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An Efficient Adaptive Channel Estimation in a Massive MIMO-OFDM Communication Network Based on Minimization of Error Entropy

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ABSTRACT

The integration of Massive MIMO, OFDM, and NOMA technologies represents a powerful solution for next-generation wireless communication networks. However, these systems face significant challenges, including accurate channel estimation under low Signal-to-Noise Ratio (SNR) conditions, slow convergence and limited adaptability of conventional algorithms such as LMS and NLMS, inter-user interference, and the complexity of modeling frequency-selective fading in large-scale antenna arrays. This study proposes an adaptive channel estimation framework based on the Minimum Error Entropy (MEE) criterion. Unlike traditional methods that rely on second-order statistics, the MEE approach utilizes higher-order statistics, making it more effective in modeling non-Gaussian and impulsive noise commonly encountered in real-world communication channels. The adaptive nature of the filter also allows it to respond dynamically to time-varying channel conditions. Simulation results demonstrate that the proposed MEE-based estimator achieves a remarkably low Mean Squared Error (MSE) of approximately $2 * 10^{-4}$ and an average Bit Error Rate (BER) of around $9 * 10^{-4}$, outperforming conventional estimators in both accuracy and robustness. The simulation results show that Leveraging Kernel Density Estimation (KDE) for improved error modeling and coefficient adaptation, the proposed method offers a scalable and efficient solution for reliable channel estimation in Massive MIMO-OFDM-NOMA systems. These results highlight the potential of the proposed framework to significantly enhance spectral efficiency and communication reliability in future 5G/6G wireless networks.

1. INTRODUCTION

The transformation in wireless communication infrastructure throughout recent decades evolved from voice-based systems to multi-server data-oriented solutions which maintain multiple application services. Channel estimation stands as the essential factor for wireless network adaptiveness because it swiftly determines the current state of communication channels [1, 2]. During implementation of precoding methods and resource distribution techniques signal detection and beamforming operate through data operations as a fundamental tool. The implementation of signal detection through beamforming operations demands both data processing with precoding methods and coherent signal detection and beamforming distribution resources. Current broadband systems require precise wireless channel measurements due to their necessity to operate in dynamic areas with doppler speed variations as well as multiple path interferences. The estimation of wireless channels functions as the essential fundamental for contemporary physical layer wireless systems per [3].

The significance of proper channel estimation reaches a crucial point in current advanced technologies including Massive MIMO (Multiple-Input Multiple-Output) and Orthogonal Frequency Division Multiplexing (OFDM) because these systems serve as essential enablers for 5G networks and beyond. The base station of Massive MIMO systems uses multiple antennas in an array configuration for simultaneous user service which enables spatial multiplexing benefits and better power efficiency [4, 5]. Implementing OFDM results in channel robustness because it divides wideband bandwidth into separate orthogonal subcarriers. These technologies present individual implementation obstacles when operated together. The accurate and efficient estimation of numerous unknown channel coefficients becomes essential because Massive MIMO channels operate at high dimensions while OFDM systems have frequency selective properties. The difficulty of the resulting estimation task increases alongside antenna quantity and user density, as well as the necessity of rapid channel adaptation. Massive MIMO-OFDM systems require effective channel estimation techniques that scale efficiently while ensuring reliable performance, as these techniques enable the full exploitation of spatial multiplexing and frequency diversity gains [6, 7]. For instance, in a typical urban deployment with 128 antennas at the base station and 32 active users, the number of unknown channel coefficients to be estimated per OFDM symbol can exceed 4000. This scale introduces high computational demands and limits the applicability of conventional estimators.

Research progress has brought many benefits to the field yet various gaps exist that restrict Massive MIMO-OFDM system scalability and practical performance. The standard LS and MMSE channel estimators require orthogonal pilot sequences and simplified propagation environments according to research [8]. Limited time-frequency resources and high user density together with pilot contamination create challenges for these assumptions because orthogonality cannot be maintained. When NOMA enters the field, it introduces significant complexity to channel estimation since users sharing time-frequency resources leads to complicated interference patterns between users as well as between estimation and detection processes which mainly occurs in two forms: Inter-user Interference and Cross-interference between the channel estimation and signal detection processes. Inter-user interference occurs when signals from different users transmitted on the same or nearby frequency subchannels interfere with each other. Due to the uncertainty in the allocation of pilot resources and their sharing in the time-frequency space, this interference causes the signals to overlap, making them difficult to separate and reducing the quality of channel estimation. In particular, in situations where the number of users and antennas is large, the cross-interference between users increases rapidly and has adverse effects on the estimation accuracy and signal detection efficiency. In addition, cross-interference between channel estimation and signal detection is also problematic. In this case, the sharing of pilot and data resources causes the channel estimation processes, which are usually designed based on pilot signals, to be affected by the data signals of other users and their performance is impaired. This creates nonlinear and non-Gaussian interference, which is challenging to model and compensate for, especially in NOMA systems where users with different signal strength levels operate simultaneously. Numerous existing research fails to investigate the collective performance impacts of Massive MIMO, OFDM and NOMA in these situations [9].

Therefore, this study specifically focuses on developing an efficient channel estimation framework tailored for Massive MIMO-OFDM systems integrated with NOMA, with the key objectives of improving estimation accuracy and enhancing robustness against noise and interference under realistic multi-user scenarios. The presented research evaluates the current gaps then introduces a specialized channel estimation solution for Massive MIMO-OFDM systems. This work introduces unique value by analyzing extensive antenna networks together with frequency-dependent connectivity and the additional technical challenges caused by NOMA. This research aims to improve the accuracy of channel estimation and enable the use of fewer pilot signals, while ensuring the scalability and future expansion capability of the system. This paper develops a new detection and estimation method which utilizes system structural information to enhance performance levels under available channel and interference scenarios.

