnn-Optimized Firefly Algorithm

Anoop Kumar Khambra

Research Scholar, Department Of Ece Madhyanchal Professional University, Bhopal, Mp (India)

Rajesh Kumar Rai

Supervisor, Department Of Ece, Mpu Bhopal.Mp (India)

Dr. Varkuti Kumara Swamy

Co-Supervisor, Department Of Ece, Sreenidhi Institute Of Science And Technology, Hyderabad, Telangana State

Abstract

The reliability and quality of services provided by communication technology are requirements for future communication systems. The reliability of communication systems depends on low latency, high data rates, and massive connectivity. The multiple input, multiple output, non-orthogonal multiple access approach fulfils the requirements of future communication systems such as 5G. The incorporation of MIMO-NOMA suddenly changing several factors such as channel condition and complex spectral structure decline the system efficiency and impede its application. Now the overcome the limitation of channel condition and resource allocation in NOMA employed deep learning algorithm. The proposed algorithm improves the energy efficiency and data rates of MIMO- NOMA model. The proposed algorithm uses convolutional neural network and firefly algorithm. The employed firefly algorithm removes the local interference and boost the feature map of convolutional layer. For the validation of the proposed algorithm, simulate in MATLAB environments with parameters of MIOM-NOMA. The results of the simulation compare with those of other existing deep learning algorithms such as recurrent neural networks, long-short term memory, and convolutional neural networks. The comparative results of the analysis suggest that the proposed algorithm is efficient in terms of power allocation and sum data rates

Keywords: MIMO-NOMA, Deep Learning, Power allocation, energy efficiency, Firefly algorithm

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I. Introduction

In Fifth Generation (5G) networks, non-orthogonal multiple access (NOMA) presents itself as a method to manage the increasing demand for resources by effectively supporting numerous users within a single resource block (RB). In comparison to conventional orthogonal multiple access (OMA) systems like code division multiple access (CDMA), frequency division multiple access (FDMA), time division multiple access (TDMA), and orthogonal frequency division multiple access (OFDMA), this improves bandwidth efficiency [1]. NOMA optimizes resource utilization by capitalizing on users' specific channel conditions, thereby serving multiple users with varying quality of service (QoS) requirements within the existing resources. This novel approach introduces an allowing NOMA systems to complement existing models of multiple access (MA) [2]. Power-domain NOMA (PD- NOMA) is one of these. Emerges as a robust contender for future 5G networks. PD-NOMA employs In order to serve several users simultaneously with the same resources, superposition coding (SC) is used at the transmitter and successive interference cancellation (SIC) is used at the receiver [3]. To improve system capacity and user sum rates, it can be difficult to integrate NOMA with adaptive coding and modulation schemes and assign power coefficients properly based on the channel conditions of individual users. To address these challenges, accurate knowledge of each user's channel conditions, known as details about the channel condition (CSI), is imperative [4]. Demonstrate promise in adapting to changing conditions and estimating individual user channel states, positioning them as viable solutions for radio networks in the future [2]. First off, among NOMA's main difficulties is the complexity associated with receiver design and signal detection. Unlike methods for orthogonal multiple access (OMA) where signals are separated in the time, frequency, or code domains, NOMA requires sophisticated receiver algorithms to decode the signals of multiple users that are superimposed in the power domain. Implementing these advanced receiver algorithms can significantly increase computational complexity and power consumption. Moreover, NOMA introduces the issue of inter-user interference, where strong users can cause interference to weaker users sharing the same resources. Managing this interference

becomes crucial for ensuring reliable communication and maintaining the quality of service (QoS) requirements for all users. Techniques such as successive interference cancellation (SIC) are employed to mitigate inter-user interference, but they add complexity to the receiver design and may not be feasible in all scenarios. Another challenge is the fairness and resource allocation optimization in NOMA systems. Since NOMA allows users to exchange similar resources non-orthogonally need to devise efficient resource allocation schemes that maximize system throughput while ensuring fairness among users. Balancing maximizing spectral efficiency and providing equitable service to all users remains a significant challenge. Additionally, NOMA relies heavily on accurate channel state data (CSI) for user categorization and power distribution. However, obtaining reliable CSI becomes challenging, especially in dynamic and fast-fading wireless channels. Imperfect CSI estimation and feedback errors can degrade the performance of NOMA systems, leading to suboptimal resource allocation and reduced system throughput. Furthermore, NOMA deployment may face regulatory and standardization challenges. Existing wireless communication standards are primarily based on orthogonal multiple access techniques, and integrating NOMA into these standards may require significant modifications and consensus among industry stakeholders. Regulatory issues related to spectrum allocation and interference management also need to be addressed to facilitate the widespread adoption of NOMA technology. In conclusion, while NOMA offers promising benefits It also presents a number of operational, technological, and regulatory issues that must be resolved for its successful use in wireless communication systems in terms of spectrum efficiency and capacity expansion. Overcoming these challenges requires concerted research efforts and collaboration among academia, industry, and regulatory bodies to unlock the full potential of NOMA technology

