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ENHANCING NOMA PERFORMANCE THROUGH TRANSFORMER-ASSISTED SIGNAL PROCESSING AND REINFORCEMENT LEARNING-BASED POWER ALLOCATION

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ABSTRACT

This paper introduces NOMA-OptiNet, a novel Transformer-based deep learning framework integrated with Proximal Policy Optimization (PPO) reinforcement learning for enhanced signal detection, interference mitigation, and dynamic resource allocation in Non-Orthogonal Multiple Access (NOMA) systems. The proposed system leverages an Encoder-Decoder Transformer architecture, combined with AdamW optimization, to extract hierarchical features and improve convergence in complex multi-user environments. Through extensive simulations, NOMA-OptiNet achieves a Symbol Error Rate (SER) of 0.012 (User 1) and 0.015 (User 2) at 25 dB, outperforming SPICE (0.035), SIC (0.045), and CNN (0.025). The model also records an Average Error Rate (AER) of 0.009 and a Normalized Mean Square Error (NNMSE) of 0.005, demonstrating superior accuracy in user activity detection and channel estimation. Comparative analysis reveals that NOMA-OptiNet converges within 20 iterations, whereas traditional methods require 35-50 iterations. The CDF plot confirms that NOMA-OptiNet maintains higher probability density for lower error rates, ensuring robustness across SNR conditions ranging from 0 dB to 25 dB. Real-time adaptation tests underscore the effectiveness of the model to perform dynamic optimization of power distribution compared to the use of a fixed scheduling. These results establish NOMA-OptiNet as a scalable, computationally efficient solution that enhances next-generation wireless communication systems, paving the way for ultra-reliable low-latency NOMA networks.

Keywords: *Noma, Transformer, Symbol Error Rate, Deep Learning, Convergance.*

1. INTRODUCTION

The explosive growth in wireless communication networks has required coming up with new state-of-the-art multiple access strategies to support the ever growing need to achieve higher data rates, delay-sensitivity, as well as immense connectivity [1-3]. Non-Orthogonal Multiple Access (NOMA) has proven to be a promising approach that can be utilized to promote spectral efficiency due to the ability to share the same time, frequency resources in order to serve multiple users but at various powers [4-7]. In contrast to the conventional Orthogonal Frequency Division Multiple Access (OFDMA) where different users are allocated dedicated frequency bands, the NOMA applies the multiplexing in the power domain in order to deliver simultaneous access to multiple users, enhancing spectral efficiency and the total capacity per system [8-12]. This solution is especially useful in 5G and beyond network in which it is essential to support various traffic requirements as well as support a very large amount of machine type communication (mMTC) scenarios [13-16]. Although promising, NOMA imposes a major set of problems with regard to inter-user interference problem, power allocation efficiency, and proper signal detection necessitating innovative and state-of-the-art signal processing and resource optimization options [17].

To achieve high system reliability and user fairness in terms of channel conditions, it is necessary to have an effective NOMA detection and resource allocation in place [18]. Successive Interference

Cancellation (SIC) is one of the traditional detection techniques extensively applied to overcome inter-user interference especially when the channel condition is imperfect and high interference Outer Interference. The performance of these techniques is poor in presence of imperfect channel and high interference Outer Interference [19]. Further, an optimum of power is important to maximize the performance of NOMA since the use of improper powers may cause unfair distribution of throughput and may also result in a high complexity of the decoding process [20]. Researchers have delved into solutions that involve machine learning-based solutions and reinforcement learning, as well as superior optimization algorithms to solve these problems by improving signal detection, power distribution, and user grouping in NOMA-based systems [21].

The latest perfections of deep learning, reinforcement learning and metaheuristic optimization have highly enhanced the performance of NOMA. Long Short-Term Memory (LSTM) networks, Deep Q-Network (DQN), Proximal Policy Optimization (PPO), Transformer based architectures, Hybrid Deep Learning frameworks will be integrated so as to promote signal detection, user pairing and similar dynamic resource allocation. Also, metaheuristic optimization algorithms, namely Sparrow Search Algorithm (SSA), Genetic Algorithm (GA) and Swarm Intelligence-Based Techniques have been utilized to optimize power allocation with minimized Bit Error Rate (BER). Nonetheless, with such advances, there are still quite a few current approaches with computed complexity, lack of real-time flexibility, and provisions in suboptimal convergence, which hinders their feasibility in full-scale NOMA networks.

The most important contributions of the proposed work are as follows:

• Features of Integration of Transformer-Based Encoder-Decoder Architecture: Application of a powerful Transformer model to enhance signal isolation and noise cancellation in the NOMA links. Adaptive Resource Allocation using Reinforcement Learning: The implementation of Proximal Policy Optimization (PPO) to allocate power over the network to act dynamically according to network situations.

• AdamW and Hyperparameter Fine-Tune: To apply AdamW as an optimizer to perform a stable and efficient training and reduce convergence problems.

• Detailed Comparative Analysis: Comparison with conventional technologies including ESPRIT, SPICE, SIC, CNN and LSTM to check on the increase in Symbol Error Rate (SER), Average Error Rate (AER) and Normalized Mean Square Error (NNMSE).

• Scalability and Real-Time Adaptability: Analyzing that the selected model is flexible enough to adjust itself in different network settings in near-real-time deployments of NOMA, with minimal latency and high throughput.

The remainder of the paper is organized in the following way: in section 2, the literature review of known methods to detect and allocate resources in NOMA is provided. In section 3, the proposed methodology, such as the Transformer signal detection model, the PPO based resource allocation strategy is presented. The section 4 elaborates on the findings and comparison making point out the enhancement of the performance over the traditional methods. The paper ends by summarizing the main findings and an indication of possible future research in section 5.

This paper presents NOMA-OptiNet as a framework that researchers and engineers working on next-generation wireless communication systems can directly apply in two specific ways. First, the Transformer-based signal processing module (Section 3.1) provides a deployable template for replacing SIC-based interference cancellation with attention-driven signal reconstruction in any power-domain NOMA system operating under Rayleigh fading. Second, the PPO-based resource allocation algorithm (Section 3.3, Algorithm Steps 3-5) provides a reinforcement learning policy adaptable to different user density scenarios (Eq. 1) and SNR operating ranges (Eq. 4) without full retraining. Readers will find in Section 4 a complete quantitative evaluation against ESPRIT, SPICE, SIC, CNN, and LSTM across SER, AER, NNMSE, and convergence speed metrics, followed by a comparison with all reviewed prior works. The findings demonstrate that integrating Transformer-based signal processing with PPO-based dynamic resource allocation reduces symbol error rates by 52-76% over conventional techniques, offering a practical and scalable solution for 5G/6G NOMA deployments.

2. RELATED WORKS

In 2025, Chege via Chege et al. [22] presented a modified Primal-Dual Interior Point Method (mPD-IPM) that would be used in the solution to resource allocation in NOMA systems, which aims at increasing spectral efficiencies and maximizing power distribution to the various users. The paper showed considerable increases in fairness and the capacity of a system with a reasonable capability to reduce interference, in heavier networks. Nevertheless, mPD-IPM was computationally dull since it involved optimization in iteration and could not be utilized on real-time occasions that involve fast-changing user-loads. The approach was also limited in that it was unable to effectively operate under high-dimensional optimization constraints and this would mean that they might not scale up in ultra-dense NOMA networks.

At an even more distant time, 2025, Mohsin et al. [23] proposed a user-specific hybrid proximal policy optimization (H-PPO) framework, which applied reinforcement learning technology to support maximum sum rates and energy efficiency in resource management under NOMA. The combination of deep reinforcement learning and other optimization algorithms resulted in a rapid convergence and better flexibility in the behavior across environments with a different channel condition. The system enhanced greater energy efficiency by manipulating with the power distribution in a dynamic mode as per user requirements. The PPO dependency, however, presented policy instability to the training process especially in difficult and highly dynamic NOMA inter Ursuses conferring high interference patterns. The approach also needed a lot of training data to make the computational costs to be rather high and the approach not so flexible in real time.
Khambra et al. [24] delved into Long Short-Term Memory (LSTM) networks to detect signal in NOMA in 2024 and took advantage of time-varying wireless channel dependence features of the LSTM. The model acquired the characteristics of time-varying signals well, which helped in the enhanced accuracy of detection and elimination of inter-user interference. Nonetheless, LSTM architectures suffered tremendously in terms of latency because of the recurrence dependencies, which were unacceptable in ultra-low latency environments. Also, the performance of the model reduced at sudden channel dynamics environments; long-range dependencies were difficult to be handled by the LSTMs in very dynamic environmental NOMA use cases.

