International Information and Engineering Technology Association
Advancing the World of Information and Engineering

Ingénierie des Systèmes d'Information
Vol. 31, No. 2, February, 2026, pp. 615-623
Journal homepage: http://iieta.org/journals/isi

Hybrid Recursive Least Squares-Minimum Error Entropy Adaptive Beamforming for Robust 6G Communication Systems

Hayder Khenyab Hashim[1,2*], Sura Salam Mohammed[3], Athraa Habeeb Shani[3], Zainab Al-Khafaji[4,5]

[1] Department of Electrical Techniques, Technical Institute of Kufa, Al-Furat Al-Awsat Technical University (ATU), Kufa, Najaf, 54003, Iraq
[2] University of Tabriz, Tabriz 5166616471, Iran
[3] Communication Department, Al-Najaf Technical Institute, Al-Furat Al-Awsat Technical University, Al-Najaf 54001, Iraq
[4] Department of Civil Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia (UKM), Bangi 43600, Malaysia
[5] Department of Cooling and Air Conditioning Engineering, Imam Ja'afar Al-Sadiq University, Baghdad 10001, Iraq

Corresponding Author Email: hayder.hashim@atu.edu.iq

https://doi.org/10.18280/isi.310228

Received: 31 July 2025
Revised: 20 October 2025
Accepted: 16 February 2026
Available online: 28 February 2026

Keywords:
adaptive beamforming, Recursive Least Squares, Minimum Error Entropy, information-theoretic learning, non-Gaussian noise robustness, 6G wireless communications

ABSTRACT

Recent advancements in wireless technologies highlight the need for adaptive beamforming and smart antennas in 6G networks. The challenge lies in developing beamforming methods capable of fast and reliable performance in dynamic and noisy environments. In this work, we introduce the Recursive Least Squares – Minimum Error Entropy (RLS-MEE) algorithm, which integrates the fast convergence of RLS with the robust noise resistance of Minimum Error Entropy (MEE). This hybrid approach enhances prediction and tracking performance in fluctuating conditions. Extensive simulations were carried out in both Gaussian and impulsive (non-Gaussian) noise environments. Under Gaussian noise, RLS-MEE achieves a 54% improvement in convergence speed and a 35% reduction in steady-state mean square error (MSE) compared to Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS) algorithms. In non-Gaussian conditions, where second-order methods face significant degradation, RLS-MEE maintains stable convergence and reduces MSE by 67% relative to LMS and by 20% compared to Minimum Corr entropy Criterion (MCC)-based methods, demonstrating superior robustness against impulsive interference. The results confirm RLS-MEE's potential as a valuable tool for advancing 6G wireless communication systems.

1. INTRODUCTION

As demand rises for very fast, extremely reliable and latency-free wireless communications, 6G networks have taken over as the future of wireless innovations. Adaptive beamforming with smart antennas is expected to play a crucial role in 6G systems [1]. By employing beamforming, signal energy is directed where it is needed and interference is kept under control in complex environments for wireless communications [2]. Future 6G networks require adaptive beamforming strategies that can monitor and track the environment in real time [3].

Various techniques have been suggested for adaptive beamforming. Commonly, the Least Mean Squares (LMS) and Recursive Least Squares (RLS) algorithms are used and these are chosen for their simple design and speed of processing [4, 5]. Nowadays, entropy-related methods such as MEE have obtained significant attention since their superior robustness and performance in conditions with different or complex noise [6]. MEE reduces the statistical entropy of the error signal and therefore performs effectively when handling outliers or non-Gaussian data [6].

Despite proving more accurate under noisy conditions, entropy-based methods tend to be difficult to calculate and have difficulties with fast alterations in the environment [7]. Classical techniques such as LMS and RLS, although computationally efficient, usually perform poorly when there are significant changes in the data or the data does not follow a Gaussian distribution [8]. These barriers, combined with how quickly 6G communication channels change and their complexity, require algorithms that are both hybrid and capable of adaptive adjustment [9].