II. Recent Work Done

In this author [1] since coordination between the device and (BS) before the data transmission in grant-free communication, the difficult work of active user's detection (AUD) must be carried out at the BS. We suggest an active user's enumeration and identification (AUD) based deep neural network (DNN) solution for NOMA with sparse spreading (AUEI). A DNN is used to estimate active first phase, and another DNN is used to identify them in the second phase. We provide a multi-stage transfer learning technique to hasten the training of the DNNs. reduce the amount of training we used the multi-stage transfer learning method when it came time for the active users identification networks. The numerical outcomes show that, especially for high sparsity levels and low SNR, our methodology is superior to previously known methods in identifying the active users. We also examined the false alarm rates, which for the relevant scenarios are insignificant, and the computing complexity, which showed that it was less difficult than previous methods.

In this author [2] the grant-free MIMO-NOMA system's sparse signal characteristics and spatial correlation across numerous antennas are both thoroughly in this work. Then simultaneous UAD and CE difficulties, we suggest the spatial correlation block sparse Bayesian learning (SC-BSBL) approach. First, we model the combination of UAD and CE problem as a three-dimensional block sparse signal recovery problem by fully mining the block sparsity of signals in the grant-free MIMO-NOMA system. Second, using the hierarchical Bayesian theory and spatial correlation, we derive the cost function. Finally, we apply quick marginal likelihood maximization to maximize the cost function and estimate the channel and the set of active users. In this study, a spatial BSBL was proposed. Algorithm for grant-free MIMO-NOMA systems to address the combined UAD and CE issues. Signal block sparsity and antenna spatial correlation were both completely utilized. First, a three-dimensional block sparse signal recovery problem was used to simulate problem by fully mining the block sparseness of the signals in the grant-free MIMO-NOMA system. Estimated channel and set of estimated active users, we then deduced the cost function to solve the problem based on hierarchical Bayesian theory and optimized it with rapid marginal likelihood maximization.

In this author [3] The paper suggests a novel reinforcement learning (RL)-based random access (RA) protocol to address this problem. This protocol allows each device to learn from its prior decisions and performance choose the best sub channels and in order to minimize strong cross-interference. The learning-based framework is designed to maximize system access efficiency, which is calculated as the relationship between the quantity of sub channels and successful transmissions. Simulation results demonstrate that our suggested architecture can greatly increase the system access efficiency in cases where it is overwhelmed. A SC and device clustering method has been developed to lessen intense interference and enhance the AE. Being taken into account for GF-NOMA transmission. Different QL techniques, including wSDC-BAP-QL, wSDC-GP-QL, and woSDC-BAP-QL, have been proposed to lessen device interference and improve system AE performance while taking into account URLLC requirements. Additionally, the effectiveness of BAP and GP, two different action selection methodologies, has been investigated. Compared to previous approaches like SA, simulation findings show that the suggested QL methods deliver greater performance.

In this author [4], in grant-free NOMA-based IoV, mMTC exhibits the characteristics of sparse concurrent active users, making the identification and retrieval of user information crucial. In this study, we introduce a novel block sparsity approach under a compressed sensing model that enables us to detect user activity

and recover user information with high accuracy and low the sparsity of active users in mMTC. The technique that was recovered and employed in our work is called the block sparse ISD algorithm, and it takes use of the ISD algorithm's block sparse structure. The user action and data are detected using the rebuilt technique, and the signal blocks are recovered and concatenated to create the restored original sparse signal. In comparison to the support set for each block is the same, and the suggested method enhances the conventional ISD algorithm with an additional block sparse structure. The measuring matrix is chosen matrix. According to simulation the suggested algorithm can increase SNR by 1.75 dB SISD algorithm and by 2.5 dB ISD algorithm. From the standpoint of algorithm complexity, the suggested method is very effective because the signal recovery time of the SISD algorithm is one-tenth ISD algorithm and half SISD algorithm.