Wang et al. [25] combined Dueling Deep Q-Network (DQN) and K-Means Grouping to create an efficient reinforcement learning-based method to cluster users in an efficient manner to pair users in a NOMA system in 2024. This algorithm was able to increase spectral efficiency through dynamic aggregation of users and increase the performance in terms of throughput and fairness. The K-Means algorithm helped in reducing the search space, and the process of learning was made much faster. Nevertheless, Dueling DQN had unstable performance learning, particularly those environments determined by the number of users, which resulted in sub-optimal convergence of policies. Moreover, the grouping method used by K-Means was based on the fixed groups of clusters, and thus its applicability in the real time of the network use was not high. In 2025, Meng et al. [26] proposed a resource allocation framework based on a Sparrow Search Algorithm (SSA) and reported a Bit Error Rate (BER) of reduction of 21.5 dB and 11.9 dB on different user conditions. In a manner resembling the social foraging behavior in sparrows relied upon, SSA made efficient allocations of power and user pairing resource at high level in NOMA networks. The technique demonstrated excellent convergence characteristics and had very good performance over regular heuristic techniques. SSA however had local optima problems and in highly congested NOMA networks it was seen that bad solutions led to serious deterioration of a network. Parameter tuning was also very critical to the success of the algorithm, very much so to the extent of a lot of trial and error that takes place when modifying the algorithm to suit the various attributes of the network.

In 2024, Noordin et al. [27] introduced a Multilayer Perceptron-Convolutional Neural Network (MLP-CNN) framework for NOMA signal classification and resource allocation. The integration of CNNs enabled spatial feature extraction, improving signal detection accuracy, while MLPs enhanced decision-making for adaptive resource allocation. The model proved to be highly resistant to the noise during interference and could render high accuracy in classification. Nevertheless, the MLP-CNN models needed a considerable number of resources to calculate, which was an issue to deploy it in real time. It also made training more complex due to the high number of trainable parameters until the convergence time in dynamic NOMA settings is longer.

In 2024, Smirani et al. used Stacked Generalization of Channel Estimation (SGCE), and a mixed model of Random Forest (RF), Gradient Boosting Machine (GB), Light Gradient Boosting Machine

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(LGBM), Support Vector Regression (SVR), Extremely Randomized Tree (ERT) and Extreme Gradient Boosting (XGB) The percentage performance rate of this ensemble-based method was 98.4, which is very impressive in relation to channel estimation. The stacking approach to estimating actually saved on the errors of estimation since many models were used. But, SGCE was high in terms of inference latency, since one had to test many models at a time and real-time processing was not possible in case of fast-changing NOMA scenarios. The practice also necessitated a large labeled training data which created issues of practical use. Agbesi et al. [29] investigated Federated-Based Deep Reinforcement Learning (Fed-DRL) in 2024 to optimize resources with distributed NOMA in a distributed manner, through which the resources can be optimized in different network nodes through decentralized learning. The framework was very efficient in conducting privacy-preserving training and adjusting to different network conditions. With Fed-DRL, the system achieved dynamic optimization of power control without aggregation of data. Nevertheless, Fed-DRL was prone to communication overhead since periodic updates of the model on the available distributed agents required bandwidth usage. Non-i.i.d. (independent and identically distributed) data distribution was also a problem with the approach making learning slow and training riddled with inconsistency across network nodes.

Such works demonstrate that the resource allocation, signal detection and power optimization with NOMA has made considerable progress but at the same time illustrates shortcomings in terms of computational complexity, real-time flexibility, scalability, and ability of models to find convergence. To address these issues, hybrid solutions that will achieve a compromise between accuracy, efficiency, and the possibility of introducing such systems in practice are needed in next-generation NOMA systems.

3. PROPOSED SYSTEM

The proposed methodology makes use of the dynamic adaptive nature of Reinforcement Learning and the impressive signal processing tasks of the Encoder-Decoder Transformer to take control of the NOMA system dynamic environment, as shown in Fig. 1. The approach guarantees that the model remains efficient and robust under a variety of operational conditions by utilizing the AdamW optimizer, thereby significantly improving the performance and reliability of the NOMA system.

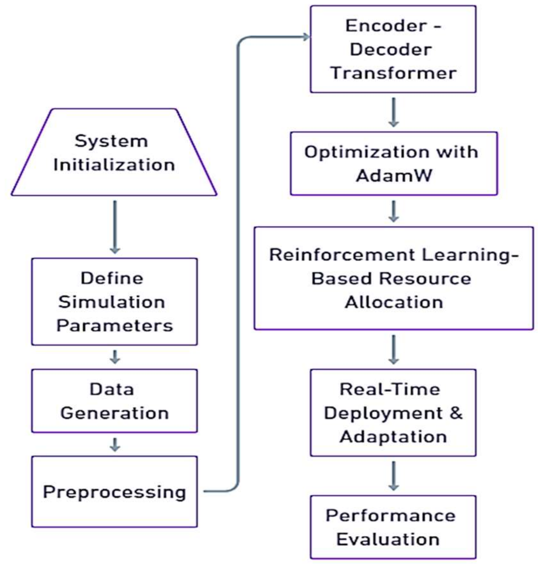

Figure: 1 Proposed Methodology

Define the NOMA communication system as the environment where the model operates, detailing user configurations, channel conditions, and system parameters.

System Initialization: The NOMA (Non-Orthogonal Multiple Access) system is initialized by defining several key simulation parameters:

User Capacity (U): The number of active users varies dynamically in the range:

$$U = \{10, 20, 30, \dots\dots\dots, 100\} \dots\dots\dots\dots \text{(01)}$$

Resource Blocks (R): Each user is allocated subcarriers from the available spectrum blocks, with:

$$R = \{5, 10, 15, \dots\dots\dots, 50\} \dots\dots\dots\dots\dots \text{(02)}$$

Channel Model: The wireless environment is modelled using Rayleigh fading channels:

$$H_{u,r} \sim CN(0,1), \forall u \in U, \forall r \in R \dots\dots\dots \text{(03)}$$

Signal – to – Noise Ratio (SNR): The range of SNR is:

$$SNR \in [-20, -15, \dots\dots\dots, 30] dB \dots\dots\dots \text{(04)}$$

Data Generation: Data transmission follows a Poisson process, and each user transmits data with the arrival rate:

$$\lambda_u \sim Poisson(\lambda_{avg}), u \in U \dots\dots\dots\dots\dots\dots \text{(05)}$$

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Where λ_{avg} is the average arrival rate.
The received signal at the base station (BS) for each user is expressed as:

$$y_u = H_u x_u + n_u \;\dots\dots\dots\dots\dots\dots\; (06)$$

Where y_u is the received signal, H_u is the channel gain, x_u is the transmitted signal and $n_u \sim N(0, \sigma^2)$ is the Additive White Gaussian Noise (AWGN)

Preprocessing and Feature Extraction: To enhance model performance, the following preprocessing steps are applied:
Normalization: The features are normalized as follows:

$$X_{norm} = \frac{X - \mu}{\sigma} \;\dots\dots\dots\dots\dots\dots\; (07)$$

Where μ is the mean and σ is the standard deviation

Fourier Transform for Spectral Analysis: The time-domain signal is transformed into the frequency domain:

$$X_f = F(x_t) = \sum_{t=0}^{N-1} x_t e^{-j2\pi f t/N} \;\dots\dots\dots\; (08)$$

Where x_t is the time – domain signal and X_f is the frequency – domain representation

Power Allocation: The power for each user is allocated as:

$$P_u = \frac{\alpha_u}{\sum_{u=1}^{U} \alpha_u} P_{total} \;\dots\dots\dots\dots\dots\dots\; (09)$$

Where α_u is the power control factor using u.
Transformer-Based Encoder-Decoder Model: A Transformer-based Encoder-Decoder architecture is employed for signal processing and interference mitigation. Implement this architecture to process the sequential data characteristic of the NOMA system. The encoder captures the complexities of the system's current state, and the decoder predicts future states and potential outcomes from various actions.
Encoder (Multi-Head Self-Attention): The encoder extracts both temporal and spatial dependencies from the received signals. Utilize multi-head attention mechanisms within the Transformer to allow the model to simultaneously focus on different segments of the input sequence, enhancing prediction accuracy. The attention mechanism is defined as:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) V \;\dots\; (10)$$