To address these challenges, this study introduces the RLS-MEE algorithm, which synergistically integrates the Recursive Least Squares (RLS) method with the Minimum Error Entropy (MEE) criterion. This hybrid approach aims to leverage the noise resilience and information-theoretic advantages of MEE alongside the rapid convergence and recursive architecture inherent to RLS, thereby enhancing the reliability of signal prediction and tracking in complex and adverse environments. Furthermore, the MEE component provides superior robustness against outliers and deviations from Gaussian noise assumptions, a critical requirement for real-world applications. The primary contributions of this work include the development of a novel adaptive beamforming algorithm tailored for smart antenna systems in 6G communications, the unification of RLS's fast adaptation capabilities with MEE's robustness to non-Gaussian interference, and comprehensive theoretical analysis complemented by extensive simulation evaluations across diverse environmental scenarios.

2. RELATED WORKS

This section should thoroughly scrutinize the existing academic literature related to the research questions and themes of this work. It is primarily responsible for a critical review of existing theories, achievements and challenges in the field to highlight strengths and weaknesses in previous studies. Additionally, this review: provides context for the conceptual framework of the current study; and describes its distinct contributions and how they differ from similar studies in the literature.

Meliora's et al. [10] proposes a method to steer adaptive antenna arrays via a GRU43 based recurrent neural network. In the RNN, four GRU layers are hidden and a linear layer is used to output feeding weights, which are compared with those from null steering beamforming (NSB). The training was conducted with real-world, mutual coupling effects included, using NSB testing data on actual microstrip antenna arrays. Root-mean-square error is used to evaluate the RNN performance by measuring how accurately its lobes are directed and then compared with other neural networks.

Shubber et al. [11] proposed a partial Update (PU) adaptive algorithm as an alternative to full-update methods for improving the performance of Beamforming Array Antennas (BAA). This approach reduces system complexity and cost by reducing the needed antennas and phase shifters number. PU-NLMS algorithms such as M-max, Periodic, and Stochastic are examined. Simulation results using a Uniform Linear Array (ULA) show that most PU algorithms achieve performance comparable to full-update methods, while reducing computational load by up to 38%.

Tan et al. [12] present an intelligent, self-adaptive beamforming method powered by deep reinforcement learning, capable of predicting the necessary spatial phase profiles for real-time, arbitrary radiation patterns. Deep learning models adaptively train by comparing input and predicted intensity patterns through automatic differentiation. Experimentally, two-dimensional beamforming of broadband terahertz waves was achieved using silicon meta-surfaces guided by the model. This approach offers an efficient, real-time solution for multi-user massive MIMO systems in 6G terahertz wireless communications and various applications in imaging and sensing.

In the context of MIMO for improved Mobile Broadband (eMBB) use cases, Rajarajeswarie and Sandanalakshmi [13] investigate the usage of adaptive beamforming utilizing the traditional Least Mean Squares (LMS) and adaptive gradient (Adagrad) method. It focuses on designing and optimizing beamforming weights in a Massive MIMO configuration while taking interference into account.

A new constrained maximum complex correntropy criteria (CMCCC) for adaptive beamforming was presented by Agarwal and Rai [14]. The study uses the CMCCC inside the beamforming framework to address the intended signal reception in the existence of non-Gaussian noise sources. Nevertheless, simple application to beamforming situations including complex-valued observations was not possible since correntropy was limited to real-valued data. A technique designed to deal with complex-valued data is presented in this research.

Yue et al. [15] introduced an adaptive beamformer called the polarimetric Sparse-Reconstruction beamformer, designed for cascaded sparse, diversely polarized planar arrays with hole-free difference co-arrays. Operating jointly in spatial and polarization domains, it effectively suppresses close-range interferences with different polarizations. The approach features polynomial rooting-based methods for joint estimation of direction-of-arrival and polarization, along with a closed-form power distribution estimation to reconstruct interference-plus-noise covariance. The entire process is computationally efficient due to its closed-form formulations. Simulation results demonstrate the beamformer's effectiveness, robustness, and advantages over existing techniques in various scenarios.