In this author [5] Things advancements in artificial intelligence for the Internet of Things, examine various computational frameworks for AI for the Internet of Things, and highlight challenges and opportunities for the successful application of AI for the Internet of Things technology to solve challenging issues across a range of applications. This article reviews recent advancements and explores the convergence of artificial intelligence and the Internet of Things from four perspectives: architectures, techniques, and hardware platforms for AI- IoT sensors, devices, and energy approaches for AI-IoT communication and networking for AI-IoT; and applications for AI-IoT. The AIoT has been covered in this paper from several angles and layered gave insights into the various obstacles and issues that still need to be handled to allow realistic deployments of the AIoT into more varied and complicated environments. Discussed the integration of the AIoT with various developing technologies

III. Proposed Methodology

Overview

This chapter delves into the proposed methodology for energy optimization and resource allocation in MIMO-NOMA systems. The primary aim is to reduce energy use while making sure high data rates during transmission. Central to this approach is the utilization of deep learning algorithms, particularly Convolutional Neural Networks (CNNs), to optimize diverse features of traffic data. To streamline the optimization process, the chapter introduces the Firefly algorithm, which effectively reduces the feature map of convolutional layers. This optimization enhances network training and ultimately improves system performance. Furthermore, the chapter introduces an additional algorithm focused on energy optimization, leveraging an enhanced version of Recurrent Neural Networks (RNNs) known as Long Short- Term Memory (LSTM). The LSTM network is employed to optimize energy usage more effectively, offering improvements over traditional RNN architectures. By integrating CNNs and LSTM networks into the proposed methodology, the chapter seeks dual objectives of energy optimization MIMO-NOMA systems. Through the utilization of these advanced deep learning techniques, the chapter aims to improve the effectiveness and functionality of wireless communication networks paving the way for more sustainable and robust networks capable of supporting high data rates while minimizing energy consumption.

Power Domain-Noma Model

The core concept of Power Optimizing power allocation to allow several users to be serviced simultaneously within the same time slot, frequency band, and code is the fundamental goal of Domain Non-Orthogonal several Access (PD-NOMA). Contrary to Multiple Access via Orthogonal Frequency Division (OFDMA), which divides available Radio Bands (RBs) among users while maintaining constant transmitted powers, NOMA allocates different power levels to individual users to ensure a more equitable distribution of resources. In OFDMA, as depicted in Figure 4.1a, RBs are divided among users with consistent power transmission. In contrast, NOMA, illustrated in Figure 4.1b, assigns varying power levels to users across all available RBs. Moreover, in Multiple Input Multiple Output (MIMO) systems, subcarrier separation adheres to specific frequency constraints to achieve orthogonally. However, NOMA does not require such separation, as all users utilize the entire bandwidth available.