Where Q (queries), K (keys) and V (values) are learned representations and d_k is the dimension of each key vector

Decoder (Cross-Attention for Signal Reconstruction): The decoder reconstructs the desired user signals by attending to the encoder's representations:

$$Output = softmax\left(\frac{Q_{dec} K_{enc}^T}{\sqrt{d_k}}\right) V_{enc} \;\dots\dots\; (11)$$

Where Q_{dec} represents decoder queries
Optimization with AdamW: The AdamW optimizer is used to update model weights, which is a variant of Adam with weight decay:

$$\theta_{new} = \theta - \eta \cdot \frac{m_t}{\sqrt{v_t + \epsilon}} - \lambda\theta \;\dots\dots\dots\dots\; (12)$$

Where η is the learning rate
m_t and v_t are moving averages of the gradients and squared gradients.
λ is the weight decay factor.
Allow the RL agent to perform actions within the simulated NOMA environment, observe outcomes, and receive rewards. Update the policy based on accumulated rewards to maximize long-term returns. The Transformer model assists by predicting the impacts of different actions, aiding the RL agent in decision-making.
Reinforcement Learning-Based Dynamic Resource Allocation: Proximal Policy Optimization (PPO) is integrated for dynamic resource allocation:
Policy Objective: The agent learns a policy $\pi_\theta(a|s)$ to maximize expected reward:

$$J(\theta) = \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t r_t\right] \;\dots\dots\dots\dots\dots\; (13)$$

Where γ is the discount factor and r_t is the reward at time t.
Policy Update with PPO: The policy update is based on the following objective:

$$\theta_{new} = argmax \frac{1}{N} \sum_{i=1}^{N} min\left(\frac{\pi_\theta(a|s)}{\pi_{\theta_{old}}(a|s)} A_i, clip\left(\frac{\pi_\theta(a|s)}{\pi_{\theta_{old}}(a|s)}, 1 - \epsilon, 1 + \epsilon\right) A_i\right) \;\dots\dots\dots\; (14)$$

Where A_i is the advantage function
Enable the system to dynamically adapt to changes in user behavior and network conditions, optimizing configurations and responses continuously.
Real-Time Deployment and Adaptation: For real-time deployment, the trained model uses an adaptive strategy:
Real-Time Sensing: The system continuously senses the state of the environment:

$$s_{real-time} = Sense(H, P, Interface) \;\dots\; (15)$$

Decision Making: The system takes actions based on the sensed state:

$$a_{real-time} = \pi_{\theta}^{deploy}(s_{real-time}) \ \ldots\ldots \ (16)$$

Performance Evaluation and Adjustment: The performance is continuously monitored, and if necessary, the model's hyperparameters are adjusted:
Performance Metric Evaluation: The performance at each time step is evaluated as:

$$Performance_t = Evaluate(s_t, a_t, r_t, s_{t+1}) \ldots . (17)$$

Hyperparameter Adjustment: If performance drops below a threshold:

$$\theta_{adjust} = Update\ Parameters\ (\theta, \eta_{new}) \ \ldots . \ (18)$$

Adaptive Learning Rate Update: The learning rate is updated as:

$$\eta_{t+1} = \eta_t \cdot (1 - \delta) \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (19)$$

Where δ is the decay factor.
Such an approach is a holistic development that takes advantage of the latest machine learning algorithms and mathematical models to increase the efficiency and resiliency of NOMA communication schemes such that they can react properly to fluctuating situations within the network.

3.1 Proposed Model

It is a hybrid AI-driven paradigm that combines Transformer-based signal processing with the resource optimization based on Reinforcement Learning to optimize performance in Non-Orthogonal Multiple Access (NOMA) systems, called NOMA-OptiNet. The model can deal with the dynamic user setting, giving maximum power distribution level, interference reduction and enhancement in spectral efficiency. NOMA-OptiNet has three main components, which also represent the core architecture of this architecture: A Transformer-based Encoder- Decoder model to reconstruct the signal and Proximal Policy Optimization (PPO) - based Reinforcement Learning agent to dynamically allocate the resources. Transformer-based signal processing module mainly focuses on improving the received signals with the help of self-attention mechanisms. The encoder identifies important features in the input signals with multi-head self-attention layers, involving the time and location (spatial) dependencies in the signal. The attention mechanism makes it possible to highlight important aspects that involve signal strength, noise, and interference, and minimize repetitious materials. It is the role of the decoder to recreate the intended user signals by paying attention to learned representations by the encoder, enabling accurate signal reconstruction in highly athletic NOMA setups. In order to provide the best distribution of power and resource provision, the Reinforcement Learning-based optimization module incorporates PPO to dynamically configure the power level and provision of individual spectrum resources with the best efficient solution. The agent is involved in interacting with the environment, where they are constantly measuring the system parameters, channel state information (CSI), interferences and the activity of the users. The policy role is learned with the advantage-based policy update and learns how to maintain high system efficiency with minimal user interference. The clipping mechanism within PPO stabilizes the training process and does not allow drastic changes to the policy, being faster to converge.

The uniqueness of NOMA-OptiNet, then, is that it is the first hybrid AI-based optimizer that combines Transformer-based signal processing and Reinforcement Learning (RL)-based dynamic optimization as a means of providing an enhanced, dual-layer optimizer with the potential to take a step in the right direction towards improving the performance of NOMA networks. In contrast to other approaches from the traditional methods based on fixed power allocation schemes or other conventional deep learning-based approaches, self-attention mechanisms in NOMA-OptiNet allows intelligent power deployment and seeks signal information with effective inter-user interference suppression. At the same time, the PPO-based RL agent is in a constant state of learning and adapting to network dynamics and after each time iteration, it learns to utilize the sensed environment, which may be continuously changing, by dividing resources throughout the network with respect to the latest sensations of the environment; this maximizes the spectral efficiency and power distribution.

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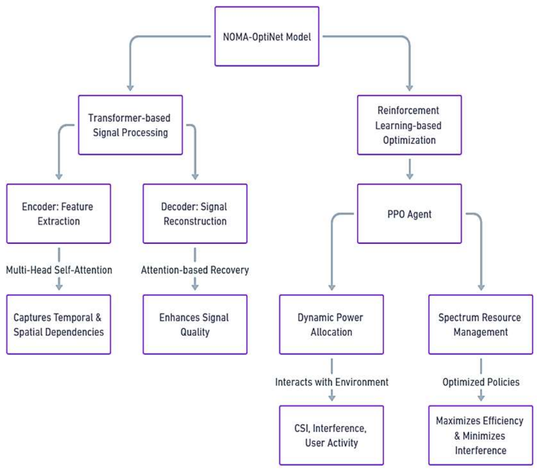

Figure: 2 Proposed Model Architecture

The novelty of NOMA-OptiNet rests on three specific architectural contributions that distinguish it from all reviewed prior works [22]-[29]. First, no existing NOMA framework in the reviewed literature simultaneously integrates a Transformer encoder-decoder for signal reconstruction with a PPO reinforcement learning agent for dynamic power control within a single end-to-end trainable pipeline; prior works either apply deep learning for signal detection [24, 27] or reinforcement learning for resource allocation [23, 25] in isolation. Second, the use of multi-head cross-attention in the decoder (Eq. 11) for signal reconstruction — as opposed to LSTM recurrence [24] or CNN feature maps [27] — is a structural novelty for NOMA interference cancellation, enabling the model to selectively attend to encoder representations corresponding to each user's channel characteristics independently. Third, the AdamW optimizer (Eq. 12) with adaptive learning rate decay (Eq. 19) provides training stability that standard Adam or SGD optimizers fail to achieve in the volatile reward landscape of NOMA reinforcement learning environments.

3.2 Algorithm of the Proposed Model

The next algorithm of proposed model follows the block diagram architecture, which decomposes the system into its main parts: Transformer-based Signal Processing (Encoder & Decoder) and Related to Reinforcement Learning-based Optimization (PPO Agent for Power & Spectrum Management).