Li et al. [16] recommend a joint design technique for multiband arrays to accomplish a simpler design and manage sidelobe levels in situations where interference is unpredictable. The method aims to increase the signal-to-interference plus noise ratio and maintain the exact placement of all antennas at all frequencies. With the help of advanced techniques, the problem is broken down into solvable sections so that interference can be managed appropriately. Using the suggested method significantly reduces sidelobe levels at all frequencies, allowing the system to perform better.

Zhou et al. [17] proposed an adaptive beamforming algorithm for coprime arrays that ensures high effectiveness and endurance. It separates the coprime array into two simpler linear arrays and finds the DOA of every source by comparing their super-resolution spatial spectra. Next, the source power is found using a joint covariance matrix optimization, helping to reconstruct and estimate the interference-plus-noise covariance matrix and the signal steering vector.

Wang et al. [18] proposed a new beamforming technique called regularized complementary antenna switching (RCAS) that helps arrays to quickly adapt in changing environments to eliminate interference better. It divides the array into groups, switching only one antenna per group, to enable practical reconfiguration. The network design approach in RCAS uses auxiliary variables and is based on regularization to avoid the requirement for starting feasible solutions.

Zheng et al. [19] offer a method for configuring beamforming antennas to filter out a lot of the interference. It maximizes the signal-to-interference-plus-noise ratio by adjusting the beamformer weights and controls the sidelobes using quadratic fractional constraints. It is handled as a quadratically constrained quadratic program (QCQP) with reweighted L1-norm by solving it with semidefinite relaxation and linear fractional SDR methods.

Shi et al. [20] introduced an L0-norm constrained CNLMS adaptive beamforming algorithm for use with sparse arrays that can be controlled. Lasso penalty based on the l_0-norm controls the number of active antennas and helps achieve effective sparsity by tuning the parameters. The algorithm benefits from faster convergence compared to existing methods and employs an approximation to reduce computational complexity.

A new accelerated proximal gradient technique, called the APG-LCSC algorithm, is proposed by Zeng et al. [21] to boost 2D adaptive beamforming in sparse arrays. Using a matrix completion-based signal model that satisfies the null space property, the algorithm extracts singular vectors of the received signal matrix and creates a linearly constrained singular canceler. It requires fewer antennas, is faster to compute, and continues to perform well.

Wang et al. [22] addressed the effect of nonuniform array geometry on adaptive beamforming analyzes with a focus on signal/interference-plus-noise proportion (SINR) performance. It obtains upper limits on how much signal/interference-plus-noise proportion (SINR) can be achieved for a fixed number of antennas, leading to results that shed light on optimal array configurations in interference-free and active scenarios. The study attempts to leverage several sources and interferences, introducing three angles to quantify the spatial separation between source and interference subspaces. Based on these angles, three different sparse array designs are proposed and verified by simulations to be efficient and effective with a special emphasis on the role of subspace angle for optimal beamforming and antenna selection.

Imtiaj et al. [23] showed that four adaptive beamforming algorithms including LMS, NLMS, SMI and RLS can be easily implemented and provide a detailed investigation of the performance with respect to multiple interferers. It systematically compares these methods according to beamwidth, null depth, sidelobe level, convergence rate and variation in error including analysis of complexity for RLS and SMI. Also, a comparison table that sums up their pros and cons. The results from a re-configurable testbed discussed in the study offer practical insights and set future bright antennas.