The proposed channel estimation method uses an adaptive filter together with the Minimum Error Entropy algorithm in Massive MIMO-OFDM systems. The filter coefficients get updated through system operation with the MEE algorithm. The MEE algorithm stands apart from traditional LMS and NLMS methods because it minimizes error estimation entropy beyond the MSE criteria to incorporate statistical information of higher order. Improved resistance to noise and external interferences occurs when implementing this technique. MEE surpasses the classical LMS and RLS techniques because it uses error entropy measurement which provides complete coverage of error distribution moments. The MEE-based technique enables faster convergence together with lower MSE and superior Bit Error Rate (BER) results in channel estimation. LMS and NLMS algorithms achieve inferior performance compared to MEE which shows exceptional results especially under low Signal-to-Noise Ratio conditions for accurate channel estimation. This proposed method delivers accurate estimates to Massive MIMO-NOMA systems and strengthens performance stability under conditions of environmental noise making it an appealing solution for future deployments.

This research puts forward three main contributions which include:

- The researchers proposed MEE-based adaptive filtering for channel estimation while offering LMS and NLMS as typical MSE-based alternatives.
- The estimation system benefits from error distribution estimation done through Kernel Density Estimation (KDE) that allows accurate and dependable channel estimation across different environmental scenarios.
- The proposed method excels in different noise environments as well as low SNR regimes where traditional methods fail because they only handle Gaussian noise.
- The research develops and tests a practical Massive MIMO-NOMA-OFDM system by using realistic parameters for multipath components along with specific subcarrier configurations and diverse power levels for different users.
- Performance evaluation tests will measure channel estimation accuracy and Bit Error Rate for the proposed approach and baseline standards using various SNR conditions.

The remainder of this paper is organized as follows: Section II presents a detailed system model of the Massive MIMO-OFDM-NOMA configuration. Section III outlines the proposed channel estimation and signal detection methodology. A thorough performance assessment and simulation outcomes are provided in Section IV to confirm the efficacy of the suggested strategy. Finally, Section V concludes the paper with a summary of findings and potential directions for future research.

2. RELATED WORK

- Rapudu et al. [10] they addressed challenges in wireless communication at millimeter-wave (mmWave) frequencies, where signal propagation is significantly hindered by obstructions. To improve transmission reliability, they proposed combining multiple reconfigurable intelligent surfaces (multi-RISs) with Massive MIMO systems. However, this approach leads to complex channels that traditional channel estimation (CE) methods struggle with. Machine learning (ML)-based CE techniques have shown promise in these scenarios. The authors introduced a novel ML framework, DnCNN-GRU, combining a denoising convolutional neural network and gated recurrent unit for accurate uplink channel estimation. Evaluations showed the DnCNN-GRU outperformed conventional methods, achieving near-optimal accuracy.
- Xu et al. [11], they introduced StructNet-CE, an online learning framework for real-time channel estimation in

MIMO-OFDM systems. In contrast to conventional techniques, StructNet-CE operates using only over-the-air reference signals (RS), performing slot-by-slot estimation without prior channel state information. It leverages structural features of MIMO-OFDM systems, such as repetitive modulation patterns and symbol classification robustness, transforming the channel estimation task into symbol detection. This enables accurate channel learning even with sparse RS configurations in 5G and 5G-Advanced systems. Experimental results showed significant performance improvements, with mean square error (MSE) reductions of up to 95.54%, highlighting the framework's potential for next-gen wireless networks.

- Alqahtani et al. [12] highlighted the importance of accurate channel estimation (CE) for wireless network performance and proposed the MIMO-OFDM-5G-CS-AGAN (Conditional Self-Attention Generative Adversarial Network), a deep learning-based CE framework designed for 5G systems that accounts for multipath channels and Doppler effects. The proposed methodology, at its core enables robust, low-error CE. Evaluation results show significant improvements, reducing bit and symbol error rates by up to 13.4% and 11.23%, respectively.
- Khan et al. [13], researched wireless channel estimation in MIMO-OFDM systems through developing a method to handle accurate channel state information (CSI) requirements for maximum performance. The authors implemented a data-aided channel estimation (DACE) method as a spectral efficiency optimization technique while minimizing resource consumption. The estimation technique uses pilot symbols together with multiple detected data symbols serving as virtual pilots to reduce training sequence requirements. The proposed algorithm demonstrated superior performance than conventional least squares (LS) and linear minimum mean square error (LMMSE) systems through enhanced mean square error (MSE) and Bit Error Rate (BER).
- Meenalakshmi et al. [14], presented a MIMO-OFDM system channel estimation framework by uniting CNNs with polar coding techniques for 5G networks. The system achieves better reliability and error resilience and data throughput through its integration of polar encoding and decoding mechanisms. The core component CNN-CENet operates as a CNN-based channel estimation module which addresses interference and noise issues that occur during challenging 5G transmissions. Research results demonstrated how CNN-CENet delivered superior performance than standard LS and MMSE techniques through its achievement of a minimized mean square error (MSE) which surpassed LS by 95.6% and surpassed MMSE by 59.7%. The system proved to offer better Bit Error Rate (BER) performance through changing mobile conditions.
- Li et al. [15] investigated the drawbacks of OFDM systems that cause inter-subcarrier interference especially when pilots are decreased in number or cyclic prefixes are shortened. Researchers developed SCBiGNet as a deep learning solution which integrates the channel estimation part of SNN alongside a CNN and BiGRU structure for signal detection purposes to address these problems. The combined architecture utilizes two distinct methods to reduce nonlinear signal distortions while transmission takes place. Simulation data indicated that SCBiGNet excelled against existing approaches as it yielded substantial Bit Error Rate (BER) improvement between 0.2 dB to 9 dB under different operational conditions.
- Yang et al. [16], they analyzed MIMO-OFDM system channel estimation through a complete analysis of information geometry approach (IGA). Researchers established equivalence between all auxiliary manifold second-order natural parameters and fixed-point convergence of first-order natural parameters. The discovery of equivalent second-order natural parameters across all auxiliary manifolds and fixed-point convergence among first-order natural parameters enabled researchers to create an effective information geometry approach (EIGA) specifically designed for Massive MIMO-OFDM systems which could be implemented using fast Fourier transform (FFT) operations. The authors demonstrated the convergence conditions along with proof that EIGA delivers near-optimal channel performance while reducing computational needs and showing rapid convergence through simulation results.
- Nandi et al. [17] developed a machine learning method to estimate channels in MIMO-OFDM systems for reducing ISI interference and improving detection accuracy. The researchers adopted an Elman recurrent neural network (E-RNN) system to conduct channel estimation operations because it brings greater scalability and adaptability. E-RNN demonstrated substantial performance improvements by delivering low PAPR value together with reduced BER rate along with enhanced capacity channel and low MSE outcome. During 40 training epochs the E-RNN generated a PAPR of 0.1272. The E-RNN produced superior results compared to other neural network-based estimators when dealing with complex environments.
- Kwon et al. [18] presented CAMPNet and MSResNet as deep learning-based channel estimators that improve accuracy through multiscale representation of channel characteristics. CAMPNet operates by applying parallel multiscale features followed by convolutional attention operations yet MSResNet connects frequency domain data across scales through multiscale convolutional layers. Under challenging frequency scenarios combined with changing Doppler shifts the two models demonstrate consistent high performance levels. Experimental tests proved that CAMPNet and MSResNet surpassed conventional techniques through their performance which led to a 48.98% decrease in Mean Squared Error (MSE) at high Signal-to-Noise Ratio (SNR) conditions and exhibited better practical wireless resilience and generalizing capability.
- Alayu et al. [19] introduces ATLMS Algorithm by authors for channel estimation when NOMA and OFDM operate together. The main goal consists of reducing Bit Error Rate (BER) and Mean Square Error (MSE) with the objective of improving system capacity along with user accessibility. The research methodology consists of creating basic LMS estimation algorithms and developing ATLMS as a novel technique to be evaluated with extensive simulation results. The newly proposed ATLMS system together with its variants shows notable improvements in MSE results by producing reduced error values than standard LMS methods do. The BER analysis shows that ATLMS provides superior performance to