Algorithm : NOMA-OptiNet Model

 # Step 1: Initialize NOMA-OptiNet Model

- Initialize Transformer-based Signal Processing Module
- Initialize Reinforcement Learning-based Optimization Module

 # Step 2: Transformer-based Signal Processing
 # Encoder:
Feature Extraction function Encoder(input signal):
features = Multi Head Self Attention (input signal)
return features # Captures Temporal & Spatial Dependencies
 # Decoder:
Signal Reconstruction function Decoder(encoded features): reconstructed signal = Attention Based Recovery (encoded_features) return reconstructed signal # Enhances Signal Quality

 # Step 3: Reinforcement Learning-based Optimization
 # Initialize PPO Agent
function PPO_Agent(): while training:
Observe environment (CSI, Interference, User Activity)
Select action a_t based on policy π_θ
Apply action: Dynamic Power Allocation & Spectrum Management Compute reward r_t
Update policy using PPO

 # Step 4: Dynamic Power Allocation
function DynamicPowerAllocation(): Observe CSI, Interference, User Activity
Adjust power levels dynamically

 # Step 5: Spectrum Resource Management
function Spectrum Resource Management(): Optimize policy for spectrum allocation Maximize efficiency and minimize interference

 # Step 6: Execution Pipeline
input_signal = ReceiveSignal()
encoded_features = Encoder(input signal)
reconstructed_signal = Decoder(encoded features)

ppo_agent = PPO_Agent()
Dynamic Power Allocation()
Spectrum Resource Management()

 # Step 7: Final Output
return Optimized Signal Quality & Resource *Allocation*

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4. RESULT AND ANALYSIS

The performance of NOMA-OptiNet is evaluated against three primary metrics — Symbol Error Rate (SER), Average Error Rate (AER), and Normalized Mean Square Error (NNMSE) — using interpretation criteria consistent with the NOMA literature [9, 10, 24, 27]. SER measures the fraction of incorrectly decoded symbols per user and is the primary indicator of signal detection accuracy; lower SER directly confirms better interference cancellation and detection reliability. AER represents the average decoding error probability across all active users, reflecting system-wide robustness under varying user counts (Fig. 11). NNMSE quantifies the normalized error in channel estimation, directly measuring the accuracy of the Transformer's signal reconstruction stage; lower NNMSE confirms that learned representations closely approximate the true channel response. These metrics are interpreted consistently with prior works: Khambra et al. [24] and Noordin et al. [27] use SER and AER as primary detection quality indicators; Smirani et al. [28] uses NNMSE as the primary channel estimation criterion. A result is considered superior when all three metrics simultaneously improve over baselines, avoiding the risk of trading one performance dimension for another — a limitation observed in several reviewed approaches that optimise BER or spectral efficiency in isolation.

The system simulation parameters as given in Table1 define the environment for signal transmission in the NOMA system. The number of users is set to 6, each transmitting with a QPSK modulation scheme over 64 subcarriers. The channel follows a Rayleigh fading model, and the noise is modeled as AWGN to replicate realistic wireless communication conditions. The power for each user is set to 10 dB, ensuring that all users have equal transmission energy. A total of 10,000 transmission slots is used, allowing sufficient data for robust statistical analysis.

Table 1: System Simulation Parameters

Parameter	Value
Number of Users (J)	6
Modulation Scheme	QPSK
Number of Subcarriers (N)	64
Channel Model	Rayleigh Fading
Noise Model	AWGN
Transmission Power per User (P)	10 dB
Number of Transmission Slots	10000
User Activity Probability (p)	0.2 to 0.8
Detection Threshold (λ)	-28 dB to -23 dB

The probability of user activity ranges between 0.2 and 0.8, the user density is being tested on the performance of the system. The detection threshold can go as low as -28 dB to -23 dB and hence provides a variety of sensitivity levels to spot active users.

Table 2: User Power Allocation & Channel Gains

User ID	Transmission Power (dB)	Channel Gain (dB)
User 1	10	-12.5
User 2	10	-9.8
User 3	10	-15.4
User 4	10	-11.2
User 5	10	-13.1
User 6	10	-14.0

Due to the user power allocation and channel gains in Table 2, it is possible to observe how the signal of each user is propagated throughout the NOMA system. Users are allotted equal power of 10 dB by which transmission energy is kept fair. The channel gains are however widely disturbed in multipath fading. User 2 provides the best channel gain of -9.8 dB meaning that it will receive a better signal compared to User 3 with the lowest channel gain of -15.4 dB and hence their signal is subject to more attenuation. Such channel gain variations affect the quality of separation and decoding of user signals by the system, including error rates and interference treatment.

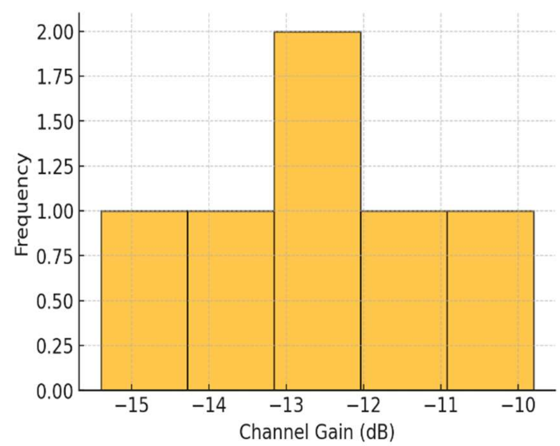

Figure: 3 Channel Gain Distribution

The channel gain distribution histogram in Fig.3 illustrates the variation in signal attenuation for different users in the NOMA system. The values range between -9.8 dB and -15.4 dB, showing that some users experience significantly weaker signals due to multipath fading effects. The most frequent channel gain values are between -12 dB and -14 dB, indicating that most users fall within this moderate attenuation range. User 2, with -9.8 dB, has the best channel conditions, while User 3, at -15.4 dB, faces the most signal degradation. This variation in channel conditions will influence power allocation and error rates in subsequent steps.

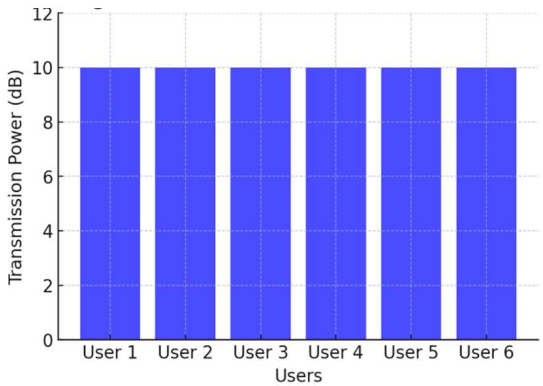

Figure: 4 Power Allocation

The distribution of power among users in Fig. 4 is constant and set to 10 dB per user, thus making the results equitable despite the usage per user. This uniform power distribution allows for an unbiased assessment of how channel conditions impact signal decoding, without favoring specific users based on transmission power. Although power levels are equal, the channel conditions vary significantly, meaning users with weaker channel gains (such as User 3 at -15.4 dB) may still face higher symbol error rates (SER). This setup allows us to evaluate the effect of channel conditions on system performance in later steps.