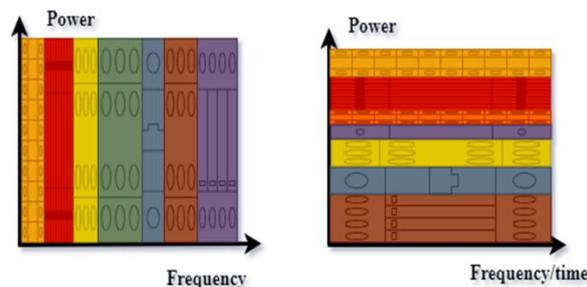


Figure.1 power allocation model in NOMA as a and b

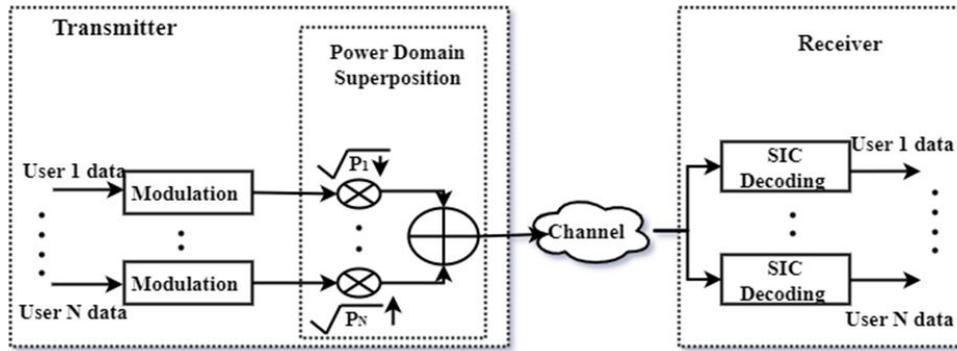


Figure 2 Block diagram of the conventional NOMA system

Massive-Mimo

Massive MIMO stands out as a technology offering remarkable spectral efficiency within 5G communication networks. Leveraging large-scale antenna arrays, it enables the simultaneous transmission of numerous data streams with distinct spatial patterns at identical frequencies. This capability significantly enhances throughput within the same spectrum, making it a pivotal component of 5G networks. When combined with NOMA technology, massive MIMO presents a promising avenue for achieving exceptionally high spectral efficiency in 5G networks. However, the integration of massive MIMO and NOMA also introduces notable technical challenges. Firstly, the inclusion of multiple-input multiple-output (MIMO) radio frequency (RF) chain elements, such as RF amplifiers and analog-to-digital/digital-to-analog converters, escalates system complexity and hardware costs. To mitigate this challenge, one crucial technique involves operating MIMO-NOMA systems with a limited number of RF chains by selecting the most optimal subset of antennas for these chains. Moreover, since channel conditions exhibit variations over time and frequency, it becomes more cost-effective to schedule users into favorable channels during each time slot. Additionally, NOMA necessitates user pairing, typically involving the scheduling of one near user (with strong channel gain) and one far user (with weak channel gain) as a user pair for successive interference cancellation (SIC). Therefore, addressing the challenges of antenna selection and user scheduling jointly becomes imperative in the context of massive MIMO-NOMA systems.

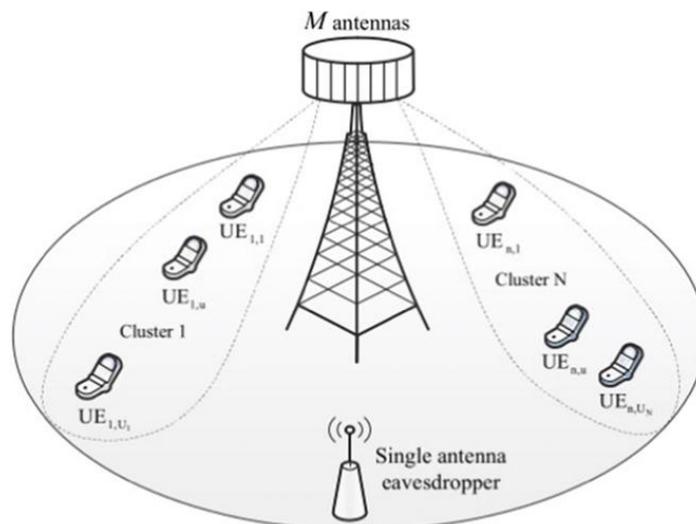


Figure 3 process block diagram of MIMO-NOMA model

Successive Interference Cancellation (SIC)

The user with the higher Signal-to-Noise Ratio (SNR) in successive interference cancellation (SIC) subtracts their message from the superimposed signal. The next strongest user then goes through this procedure again, and so on, recursively, until the desired signal is deciphered. Because SIC functions in an iterative fashion, it requires less hardware at the receiver than traditional multi-user detection techniques. The ability of SIC algorithms to reach the capacity zones of Broadcast Channels (BCs) has been proven. In wireless networks, effective interference management, such that offered by SIC, has the potential to greatly increase network capacity. SIC is executed at the receiver in accordance with the User Equipment (UE) channel conditions. The Base Station (BS) receives pilot data from each UE, which is used for Channel Estimation (CE) and Signal-to-Noise Ratio (SNR) prediction. Figure 4.3 provides an illustration of the decoding procedure.