LMS by delivering better error rate performance for both close and distant users hence improving the NOMA-OFDM system performance overall.

- Nayak et al. [20], they developed the Variable Forgetting Factor Recursive Least Squares (VFFRLS) algorithm to estimate MIMO-NOMA system channels. The research team aims to tackle channel impairments by implementing VFFRLS because this algorithm demonstrates better performance and faster convergence than traditional RLS. The algorithm conducts virtual experiments that measure MSE and BER performance of both VFFRLS and RLS algorithms. According to simulation trials VFFRLS demonstrates the best ability to minimize mean square errors among adaptive algorithms while proving its accurate parameter estimation performance at multiple Signal-to-Noise Ratio points.

This paper investigates MIMO-OFDM by combining both advanced methods of Multiple Input Multiple Output (MIMO) and Orthogonal Frequency Division Multiplexing (OFDM). MIMO technology delivers better data rates through its communication nodes equipped with multiple antennas which manage radio frequency interference and increase the transmission coverage area. Despite being split into multiple orthogonal subcarrier channels by OFDM the system retains excellent protection against fading along with interference issues. The transmission of data and reliability together with spectral efficiency enhance through implementing MIMO-OFDM systems in channels with challenging conditions.

3. METHODOLOGY

This section presents the adaptive channel estimation method for Massive MIMO-OFDM-NOMA systems. The approach is based on employing the Minimum Error Entropy (MEE) algorithm in adaptive filters to estimate the communication channel in Massive MIMO scenarios. The following subsections provide a detailed explanation of the proposed method.

3.1 Massive MIMO-NOMA system model

Paper titles should be written in upper-case and lower-case We consider a single-cell Massive MIMO system comprising N_t transmit antennas arranged in a Uniform Linear Array (ULA) at the Base Station (BS), and K single-antenna users, where $N_t \gg K$, as depicted in Figure 1 [21], Orthogonal Frequency Division Multiplexing (OFDM) is used for modulation across N_s subcarriers.

To implement the NOMA scheme, the system architecture shown in Figure 2 is adopted. By assigning different power levels to their signals, NOMA can serve several users concurrently inside a single cell, improving spectral efficiency. Signals intended for each user are assigned different power levels such that they can be separated at the receiver using power-domain multiplexing. In a general NOMA system, a BS serves MM users, all equipped with single antennas. The BS transmits signals to users through superposition coding over shared time-frequency resources. Figure 2 illustrates a SISO-NOMA system with two users. Initially, the system model is formulated under the Single Input Single Output (SISO) configuration, where the signal relationships are represented in vector form. Subsequently, the analysis is extended to the Multiple Input Multiple Output (MIMO) case, where the corresponding equations are reformulated using matrix representations in MIMO systems.

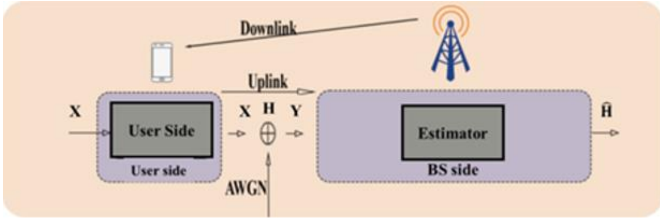

Figure 1. Massive MIMO system

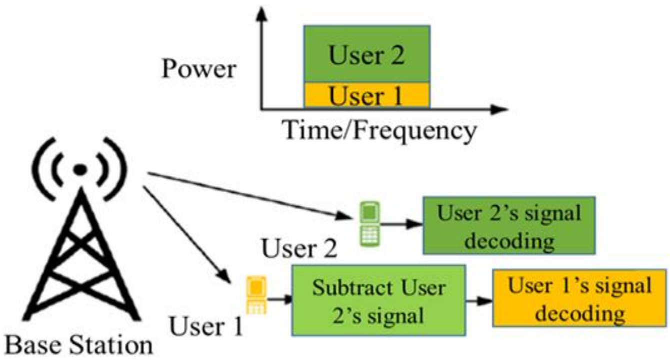

Figure 2. SISO-NOMA system

As illustrated in Figure 2, the system includes two users, labeled User1 and User2. The transmit power of User1 is lower than that of User2. Extending this scenario to MM users, the transmitted signal at the base station (BS) can be expressed as follows:

$$x = \sum_{k=1}^{M} \sqrt{p_k\, s_k}.\ E\{|s_k|^2\} = 1 \tag{1}$$

In this expression, p_k denotes the power allocated to the k-th user, and s_k represents the transmitted signal for that user. The channel gain between the transmitter and the k-th user (for $1 \leq k \leq M$) is denoted by h_k. In this study, assuming channel estimation is done leveraging an adaptive filter, the estimated channel corresponding to h_k is represented by $\hat{h}_k$. Accordingly, in a channel estimation system, the actual channel can be modeled as $h_k = \hat{h}_k + e$, where e denotes the estimation error. Assuming that the estimated channels are ordered as follows:

$$|\hat{h}_1|^2 > |\hat{h}_2|^2 > \cdots > |\hat{h}_M|^2 \tag{2}$$

It follows that greater transmission power is allocated to users with weaker channel gains. This implies that the power allocation across users is arranged as $p_1 < p_2 < \cdots < p_M$. The total power of the system is then computed according to the following relation:

$$P_t = \sum\nolimits_{k=1}^{M} p_k \tag{3}$$

The received signal at user k is:

$$\mathcal{Y}_k = h_k x + n_k \tag{4}$$

Substituting (1) into (4), we get:

$$\mathcal{Y}_k = h_k \sum_{j=1}^{M} \sqrt{p_j}\, s_j + n_k \tag{5}$$

To extend the SISO-NOMA system to a MIMO-NOMA framework, consider the configuration illustrated in Figure 3. This system comprises M users and a base station (BS), equipped with M antennas at both the transmitter and the receiver sides. Here, it is assumed that each user transmits at an identical data rate R.

In this system, when the signals transmitted by all K users simultaneously arrive at the BS, the received signal can be expressed as:

$$\mathrm{Y} = \mathrm{HX} + N \tag{6}$$

where,

$$X = [x_1 \ldots . x_k]^T \tag{7}$$

where, X represents the transmitted signal vector from users, H is the channel matrix, and N is an additive Gaussian noise vector. We assume that the BS has knowledge of the channel matrix H, whereas users do not. The BS uses a multi-user detector (MUD) to recover the users' signals, as illustrated in Figure 3.

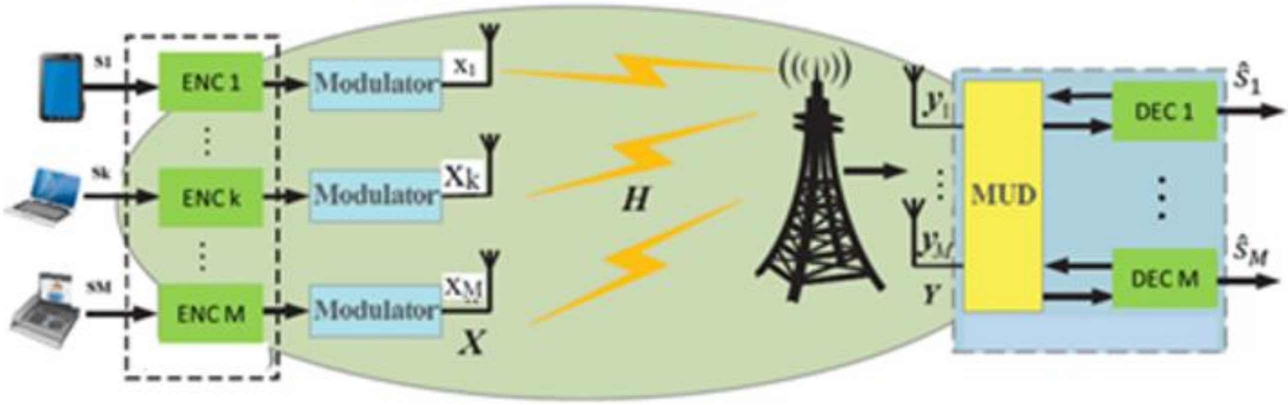

Figure 3. Uplink MIMO-NOMA system scenario with M users

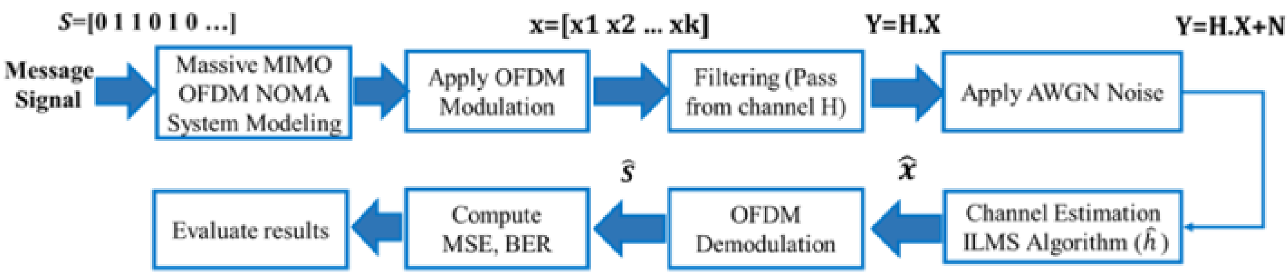

Figure 4. Channel estimation in massive MIMO-OFDM-NOMA diagram

3.2 Channel gain computation for proposed massive MIMO

In a Massive MIMO model with m subcarriers, the received signal at the m-th subcarrier, $\bar{y}_m \in \mathbb{C}^{1\times L}$, is expressed as:

$$\bar{y}_m = h_m X + n_m \tag{8}$$

where, L denotes the data length, and $X \in \mathbb{C}^{N_t \times L}$ represents the transmitted data matrix. The vector $n_m \in \mathbb{C}^{1\times L}$corresponds to the additive white Gaussian noise (AWGN) associated with the m-th subcarrier. The gain vector for m-th subcarrier, $h_m \in \mathbb{C}^{1\times N_t}$, is modeled as the sum of multipath components, given by:

$$h_m = \sqrt{\frac{N_t}{P}} \sum_{p=1}^{P} \alpha_p\, e^{-j2\pi\tau_p f_s \frac{m}{M}}\, a(\emptyset_p) \tag{9}$$

where, P is the number of multipath components, α_p is the complex path gain, f_s is the sampling rate, τ_p is the delay, and $a(\emptyset)$is the steering vector, defined as:

$$a(\emptyset) = \frac{1}{\sqrt{N_t}} \left[1. e^{-j\frac{2\pi d}{\lambda}\sin\phi} . \ldots\ e^{-j\frac{2\pi d}{\lambda}(N_t-1)\sin\phi}\right]^T \tag{10}$$

where, λ is the signal wavelength and $\emptyset_p$ represents the direction of arrival (DOA) for the p-th path. The goal of channel estimation is to obtain $\widehat{h_m}$, from which the transmitted signal x can be estimated as $\hat{x}$, allowing for computation of BER and MSE.