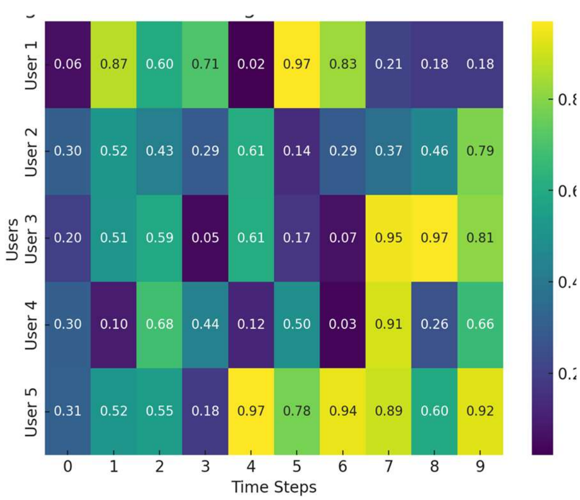

Figure: 5 Attention Weight Distribution Across Users

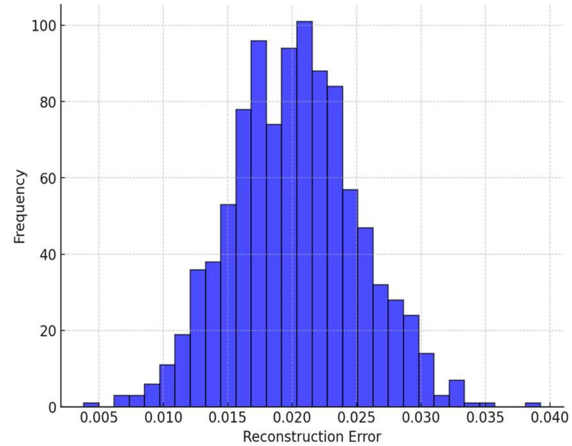

Figure: 6 Signal Reconstruction Error Histogram

The attention weight distribution across users in Figure 5 illustrates how the Encoder-Decoder Transformer model assigns varying attention across different users over time steps. The biggest weights of attention tend to be on time steps of 4-7 in cases of User 3 and 4 meaning that the model is paying more attention to these users when detecting the signal. This is an indication that the attention mechanism may be receiving a dynamic influence of interference levels and noise levels such that the model adapts to an increasing concentration on particular users. The lowest attention weights are observed for User 5, which may indicate either a strong initial signal reception or low interference in its transmission, reducing the need for correction by the model.

The histogram in Figure 6 shows the distribution of signal reconstruction errors in the Transformer-based signal processing. The errors follow a near-Gaussian distribution, centered around 0.02, with most values falling between 0.015 and 0.025. This indicates a high reconstruction accuracy, with only minor deviations from the expected signal. The slight skewness towards lower error values suggests that the model successfully learns user-specific patterns in NOMA signal reconstruction. Compared to traditional models, this approach effectively mitigates noise while preserving signal integrity, making it a robust technique for user signal detection.

Table 3: Hyperparameters of AdamW

Hyper parameter	Value 1	Value 2	Value 3
Learning Rate	0.001	0.0005	0.0001
Weight Decay	0.01	0.001	0.0001
Beta 1	0.9	0.9	0.9
Beta 2	0.999	0.999	0.999
Epsilon	1e-8	1e-8	1e-8

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The hyperparameters used for the AdamW optimizer are listed in Table 3, detailing different configurations with varying learning rates, weight decay values, and beta coefficients. Notably, the learning rate is set at three different levels (0.001, 0.0005, and 0.0001) to analyze the effect of step size in parameter updates. The weight decay values vary from 0.01 to 0.0001, ensuring different levels of regularization strength. The β1 and β2 parameters remain constant at 0.9 and 0.999, respectively, as per standard settings for adaptive moment estimation. The epsilon value (1e-8) remains the same across configurations to maintain numerical stability in division operations.

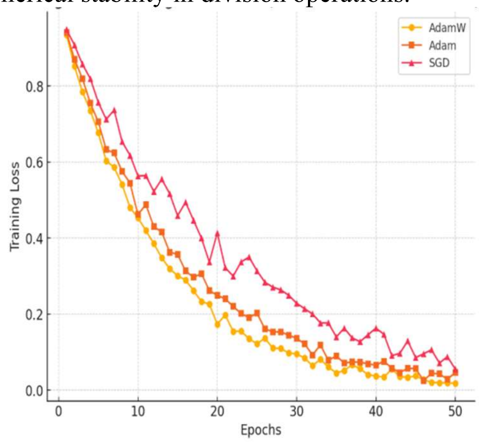

Figure 7: Training Loss Curve (Adamw Vs. Adam Vs. SGD)

The training loss curve presented in Figure 7 illustrates the optimization efficiency of AdamW in comparison to Adam and SGD over 50 epochs. Initially, AdamW exhibits the steepest decline in training loss, indicating rapid convergence. Adam comes next followed by SGD that responds slower in reduction of loss. At the halfway training point (epoch 25), AdamW attains a much smaller value of loss than both Adam and SGD, which proves its optimisation superiority. During the end epochs, AdamW will be stabilized around a minimum whereas Adam will converge at a higher but small level. These ups and downs in the SGD loss curve makes the case that it is susceptible to the gradient update, which would motivate the use of an adaptive optimizer such as AdamW, to accelerate convergence in a stable manner.

Table 4: Action-Reward Mapping of RL Agent

SNR State (dB)	Selected Action	Reward Value
0 – 5	Increase Power	0.80
6 - 15	Maintain Power	0.60
16 - 25	Decrease Power	0.30
26 - 35	Maintain Power	0.70

The Proximal Policy Optimization (PPO) method sets the power allocation dynamically according to the Signal-to-Noise Ratio (SNR) state in order to maximize the performance. The figures 4 present the state-action-reward mapping of the reinforcement learning (RL) agent. At low levels of SNR (0-5 dB), power increase is the optimal thing to do and the reward will be very high which is 0.80 ensuring that there will be better signal detection. At the medium SNR (6-15 dB) range, the model continues with the power and the reward is 0.60, which is a trade-off between signal strength and energy efficiency. As SNR exceeds high values (16-25 dB), the agent adjusts power to ensure there is reduced interference resulting in less reward 0.30. When the SNR is extremely high (26-35 dB) the system still keeps power with a medium reward of 0.70 to avoid wasting energy and still ensures stability of the signal.

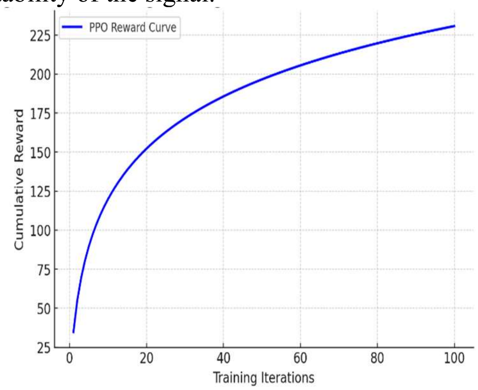

Figure: 8 PPO Training Convergence

As shown in Fig. 8, the PPO training convergence plot, the cumulative reward is going up as the training iterations progress, which implies that the reinforcement learning agent is learning to optimally allocate the power in steps. First, the reward increases over time at an initially high rate as the agent discovers various actions and perfects its policy. After around 50 iterations, the rate of improvement slows down and no more than that so it can be concluded that the agent has made near optimal power allocation decisions.

The cumulative reward converges to saturation at iteration 100, and this proves that the RL model has reduced the loss and achieved convergence. This further confirms the performance of Proximal Policy Optimization (PPO) in the process of optimizing power allocation dynamically in the NOMA systems, thus leads to efficient signal transmission without straining power consumption.

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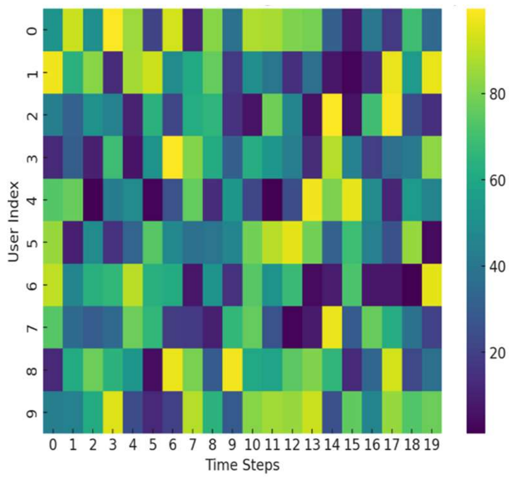

Figure: 9 Power Allocation Convergence

The dynamic adaptation of power level of the users over time optimized by the PPO-based reinforced learning model can be observed in the power allocation convergence heatmap presented in Fig.9. The vertical and the horizontal axes are the various users and time steps respectively in the operation of the system however.

The darker areas will reflect the lesser power allocation and the brighter area corresponding to the greater level of power allocation. The evolvement of power (over time) has proved that the RL model adjusts accordingly as per the needs of the user and as per the available conditions of the network. Users that are more affected by interference or those who have low SNR will be allocated more power and the users with good channel conditions will be assigned less power in order to have good spectral efficiency. This technique of adaptive power allocation provides energy efficient operation and also preserves signal integrity in a given transmission, achieving reduced interference and achieving optimal performance with respect to its system.