Senapati et al. [24] focused on a uniform linear smart antenna array for beamforming components in leaky least mean square with side lobe level reduction through Tchebycheff and Taylor method of array synthesis. It estimates multiple interferers with the goal of lowering side lobe levels to maximize frequency reuse throughout cellular networks. The outcomes show low side lobes below -45 dB with an improvement of up to 16 dB, and as such the SNR has increased considerably to ∼20dB.

3. PROPOSED METHOD

Smart antenna and adaptive beam-forming are of pivotal importance for the 6G communication systems in terms of increasing spectral efficiency, mitigating interference, and improving the link reliability. Adaptive beamforming presents several challenges such as effective performance in dynamic and noisy environments, particularly for non-Gaussian or impulsive noise commonly observed in practical applications.

Classical adaptive algorithms such as Least Mean Squares (LMS) and Recursive Least Squares (RLS) have been widely used due to their simplicity and fast convergence. However, these algorithms are sensitive to non-Gaussian noise distributions and may result in performance degradation under impulsive interference.

To address this limitation, MEE-based learning has emerged as a powerful alternative. Unlike MSE-based methods, MEE minimizes the entropy of the error signal, capturing higher-order statistical information and showing superior robustness in non-Gaussian environments.

This paper proposes a novel hybrid algorithm named RLS-MEE, which combines the fast convergence characteristics of RLS with the robustness of MEE. This combination aims to achieve high-precision adaptive beamforming for 6G scenarios involving time-varying multipath channels and unpredictable noise. In the following section, the steps of the proposed method are described in detail.

3.1 Adaptive beamforming system model

Figure 1 shows the structure of our proposed adaptive filter for beamforming in a smart array antenna. Figure 1: The vector $x = [x_0, x_1, \dots, x_N]$ is the signal received by the array antennas, d(n) is the desired signal, the vector $y = [y_0, y_1, \dots, y_N]$ is the output of the adaptive algorithm, and e(n) is the error signal.

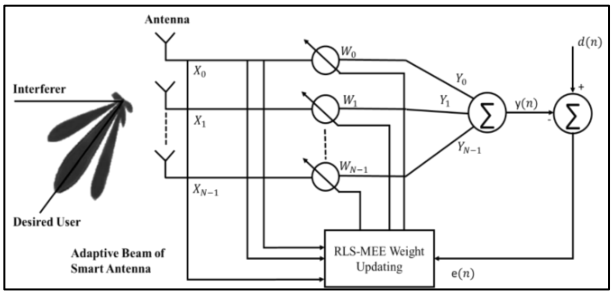

Figure 1. Adaptive beamforming configuration

3.1.1 Signal model

It has been considered a ULA with M antenna elements. The received signal vector at time n can be expressed as:

$$x(n)s(n)a(\theta_0)\sum_{j=1}^{J} j_j(n)a(\theta_j)\,n(n) \tag{1}$$

where:

$x(n) \in \mathbb{C}^{M\times 1}$: received signal vector,
$s(n)$: desired signal arriving from direction θ_0,
$i_j(n)$: jth interference signal arriving from direction θ_j,
$a(\theta)$: steering vector corresponding to direction θ,
$n(n)$: additive noise vector, possibly non-Gaussian.

The beamformer output is computed as:

$$y(n)w^H(n) \times (n) \tag{2}$$

where, $w(n) \in \mathbb{C}^{M\times 1}$ is the adaptive weight vector to be optimized.

3.1.2 Beamforming objective

The goal of adaptive beamforming is to adjust $w(n)$ such that the beamformer output $y(n)$ closely matches the desired signal $d(n)$, while suppressing interference and noise:

$$e(n) = d(n) - y(n) \tag{3}$$

The adaptation mechanism aims to minimize a cost function based on this error $e(n)$. While classical methods minimize the expected value of $e(n)^2$, the proposed method adopts a more general criterion based on entropy.