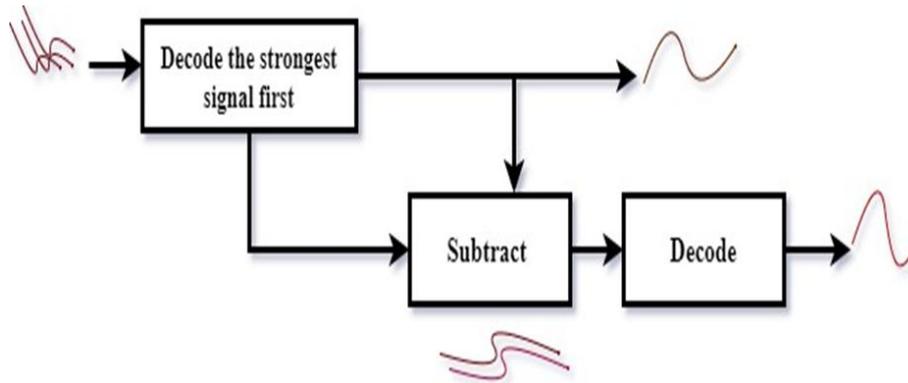


Figure 4 Successive interference cancellation (SIC) algorithm

IV. Experimental Analysis Of Performance Evaluation Parameters

Performance evaluation parameters of MIMO-NOMA systems typically include:

- Sum Rate: The total data rate achieved by all users in the system. It is a key metric for assessing the overall system capacity and throughput.
- User Fairness: The fairness in allocating resources among users, ensuring that all users receive a reasonable share of the system's capacity.
- Spectral Efficiency: The efficiency of utilizing the available spectrum to transmit data. It is often measured in terms of bits per second per Hertz (bps/Hz).
- Outage Probability: The probability that the communication link fails to meet a *certain quality of service* (QoS) requirement, such as a minimum data rate. Lower outage probability indicates better reliability.
- Bit Error Rate (BER): The probability of errors in received bits due to noise, interference, or channel impairments. A lower BER indicates better reliability of the communication system.
- Energy Efficiency: The ratio of the system's throughput (or sum rate) to the total energy consumption. It quantifies the system's ability to achieve high throughput while minimizing energy consumption.
- System Capacity: The maximum *number of users or data streams that can be supported by the MIMO - NOMA system* while maintaining acceptable performance metrics.
- Complexity: The computational complexity of the algorithms and techniques used in the MIMO-NOMA system, including channel estimation, precoding, decoding, and user scheduling.

Simulation Process

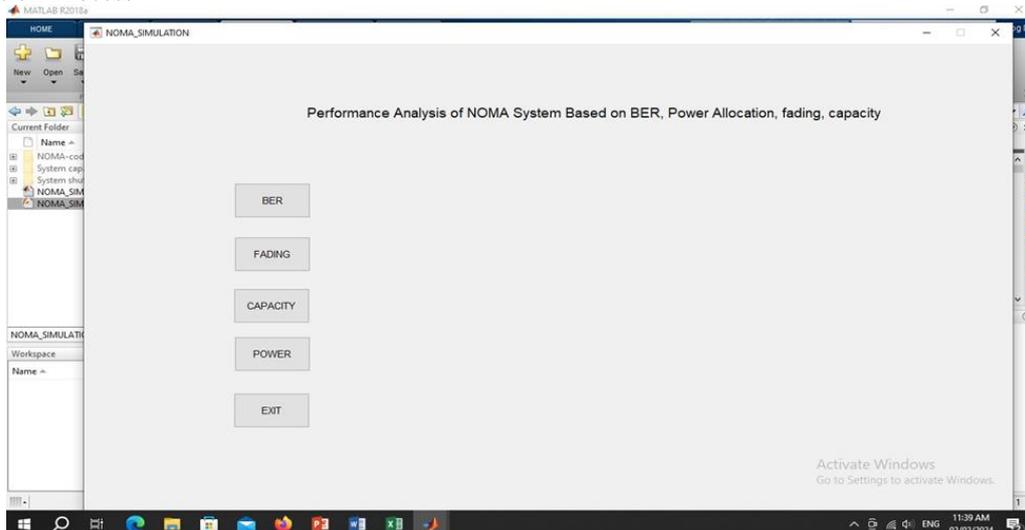


Figure 5: Window show that the performance analysis of NOMA system based on BER, power allocation, fading, and capacity.