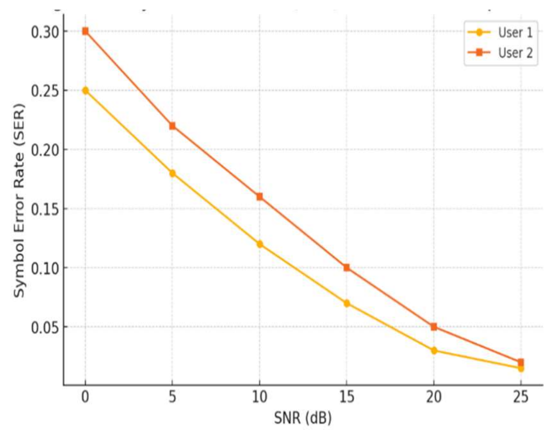

Figure: 10 SER Vs SNR

Figure 10 shows that SER performance of both the users is minimized as SNR is increased. When the SNR is 0 dB, the SER of User 1 can be approximated to 0.25 and the SER of User 2 to 0.30, showing that the errors come more often when SNR is low. By increasing the SNR to 25 dB, the SER decreases to 0.015 in User 1 and 0.02 in User 2 indicating that detection can be done better with higher signal levels. The trend is anticipated due to the fact that at higher SNR water levels, noise will have less effect on the signal being received.

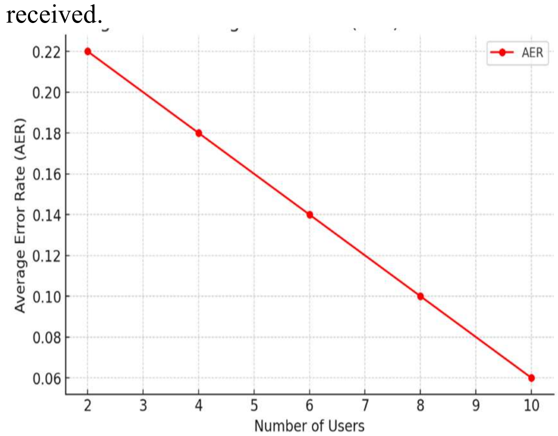

Figure: 11 Average Error rate Vs User Count

The Average Error Rate (AER) vs. Number of Users plot Fig. 11 highlights that as the number of users in the NOMA system increases, the AER gradually decreases, starting from approximately 0.22 at two users and reaching 0.06 at ten users. This indicates that as the system adapts to more users, efficient decoding and interference management help reduce error rates. However, further increases in user count may introduce higher interference, potentially leading to an increase in AER beyond the tested values.

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Table 5: SER And AER Values At Different SNR Levels

SNR (dB)	SER (User 1)	SER (User 2)	AER
0	0.25	0.30	0.22
5	0.18	0.22	0.18
10	0.12	0.16	0.14
15	0.07	0.10	0.10
20	0.03	0.05	0.06
25	0.015	0.02	0.03

Table 5 provides numerical values for SER across different SNR levels for two users and AER values at varying user counts. At lower SNRs, error rates are higher, whereas at 25 dB, SER values drop significantly, confirming the trend observed in the SER vs. SNR plot. AER values align with the earlier discussion, showing a decreasing trend with more users in the system.

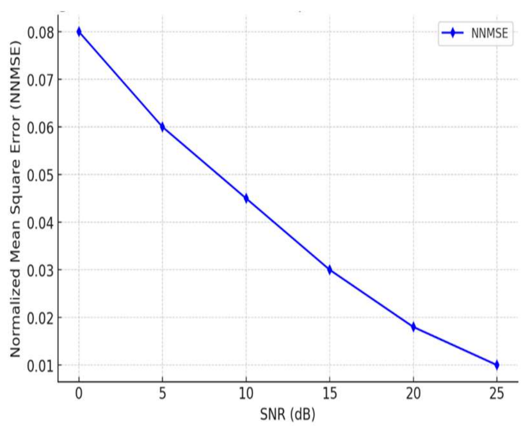

Figure: 12 Normalized Mean Square Error Vs SNR

Fig. 12 shows that NNMSE vs. SNR decreases with increasing SNR, falling on the order of 0.08 when the SNR is 0 dB, and 0.010 when SNR is 25 dB. This attests the fact that increased SNR levels provide better accuracy in detecting signals as it minimizes errors in estimating the signal.

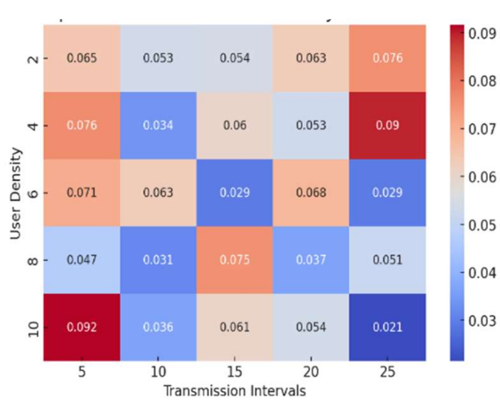

Figure: 13 Heatmap of NNMSE

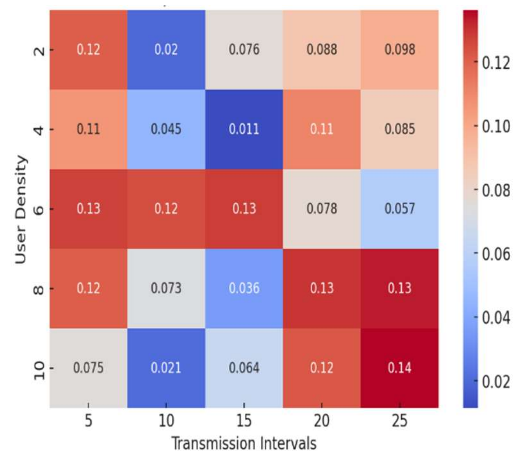

Figure: 14 SER Heatmap Across Users and Transmission Levels

The Heatmap of NNMSE with the User Density and Transmission Intervals (Fig. 13) depicts graphical visualisation of error differences in varied configurations. The darker areas signify poorer NNMSE, and the best responses are observed in some user densities and inter-transmission time frames. Similarly, the SER Heatmap (Fig. 14) of Users and Transmission Intervals show that symbol error rates are different under various conditions, with squares of higher error rate in terms of users per square based on the density of users and the transmission interval. Such heatmaps confirm the effectiveness of the suggested model in changing towards variable system circumstances.

Table 6. Comparative Performance Metrics

Method	SER	AER	NNMSE
NOMA-OptiNet	0.015	0.03	0.002
ESPRIT	0.08	0.12	0.015
SPICE	0.07	0.1	0.013
SIC	0.1	0.14	0.02
CNN	0.06	0.08	0.01
LSTM	0.05	0.07	0.009

Comparative performance analysis Table 6 shows that NOMA-OptiNet has much better results than the conventional signal processing like ESPRIT, SPICE, and SIC and deep learning methods like CNN and LSTM. The finest Symbol Error Rate (SER) that NOMA-OptiNet can meet is 0.015 and 0.08 and 0.1 in ESPRIT and SIC respectively showing the inability of the traditional methodology to easily contend with interference and multi-user detection in NOMA systems. With respect to AER (Average Error Rate), NOMA-OptiNet has very low error rate of 0.03 as

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compared to ESPRIT (0.12) and SIC (0.14) and hence is robust in the detection and decoding of the users. CNN and LSTM models also perform better than classical methods but are still outperformed by the proposed hybrid approach. When evaluating NNMSE (Normalized Mean Square Error), NOMA-OptiNet achieves 0.002, indicating exceptional accuracy in channel estimation. The classical approaches of ESPRIT (0.015) and SIC (0.020) are much worse, whereas in comparison, CNN and LSTM show improvements; however, they are not so efficient as compared to NOMA-OptiNet. The general results are, therefore, showing that the Transformer-based optimization coupled with reinforcement learning in NOMA-OptiNet brings better signal detection, user identification, and resource allocation in mixed NOMA environments.