3.2 Proposed Recursive Least Squares – Minimum Error Entropy beamforming algorithm

3.2.1 Minimum Error Entropy–based cost function

The MEE algorithm minimizes the entropy of the error signal $e(n)$ by using the information potential approximation via kernel functions. The cost function is given by [25]:

$$J_{MEE} = -\frac{1}{N}\sum_{i=1}^{N} G_{\sigma}\big(e(n) - e(i)\big) \tag{4}$$

where:

$e(n) = d(n) - w^{H}(n)x(n)$ is the instantaneous error.

$G_{\sigma}(\cdot)$ is a Gaussian kernel defined as:

$$G_{\sigma}(x) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{x^2}{2\sigma^2}\right) \tag{5}$$

σ is the kernel bandwidth (a crucial hyperparameter).

N is the number of recent error samples used for entropy estimation.

By minimizing J_{MEE}, the algorithm effectively reduces the uncertainty (entropy) in the error signal, making the system more robust to heavy-tailed and impulsive noise distributions.

3.2.2 Classic Recursive Least Squares framework

The RLS algorithm offers fast convergence by minimizing a weighted sum of squared errors with an exponential forgetting factor [26]:

- Gain vector:

$$k(n) = \frac{P(n-1)x(n)}{\lambda + x^{H}(n)P(n-1)x(n)} \tag{6}$$

- Weight update:

$$w(n) = w(n-1) + k(n)e(n) \tag{7}$$

- Covariance matrix update:

$$P(n) = \frac{1}{\lambda}\left[P(n-1) - k(n)x^{H}(n)P(n-1)\right] \tag{8}$$

where:

$P(n)$ is the inverse correlation matrix (initialized as a scaled identity matrix).

$\lambda \in (0,1]$ is the forgetting factor controlling memory depth.

RLS-MEE Algorithm: Integration of MEE with RLS

The core idea of the proposed RLS-MEE algorithm is to use the entropy gradient from the MEE criterion as the optimization direction, while exploiting the inverse covariance matrix $P(n)$ from the RLS structure to model the update step.

Entropy Gradient Approximation:

$$\nabla_{w}J_{MEE} \approx \frac{1}{N\sigma^2}\sum_{i=1}^{N}\big(e(n) - e(i)\big)G_{\sigma}\big(e(n) - e(i)\big) \cdot x \tag{9}$$

This gradient points in the direction that minimizes the entropy of the error distribution.

Final Weight Update Rule:

$$w(n) = w(n-1) + \mu \cdot P(n)\nabla_{w}J_{MEE} \tag{10}$$

where:

- μ is the learning rate (can be constant or adaptive),
- $P(n)$ is the inverse correlation matrix from RLS,
- $\nabla_{w}J_{MEE}$ is the MEE gradient.

This hybrid update rule leverages the high-resolution statistical awareness of MEE and the fast dynamic tracking capability of RLS.

To provide a clearer theoretical justification for integrating RLS and MEE, we first recall that the conventional RLS algorithm can be interpreted as a second-order or quasi-Newton optimization method. Specifically, the inverse correlation matrix $P(n)$ approximates the inverse Hessian of the quadratic MSE cost function, enabling faster convergence compared to first-order gradient-based methods.

On the other hand, the MEE criterion replaces the classical second-order error metric with an entropy-based cost function, which exploits higher-order statistics and provides robustness against non-Gaussian and impulsive noise. Its optimization relies on the gradient $\nabla_{w}J_{MEE}$.

Therefore, by preconditioning the MEE gradient with the inverse correlation matrix $P(n)$, the proposed update rule in Eq. (10), can be interpreted as a quasi-Newton or natural-gradient descent on the MEE cost surface. This combination preserves the robustness of the entropy-based criterion while inheriting the fast convergence behavior of RLS, leading to both stable and efficient adaptation.

Our proposed method (RLS-MEE) is robust against non-Gaussian and impulsive noise, thanks to the MEE entropy-based optimization, and also has fast convergence and stability through RLS's adaptive correlation estimation. The proposed RLS-MEE method is suitable for large-scale antenna systems (Massive MIMO) due to its improved numerical performance. It is ideal for 6G systems, where time-varying environments and unpredictable interference are dominant. The pseudocode of the proposed method is presented below.