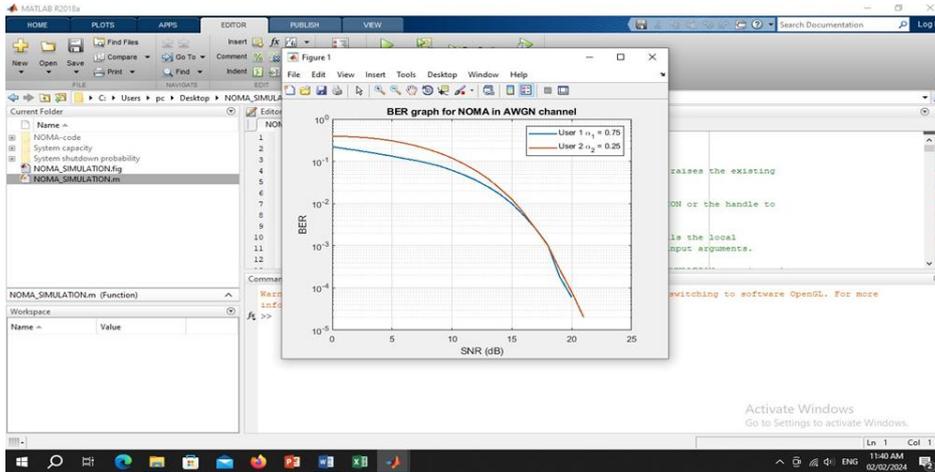


Figure 6 Window show that the performance analysis of NOMA system based on BER graph for NOMA in AWGN channel and SNR (dB) user 1 $a_1 = 0.75$ is less than user 2 $a_2 = 0.25$

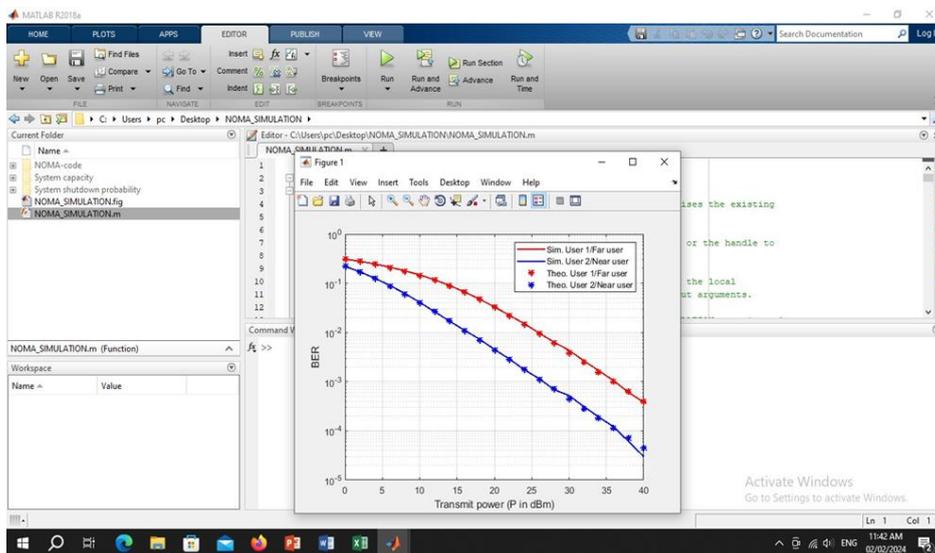


Figure 7 Window show that the performance analysis of NOMA system based on BER and transmit power (P in (dB) sim. user1/far user is better than sim. user2/near.