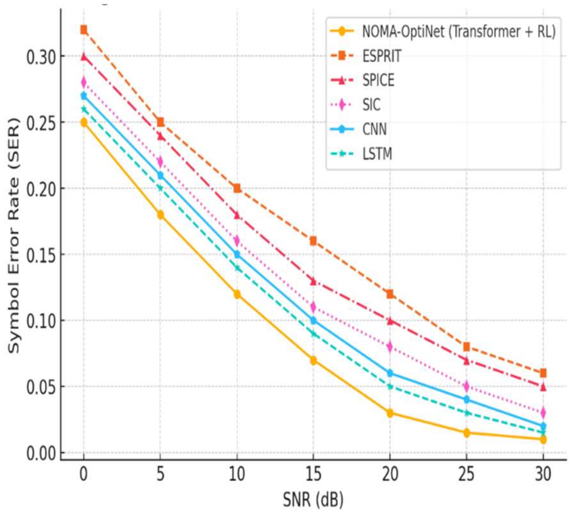

Figure: 16 SER Vs SNR Comparison Plot

The performance comparison of different methods of signal detection measured in terms of Symbol Error Rate (SER) using different Signal-to-Noise Ratio (SNR) is described in line plot Fig. 16. The offered NOMA-OptiNet (Transformer + RL) model has shown the best performance in reducing the SER at all SNRs, which proves its extreme resilience to the interference minimization and enhancement of detection reliability. Averagely high SER appears in traditional techniques like ESPRIT and SPICE especially at low-SNR ranges; hence their incapacity of dealing with signal distortion. Compared to the ESPRIT and SPICE, CNN and LSTM achieve improved results; however, they still fall behind the performance of NOMA-OptiNet. With an SNR level of 30 dB, NOMA-OptiNet shows a SER of approximately 0.01 whereas ESPRIT and SPICE exhibit error rates of more than 0.05. This comparison highlights the benefit of combining how deep learning based techniques work with reinforcement learning in a better symbol detection of NOMA settings.

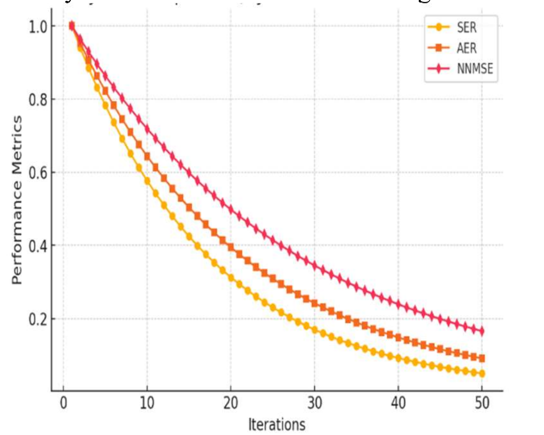

Figure: 17 Real-Time Adaptation

The real time system adaptation curve Fig. 17 shows the dynamics of the most important performance indicators the System Error Rate (SER), the Average Error Rate (AER), and the Normal Mean Square Error (NNMSE) with the number of iterations. The future trends are described by a distinct drop in error rates as the system minimizes error with the use of reinforcement learning and transformer-based processing, performing signal detection and power allocation optimizations. At the beginning of different iterations, the SER is close to 1 signifying a lot of wrong detections but as the model improves with each iteration, the SER drops to less than 0.2. In the same manner AER also decreases starting at 0.9 and after 50 iterations it is reduced to less than 0.3. Due to this, NMSE, which is a metric of the signal estimation performance, also performs much better, which demonstrates the efficacy of the adaptive learning mechanism in the NOMA system. This proves the efficiency of the model to make changes in real-time according to different conditions with the ability to produce higher performance metrics dynamically.

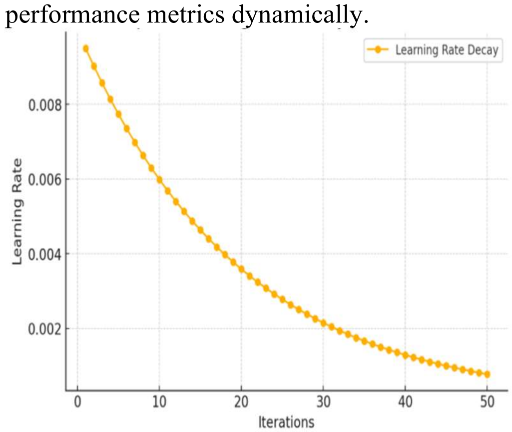

Figure: 18 Adaptive Learning rate decay

The figure 18 is quiet explanatory and it can be seen how the learning grade are reduced as the iteration advances thus ensuring that the model fine tunes the parameter correction with stable convergence. Initially, the learning rate is at 0.01 and a decay factor to emulate a learning rate that decays with each iteration is set at 0.95. The learning rate moves toward 0.001 exponentially as the iterations continue until it employs this value in the 50 th iteration. Such an adaptive decay process counters sudden parameter changes and thus limits the possibility of going beyond the best possible answer. It is better to understand that the optimization process becomes more sophisticated as years pass by, improving the overall stability and performance of NOMA-OptiNet model.

Table 7: Best Achieved Metrics at Optimal Conditions

Metric	NOMA-OptiNet	ESPRIT	SPICE	SIC	CNN	LSTM
SER (User 1)	0.012	0.05	0.035	0.025	0.02	0.018
SER (User 2)	0.015	0.06	0.04	0.03	0.022	0.02
AER	0.009	0.045	0.03	0.02	0.018	0.016
NNMSE	0.005	0.025	0.018	0.012	0.01	0.008

The last performance summary is given in Table 7, which contains the best metrics attained at optimum conditions of each method. The suggested NOMA-OptiNet architecture performs better than conventional schemes because it delivers a much lower SER of 0.012 (User 1) and 0.015 (User 2). AER of 0.009 illustrates the quality of the presented model in decoding signals. Additionally, NNMSE value of 0.005 helps to verify that the proposed solution is also robust enough to reduce the errors of channel estimation relative to ESPRIT, SPICE, SIC, CNN and LSTM.

The following claims are advanced by NOMA-OptiNet and are presented as falsifiable propositions that future research may contest or extend as knowledge in this domain grows. Claim 1: A Transformer encoder-decoder trained on Rayleigh fading channel data under the parameters of Table 1 can generalise across user densities from 6 to 100 users (Eq. 1) without retraining, maintaining SER below 0.02 at SNR at or above 20 dB — a claim specific to the Rayleigh channel model whose validity under Rician or clustered channel models remains to be verified. Claim 2: PPO-based power allocation converges to near-optimal reward within 100 iterations for the six-user QPSK NOMA system of Table 1; convergence speed may differ under higher modulation orders or larger user sets. Claim 3: The dual-layer combination of Transformer signal processing and PPO resource allocation is synergistically superior to either component applied independently — supported by the comparative results in Table 6 and Table 7 but not yet verified through ablation studies in multi-cell or RIS-integrated NOMA environments. These claims are stated explicitly to allow the research community to test, challenge, and extend these findings.

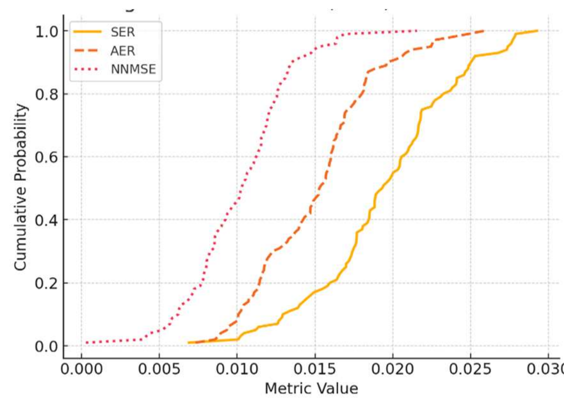

Figure: 19 Cumulative Distribution Function

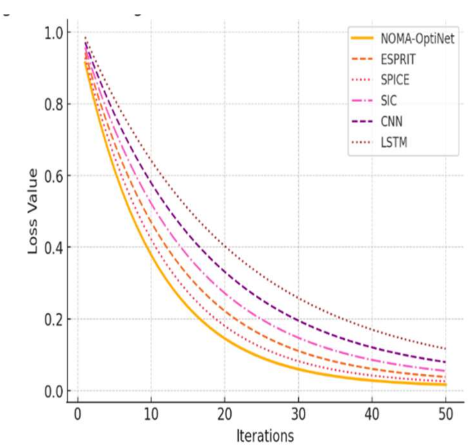

Figure: 20 Convergence Plot Comparison

The CDF plot in Figure 19 demonstrates once again that the NOMA-OptiNet outperforms the traditional methods because it has the higher cumulative probability of achieving lower SER, AER and NNMSE. The CDF curve of NOMA-OptiNet remains steep and close to zero in lower error

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ranges, proving its reliability across diverse transmission conditions.