3.3 MEE-Based channel estimation for massive MIMO-OFDM-NOMA

Adaptive filtering is employed for channel estimation in this study. Adaptive filters are particularly useful in scenarios where system parameters or signal characteristics vary over time, necessitating real-time adjustments to maintain optimal performance. Unlike fixed-parameter FIR and IIR filters, which assume predetermined system dynamics, adaptive filters adjust their coefficients dynamically to compensate for unpredictable changes and uncertainties in the signal environment. In practical applications, lack of prior knowledge and the presence of non-stationary signals often require filters capable of self-adjustment. Adaptive filters achieve this by learning from the input-output relationship over time. The proposed MEE-based adaptive filter continuously updates its coefficients to adapt to changes in signal and system parameters. Figure 4 presents the general schematic of the suggested channel estimate approach for Massive MIMO-OFDM-NOMA systems; the following sections provide a detailed explanation of each block.

3.3.1 OFDM modulation

Orthogonal Frequency Division Multiplexing (OFDM) is a multicarrier modulation technique that mitigates inter-symbol interference (ISI) by dividing a wideband channel into several narrowband orthogonal subcarriers. This technique is particularly effective in multipath fading environments and is efficiently implemented through the Fast Fourier Transform (FFT) and Inverse FFT (IFFT), along with the insertion of a cyclic prefix (CP). In massive MIMO systems, which utilize tens to hundreds of antennas at the base station, the integration of OFDM with multiple-input multiple-output (MIMO) techniques, enables the exploitation of spatial diversity and enhances spectral efficiency.

3.3.2 AWGN channel modeling

In this study, the Additive White Gaussian Noise (AWGN) channel is employed to model noise within the proposed communication system. In this model, the transmitted signal $x(t)$ is corrupted by a stochastic noise process $n(t)$. In an AWGN communication system, where the transmitted signal is attenuated during propagation through the channel, the received signal in the time domain is expressed as:

$$y(t) = \alpha x(t) + n(t) \tag{11}$$

where, α denotes the attenuation coefficient, $x(t)$ is the modulated input signal, and $y(t)$ represents the received signal. Physically, the noise may originate from various sources such as electronic components, receiver amplifiers, or interference encountered during transmission. When the noise is predominantly generated by electronic components and amplifiers in the receiver, it can be characterized as thermal noise.

3.3.3 Adaptive channel estimation model

In a communication system, the channel estimation problem can be formulated as a system identification task, where the objective is to determine the channel characteristics based on a set of known input and output signals. As previously discussed, a communication system can be modeled as follows:

$$y(t) = hx(t) + n(t) \tag{12}$$

where, x is the known input signal to the communication channel, h represents the channel coefficients to be estimated, n denotes the additive noise, and y is the observed output signal, which depends on both the input and the channel characteristics. Based on this model, an adaptive system for channel estimation is illustrated in Figure 5. In this structure, the input signal x is passed through the channel (modeled as multiplication with h) and combined with noise to produce the channel output y. This output serves as the desired signal $d(t)$ for the adaptive filter. The primary goal is to estimate the channel coefficients $\hat{h}$ using the adaptive filtering process. If the output of the adaptive filter is denoted by $\hat{y}$, then the estimation error signal e(t) is defined as the difference between the actual channel output y and the filter output $\hat{y}$. The aim of the adaptive system is to minimize this error, ideally driving it to zero. In such a case, $\hat{y}$ would converge to y, implying that the adaptive filter coefficients W converge to the actual channel coefficients h. Through iterative updates at each step, the adaptive filter continuously refines its coefficients. Ultimately, the filter weights W provide an estimate $\hat{h}$ of the channel coefficients. The filter is thus configured to ensure that $\hat{h}$ closely approximates h, achieving accurate channel identification.

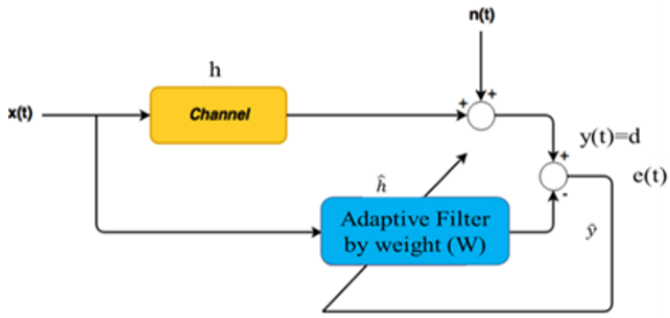

Figure 5. Adaptive channel estimation

Several algorithms exist for updating the adaptive filter coefficients. In this work, the Minimum Error Entropy (MEE) algorithm is employed for channel estimation in a Massive MIMO-OFDM-NOMA system. In the MEE algorithm, filter weights are updated to minimize the error entropy, as detailed in the following subsection.

3.3.4 Minimum Error Entropy (MEE) algorithm

Entropy is a scalar quantity that reflects the mean amount of data in a particular distribution. Information is regarded as an optimality metric. While lowering the Mean Squared Error (MSE) simply lowers the second-order moment of the error, minimizing the error entropy minimizes the entire distribution of error moments [22, 23]. Therefore, entropy can serve as an information-theoretic criterion, replacing MSE in adaptive systems. In this work, Rényi entropy is employed, which generalizes the notion of entropy; Shannon entropy is a special case of Rényi entropy when $\alpha = 1$. The Rényi entropy of the error e of order α is defined as:

$$H_\alpha(e) = \frac{1}{1-\alpha} \log \int f^\alpha(e)\, de \tag{13}$$

where, f(e) denotes the probability density function (PDF) of the error variable. The PDF of the error is considered impulsive. In this work, we focus on Rényi entropy of order $\alpha = 2$, expressed as:

$$H_2(e) = -\log \int f^2(e)\, de \tag{14}$$

As indicated in Eqs. (13) and (14), computation of entropy requires estimation of the error's PDF. The Parzen window method is utilized to calculate the PDF based on received data samples:

$$\hat{f}(e) = \frac{1}{N}\sum_{i=1}^{N} k_\sigma\left(e - e(i)\right) \tag{15}$$

where, $k(e)$ denotes the kernel function, σ represents the kernel bandwidth, and {e(1), e(2), …, e(N)} are the error samples. For mathematical simplicity, we adopt a Gaussian kernel with symmetric radial variance σ^2 as the kernel function. Consequently, the second-order Rényi entropy for the error samples can be reformulated as:

$$\hat{H}_2(e) = -\log \int_{-\infty}^{+\infty} \left(\frac{1}{N}\sum_{i=1}^{N} G_\sigma\left(e - e(i)\right)\right)^2 de$$

$$\hat{H}_2(e) = -\log \frac{1}{N^2}\int_{-\infty}^{+\infty} \left(\sum_{i=1}^{N}\sum_{j=1}^{N} G_\sigma\left(e - e(j)\right)G_\sigma\left(e - e(i)\right)\right) de \tag{16}$$

$$\hat{H}_2(e) = -\log \frac{1}{N^2}\left(\sum_{i=1}^{N}\sum_{j=1}^{N}\int_{-\infty}^{+\infty} G_\sigma\left(e - e(j)\right)G_\sigma\left(e - e(i)\right) de\right)$$

$$\hat{H}_2(e) = -\log\left(\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} G_{\sigma\sqrt{2}}\left(e(j) - e(i)\right)\right) \tag{17}$$

In this work, $G_\sigma(.)$ denotes a Gaussian kernel. The Information Potential (IP), which is the expression inside the logarithm, is provided by:

$$\hat{V}_2(e) = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} G_{\sigma\sqrt{2}}\left(e(j) - e(i)\right) \tag{18}$$

Thus, the entropy expression can be rewritten as:

$$\hat{H}_2(e) = -\log\left(\hat{V}_2(e)\right) \tag{19}$$

As the logarithm is a monotonic function, increasing the information potential is the same as decreasing entropy, as stated in Eq. (19). Consequently, the following is an expression for the cost function J(e) for the MEE metric:

$$J_{\mathrm{MEE}}(e) = \max_{\mathrm{w}} V(e) \tag{20}$$

As shown in Eq. (21), in an online learning scenario, the information potential can be efficiently approximated using the Stochastic Information Gradient (SIG). To create a stochastic gradient version, the outer summation is eliminated and the summation is limited to the most recent C samples at time n:

$$\hat{V}_2\left(e(n)\right) \approx \frac{1}{C}\sum_{i=n-C}^{n-1} G_{\sigma\sqrt{2}}\left(e(n) - e(i)\right) \tag{21}$$

To reduce the error entropy, an adaptive filter's weights can be modified using the MEE-SIG algorithm in the manner described below:

$$W[n+1] = W[n] + \mu.\nabla V\left(e(n)\right) \tag{22}$$

where, the gradient is given by:

$$\nabla V\left(e(n)\right) = \frac{1}{2\sigma^2 C}\sum_{i=n-C}^{n-1} G_{\sigma\sqrt{2}}\left(e(n) - e(i)\right)\{e(n) - e(i)\}\{X(n) - X(i)\} \tag{23}$$

where, μ represents the step size in the MEE-SIG algorithm.

3.3.5 Kernel Density Estimation

Kernel Density Estimation (KDE) is a non-parametric technique used for estimating the probability density function (PDF) of a random variable. Unlike parametric methods that assume a specific functional form for the underlying distribution, KDE constructs the PDF directly from the observed data samples, making it particularly useful for modeling complex or non-Gaussian noise distributions, which are often encountered in real-world communication channels.

For a given set of N error samples {e(1), e(2), …, e(N)}, the KDE for the error e is formally defined as:

$$\hat{f}(e) = \frac{1}{N\sigma}\sum_{i=1}^{N} K\left(\frac{e - e^{(i)}}{\sigma}\right) \tag{24}$$

where, $K(\cdot)$ represents the kernel function, and σ is the kernel bandwidth (also known as the smoothing parameter). The kernel function, which is typically a symmetric, non-negative function that integrates to one, determines the shape of the contribution of each data point to the overall PDF estimate. A common choice for the kernel function, and the one adopted in this study for mathematical simplicity, is the Gaussian kernel, given by:

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} \tag{25}$$

The bandwidth σ plays a crucial role in the smoothness of the estimated PDF. A smaller σ results in a more spiky and less smooth estimate, potentially overfitting the data, while a larger σ leads to a smoother but possibly over-smoothed estimate, potentially obscuring important features of the distribution. The optimal selection of σ is critical for accurate PDF estimation.

In the context of the Minimum Error Entropy (MEE) algorithm, KDE is fundamental for estimating the error's PDF, which is required for the computation of Rényi entropy. By providing a robust estimate of the error distribution, KDE enables the MEE algorithm to leverage higher-order statistical information beyond just the second-order moments, thereby enhancing its performance in non-Gaussian and impulsive noise environments. This capability is key to the improved accuracy and robustness demonstrated by the proposed MEE-based channel estimator in Massive MIMO-OFDM-NOMA systems.

3.3.6 The OFDM demodulation process

After estimating the channel coefficients, the signal that has passed through the channel is processed by the OFDM demodulator, which performs inverse demodulation to reconstruct the originally transmitted message. Based on the reconstructed message and the transmitted signal, performance metrics such as Mean Squared Error (MSE) and Bit Error Rate (BER) are computed to evaluate the effectiveness of the proposed method.

4. EXPERIMENTAL RESULTS

This section presents the simulation results to demonstrate the effectiveness of the proposed technique. To this end, a Massive MIMO-NOMA communication system is modeled, in which Orthogonal Frequency Division Multiplexing (OFDM) is employed for signal transmission over the wireless channel. The system is configured with the following parameters: number of subcarriers Ns=16, number of multipath components P=6, sampling frequency fs= 15khz, modulation order M=4, message length L=600, and Signal-to-Noise Ratio values snr_range = [0,5,10,15,20]. Table 1 summarizes the simulation parameters used in the proposed model.