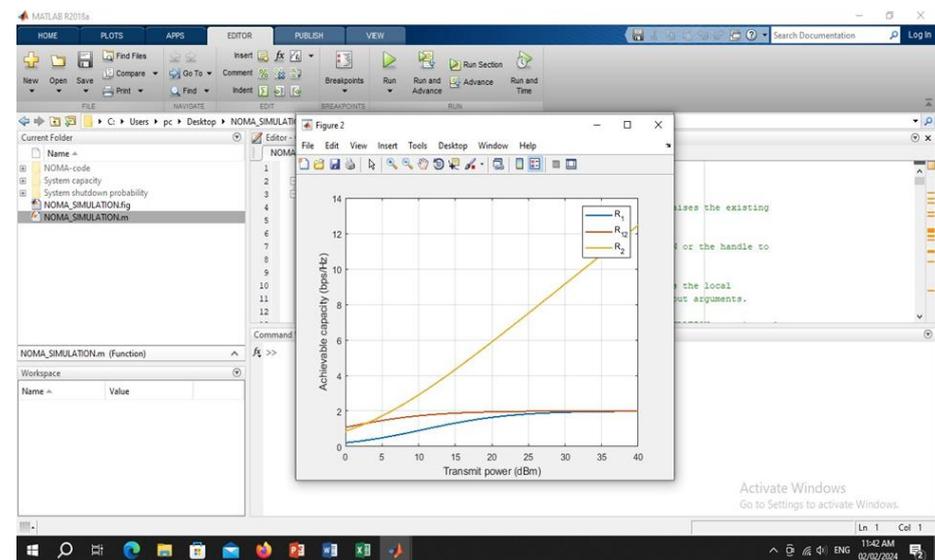


Figure 8 Window show that the performance analysis of NOMA system in achievable capacity (bps/Hz) and transmit power (dBm) of using R1, R12, and R2.

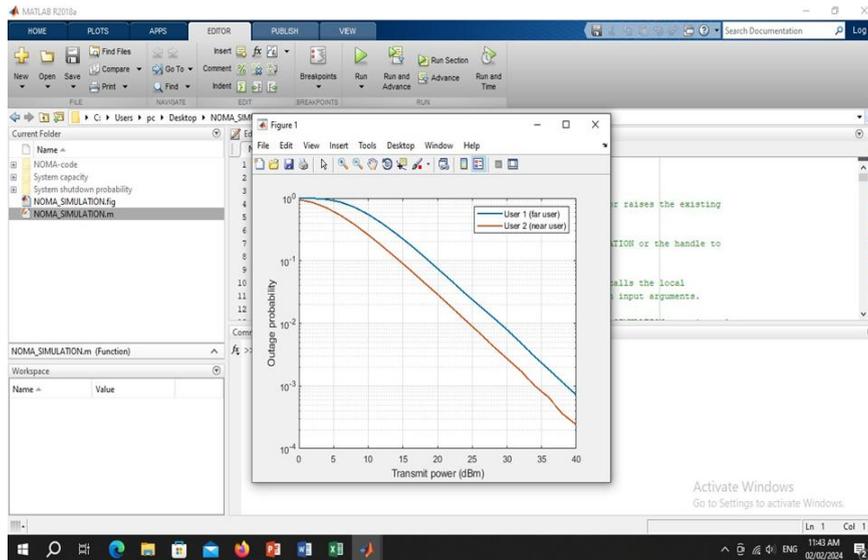


Figure 9 Window show that the performance analysis of NOMA system in outage probability and transmit power (dBm) of user 1(far user) and user 2 (near user).

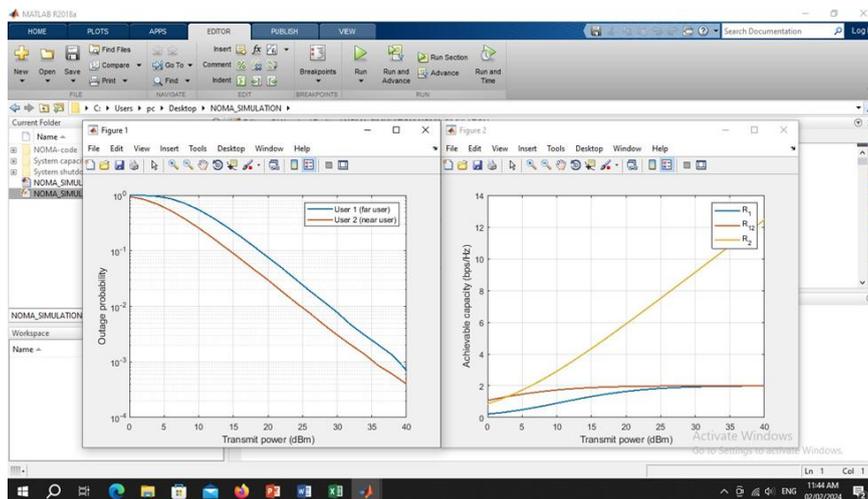


Figure 10 Window show that the performance analysis of NOMA system in achievable capacity (bps/Hz) and transmit power (dBm) of using R_1 , R_2 , and R_2 outage probability and transmit power (dBm) of user 1(far user) and user 2 (near user).

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