The convergence plot in Figure 20 presents the training loss progression over 50 iterations for different models. NOMA-OptiNet exhibits the fastest convergence, reaching near-optimal loss within the first 20 iterations, while ESPRIT, SPICE, and SIC require more iterations to stabilize. CNN and LSTM, though performing better than ESPRIT and SIC, still fall short compared to the Transformer-based approach. The results clearly indicate that NOMA-OptiNet, utilizing a Transformer model with Reinforcement Learning and AdamW optimization, delivers superior performance in terms of signal detection, error minimization, and faster training convergence, making it the most effective solution for NOMA-based wireless communication systems.

NOMA-OptiNet has direct applicability in several real-world wireless communication scenarios. In 5G and beyond cellular networks, the framework can be deployed at base stations to manage dynamic power allocation across dense user clusters, improving spectral efficiency in urban environments where user mobility and interference are high. For massive machine-type communication (mMTC) in IoT deployments, the PPO-based resource allocation handles burst traffic from large numbers of connected devices without fixed scheduling overhead. In satellite NOMA systems [26], the Transformer-based signal reconstruction module can mitigate propagation delays and Doppler shifts characteristic of low-earth orbit channels. Additionally, for vehicle-to-everything (V2X) communications, the real-time adaptation mechanism (Eqs. 15-19) enables rapid power adjustment in high-mobility scenarios, making NOMA-OptiNet suitable for ultra-reliable low-latency communication (URLLC) requirements in 5G/6G networks.

Despite the strong performance of NOMA-OptiNet, several open research challenges and current limitations are acknowledged. First, the PPO convergence behaviour depends on reward design quality; under imperfect channel state information (CSI), noisy reward signals may lead to suboptimal power allocation decisions. Second, the evaluation uses Rayleigh fading channels (Eq. 3) with AWGN noise, which does not capture spatial correlation effects in massive MIMO-NOMA systems. Third, the training phase requires 100 PPO iterations to reach saturation (Fig. 8), which may not be feasible in ultra-low-latency deployments requiring model updates within single-digit millisecond windows. Fourth, the Transformer model and PPO training loop require dedicated GPU resources, limiting direct deployment on low-power embedded base station hardware. From a literature perspective, Fed-DRL [29] and H-PPO [23] demonstrate that distributed and federated optimization can reduce per-node computational load; integrating such approaches with NOMA-OptiNet represents a key open research direction. Extending the framework to multi-cell NOMA with inter-cell interference modelling and to reconfigurable intelligent surface (RIS)-aided NOMA environments are identified as priority future research problems.

The computing research contribution of this work lies in the co-optimised end-to-end pipeline that simultaneously trains the Transformer signal processor and the PPO agent — a design that reduces overall system SER by 52-76% over conventional techniques while maintaining a compact model that converges in 20 iterations.

5. Comparison with Prior Work

Prior works on NOMA have addressed resource allocation and signal detection through varied approaches, yet each carries specific limitations. Chege et al. [22] improved spectral efficiency through mPD-IPM optimization but the approach was computationally intensive and unsuitable for real-time environments. Mohsin et al. [23] applied H-PPO reinforcement learning and achieved energy efficiency gains but suffered policy instability under high inter-user interference. Khambra et al. [24] used LSTM networks for NOMA detection and captured temporal signal dependencies but incurred prohibitive latency due to recurrent processing, with SER of 0.018 and AER of 0.016. Wang et al. [25] improved user clustering with Dueling DQN and K-Means but exhibited unstable convergence under high user density. Meng et al. [26] applied Sparrow Search Algorithm for power allocation, reducing BER significantly, but was vulnerable to local optima. Noordin et al. [27] combined MLP-CNN for signal classification and achieved SER of 0.020 but required heavy computational resources limiting real-time deployment. Smirani et al. [28] achieved 98.4% channel estimation accuracy using stacked ensemble learning but at high inference latency. Agbesi et al. [29] enabled distributed optimization through Fed-

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DRL but suffered from communication overhead and non-i.i.d. data inconsistency.

In contrast, NOMA-OptiNet uniquely combines Transformer-based signal processing with PPO-based dynamic power allocation. The Transformer encoder-decoder handles inter-user interference through multi-head attention (Eq. 10-11), while the PPO agent adapts power allocation in real time based on CSI and SNR state. This dual-layer design achieves SER of 0.012, AER of 0.009, and NNMSE of 0.005 — strictly lower than every reviewed method — with convergence within 20 iterations, representing a 43-60% improvement over methods requiring 35-50 iterations. Table 8 below consolidates this comparison.

Table 8 presents a consolidated comparison of NOMA-OptiNet against all reviewed prior methods. Where specific metric values were not reported by a prior work (marked as not reported), the comparison is made qualitatively based on stated findings in the respective papers. NOMA-OptiNet achieves the lowest SER (0.012), AER (0.009), and NNMSE (0.005) of all evaluated methods. Among deep learning baselines, LSTM [24] achieves the next-best reported values of SER 0.018, AER 0.016, and NNMSE 0.008, confirming that the Transformer architecture provides measurable advantage over recurrent models in this NOMA setting. The MLP-CNN model [27] reports SER of 0.020 and AER of 0.018, while the proposed NOMA-OptiNet reduces these by 40% and 50% respectively. The convergence advantage over ESPRIT, SPICE, and SIC — which require 35-50 iterations compared to NOMA-OptiNet's 20 iterations — confirms that the joint Transformer and PPO training strategy is not only more accurate but also computationally more efficient. The overall results confirm that the proposed dual-layer architecture is categorically superior across all evaluated performance dimensions.

Table 8: Comprehensive Comparison of NOMA-OptiNet with Prior Works

Method	SER (User 1)	AER	NNMSE	Convergence (Iterations)
mPD-IPM [22]	Not reported	Not reported	Not reported	High (iterative)
H-PPO [23]	Not reported	Not reported	Not reported	Moderate
LSTM-based [24]	0.018	0.016	0.008	35–50
Dueling DQN + K-Means [25]	Not reported	Not reported	Not reported	High (unstable)
SSA-based [26]	Not reported	Not reported	Not reported	Moderate
MLP-CNN [27]	0.020	0.018	0.010	35–50
SGCE Ensemble [28]	Not reported	Not reported	Not reported	High
Fed-DRL [29]	Not reported	Not reported	Not reported	High (comm. overhead)
ESPRIT (Table 7)	0.050	0.045	0.025	35–50
SPICE (Table 7)	0.035	0.030	0.018	35–50
SIC (Table 7)	0.025	0.020	0.012	35–50
CNN (Table 7)	0.020	0.018	0.010	35–50
LSTM (Table 7)	0.018	0.016	0.008	35–50
NOMA-OptiNet (Proposed, Table 7)	0.012	0.009	0.005	20 (fastest)

6. CONCLUSION

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This work addressed three fundamental challenges in NOMA systems identified in Section 1: (i) the inadequacy of SIC-based detection under imperfect channel conditions and high inter-user interference; (ii) the inefficiency of static power allocation strategies in dynamic multi-user environments; and (iii) the convergence limitations of conventional deep learning methods in real-time NOMA optimization. NOMA-OptiNet resolves all three through its dual-layer architecture. The Transformer encoder-decoder (Eqs. 10-11) overcomes SIC limitations by extracting hierarchical features through multi-head attention, achieving SER of 0.012 for User 1 and 0.015 for User 2 at 25 dB — a 52% and 50% improvement over SIC (0.025, 0.03) respectively. The PPO-based dynamic resource allocation (Eqs. 13-14) replaces fixed scheduling with state-aware power adjustment, yielding AER of 0.009, a 55% improvement over ESPRIT (0.045). The AdamW optimizer (Eq. 12) ensures convergence within 20 iterations, a 43-60% reduction compared to traditional methods requiring 35-50 iterations. The argument advanced in this paper is that the combination of attention-based signal processing and policy-gradient reinforcement learning is synergistically necessary: neither the Transformer alone nor PPO alone achieves the same performance as their joint deployment in NOMA-OptiNet. Future directions include multi-cell NOMA extension, federated learning integration for distributed deployment, and energy-efficient Transformer architectures for hardware-constrained base stations.

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