Table 1. Simulation parameters

Parameter	Symbol	Value
Number of subcarriers	Ns	16
Number of multipath	P	6
Frequency of sampling	fs	15Khz
Modulation order	M	4
Message length	L	600
SNR range	SNR_range	[0,5,10,15,20]

To evaluate the performance of channel estimation in the proposed model, two metrics are used: Mean Square Error (MSE) and Bit Error Rate (BER). If the actual channel gain is denoted by h, and the estimated channel gain by $\hat{h}$, then the MSE is computed using Eq. (26):

$$MSE = \frac{1}{m}\sum\left(h - \hat{h}\right)^2 \tag{26}$$

where, m represents the number of channel coefficients. Additionally, the BER is defined as the ratio of the number of incorrectly detected bits to the total number of transmitted bits, as shown in Eq. (27):

$$BER = \frac{(Number\ of\ errored\ bits)}{(Total\ number\ of\ bits)} = \frac{\sum_{i=1}^{N}(S_i - \hat{S_i})}{N} \tag{27}$$

where, S denotes the transmitted message, $\hat{S}$ is the detected message, and N represents the length of message.

4.1 Evaluation of the convergence curve of the proposed MEE algorithm

Figure 6 illustrates the convergence behavior of the proposed Minimum Error Entropy (MEE)-based algorithm in comparison with conventional channel estimation algorithms such as Least Mean Square (LMS) and Normalized LMS (NLMS), which are based on the MSE criterion. As shown, the MEE algorithm converges more rapidly to a steady-state value than LMS and NLMS. For instance, during the initial iterations (fewer than 100), the MSE of the MEE algorithm decreases significantly faster, whereas LMS and NLMS require more iterations to reach their final values. This improvement is attributed to the use of the Minimum Error Entropy criterion, which incorporates higher-order statistical information, resulting in reduced coefficient fluctuations and faster convergence to optimal values. For example, at iteration 100, the MSE of the MEE algorithm is approximately 10^{-3}, whereas LMS and NLMS still exhibit higher values around 10^{-2}.

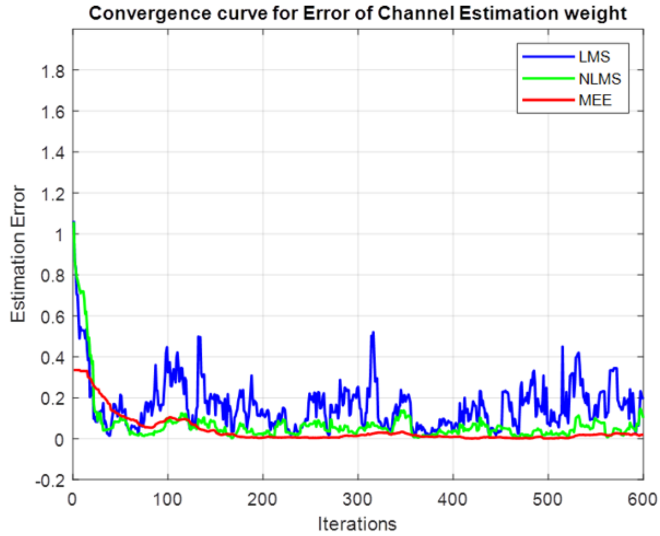

Figure 6. Convergence curves of LMS, NLMS, and the proposed MEE channel estimation algorithms

4.2 Performance evaluation of the proposed MEE algorithm in terms of mean square error

Figure 7 evaluates the channel estimation performance under different SNR levels. The proposed MEE method is compared with several conventional techniques, like Least Mean Square (LMS), Least Square (LS), Normalized LMS (NLMS), Arctangent LMS (ATLMS) [19], and Variable Forgetting Factor Recursive Least Square (VFFRLS) [20]. It is evident that the proposed MEE algorithm consistently achieves lower MSE values across all SNR levels compared to the benchmark methods. For instance, at an SNR of 10 dB, the MSE for the MEE algorithm is approximately $5.6 * 10^{-5}$, whereas the MSE for VFFRLS is around $8 * 10^{-3}$, for ATLMS around $2.2 * 10^{-3}$, and for NLMS approximately $1.2 * 10^{-4}$.

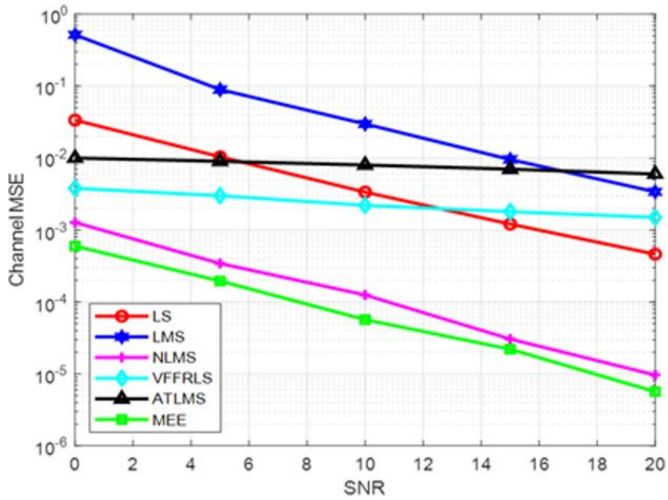

Figure 7. MSE comparison under various SNR levels

4.3 Performance evaluation of the proposed MEE algorithm in terms of Bit Error Rate

The Bit Error Rate (BER) analysis of different models occurs at various Signal-to-Noise Ratio levels according to Figure 8. Through its implementation the proposed MEE algorithm leads to substantial BER reduction which allows better reconstruction of received signals. When the SNR reaches 10 dB the Bit Error Rate (BER) of MEE stands at $6.6 * 10^{-5}$ while VFFRLS reaches $1.2 * 10^{-1}$ and ATLMS measures $2 * 10^{-1}$ and NLMS shows $9.4 * 10^{-5}$. The BER for MEE at 0 dB SNR stands at $3.4 * 10^{-3}$ whereas VFFRLS reaches $3.5 * 10^{-1}$ and ATLMS achieves 1 and NLMS gets $3.5 * 10^{-3}$. The proposed method demonstrates better signal quality enhancement alongside lower Bit Error Rates which are essential elements for fast and impaired communication channels.

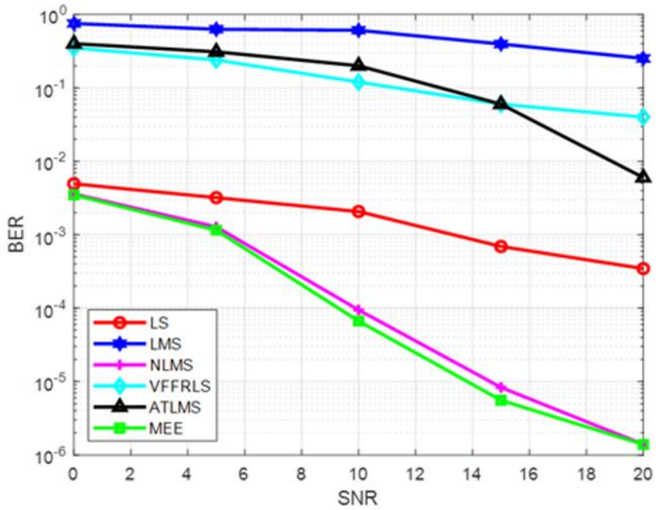

Figure 8. BER comparison under various SNR levels

4.4 Evaluate the average performance of the proposed compared to other channel estimation techniques

Figures 9 and 10 compare the average performance of the proposed method with several conventional channel estimation algorithms in terms of the MSE and BER metrics. Across all SNR values the proposed MEE-based approach demonstrates better stability and consistency than other techniques particularly VFFRLS ATLMS and NLMS. The MEE algorithm maintains an average MSE of $2 * 10^{-4}$ across all SNR levels whereas VFFRLS shows $2.5 * 10^{-3}$ and ATLMS shows $8 * 10^{-3}$ and NLMS displays $4 * 10^{-4}$ average MSE. Across all SNR levels the MEE algorithm reaches approximately $9 * 10^{-4}$ average BER which outperforms VFFRLS which has $1.62 * 10^{-1}$ and ATLMS with $1.952 * 10^{-1}$ and NLMS uses $1 * 10^{-3}$ BER. The suggested MEE-based method obtains highly precise channel estimation performance which leads to substantial Bit Error Rate reduction.

The analysis proves the MEE algorithm enhances signal precision and system dependability when used for adaptive filter coefficient adjustment in Massive MIMO-OFDM channel estimation. The proposed method both reaches convergence speed faster while maintaining lower error rates across all SNR ranges which indicates its excellence in harsh communication conditions. The proposed MEE-based channel estimation technique proves itself as an efficient solution for improving estimation quality in Massive MIMO-NOMA systems.

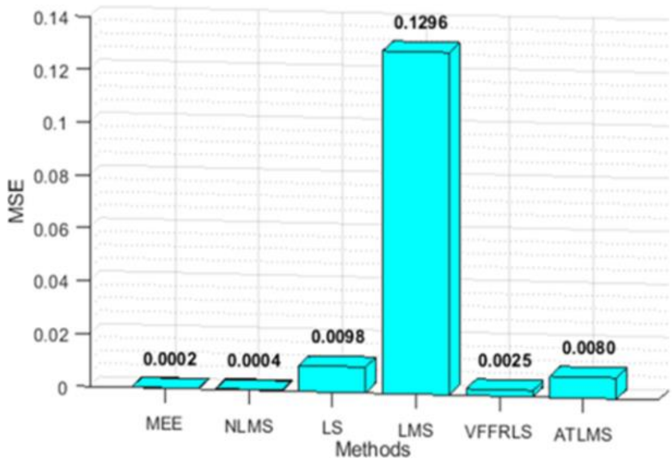

Figure 9. Comparison of average MSE between the proposed method and other channel estimation techniques

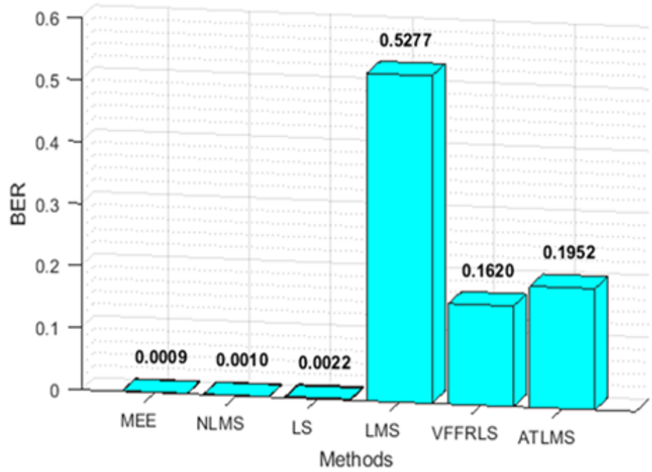

Figure 10. Comparison of average BER between the proposed method and other channel estimation techniques

5. CONCLUSIONS

The research presents an innovative adaptive channel estimation approach for Massive MIMO-OFDM-NOMA systems that depends on the Minimum Error Entropy (MEE) algorithm. Higher-order statistical data from estimation error distributions enables the MEE approach to boost channel estimation accuracy and robustness especially when Signal-to-Noise Ratio (SNR) levels are low. The MEE algorithm outperforms traditional estimation methods according to comparative studies because it decreases MSE and BER rates under multiple noise conditions. The proposed method achieves its effectiveness through multiple simulated experiments. The mean square error (MSE) reaches lower levels during channel estimation when using this method over regular techniques. The MEE algorithm shows effective results according to simulation data which surpass traditional algorithms Least Mean Squares (LMS) and Normalized LMS (NLMS) when measuring convergence performance. The MEE algorithm demonstrates stable channel estimation ability with an average Mean Squared Error value of $2 * 10^{-4}$ for various Signal-to-Noise Ratio testing conditions. The proposed method demonstrates outstanding performance in signal reliability through an average Bit Error Rate (BER) measurement of $9 * 10^{-4}$ that spans across all SNR settings.

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