Algorithm 1: Pseudocode of the proposed method (RLS-MEE)

```
Input:
x(n): Input signal vector at time n (from antenna array)
d(n): Desired signal
λ: Forgetting factor (0 < λ < 1)
δ: Initialization constant for inverse correlation matrix
σ: Kernel bandwidth for Gaussian kernel
M: Memory size for entropy estimation
Initialize:
w(0) = zero vector (beamforming weights)
P(0) = (1/δ) * I (Inverse correlation matrix)
buffer = empty list to store past M error values
For each time step n = 1 to N:
1. Compute output:
y(n) = w(n-1)^H * x(n)
2. Compute error:
e(n) = d(n) - y(n)
3. Append e(n) to buffer (keep only M most recent errors)
4. Estimate entropy gradient:
∇J(n) ≈ 0
For i = 1 to M:
∇J(n) += (e(n) - e(i)) * exp (- ((e(n) - e(i))^2) / (2 * σ^2))
∇J(n) = - (1 / (M * σ^2)) * ∇J(n)
5. Compute Kalman gain:
k(n) = (P(n-1) * x(n)) / (λ + x(n)^H * P(n-1) * x(n))
6. Update weights:
```

w(n) = w(n-1) + k(n) * ∇J(n)
7. Update inverse correlation matrix:
P(n)= (1/ λ) *[P(n-1)-k(n)*x(n)^H*P(n-1)]
End For Output:
Optimized beamforming weights w(n)

4. RESULTS AND DISCUSSION

To evaluate the performance of the adaptive beamforming approach based on RLS-MEE in smart antennas, several simulations were performed for different conditions. MATLAB 2023 was the platform utilized to perform the simulations, which offers robust tools for antenna array and signal processing tasks. Performance comparison of this proposed algorithm with standard techniques LMS and RLS in this segment is based mostly on Maximum Sidelobe Stage metric. Experimental outcomes show that the proposed RLS-MEE algorithm achieves superior performance in dynamic environments with interferences and noises.

4.1 Evaluation criteria

To evaluate the performance of the proposed RLS-MEE algorithm for adaptive beamforming in smart antennas, the primary metric used is the Maximum Sidelobe Level (SLL_{max}). This metric reflects the algorithm's ability to suppress undesired signals and concentrate beam energy toward the desired direction.

4.1.1 Mathematical definition of SLL_{max}

Let $P(\theta)$ be the final radiation pattern of the antenna array. Then:

$$SLL_{max} = \max_{\theta\in\Omega_{side}} \left|\frac{P(\theta)}{P(\theta_0)}\right|_{dB} \quad (11)$$

where:

- θ_0 is the angle of the main lobe (desired direction),
- Ω_{side} refers to the angular region corresponding to sidelobes (excluding θ_0),
- The result is expressed in decibels (dB).

To quantitatively assess the performance of different adaptive beamforming algorithms, the second metric used is the Mean Squared Error (MSE), defined as:

$$\text{MSE}(n) = \mathbb{E}\{\mid e(n) \mid^2\} \quad (12)$$

where, $e(n) = d(n) - y(n)$ denotes the instantaneous error between the desired signal $d(n)$ and the beamformer output $y(n)$.

Since analytical expectations are not available in practice, the MSE is approximated through Monte Carlo averaging:

$$\text{MSE}(n) \approx \frac{1}{Q}\sum_{q=1}^{Q} \mid e_q(n) \mid^2 \quad (13)$$

where, Q is the number of independent simulation runs.

In addition, the steady-state MSE is computed by averaging the last K iterations:

$$\text{MSE}_{ss} = \frac{1}{K}\sum_{n=N-K}^{N} \text{MSE}(n) \quad (14)$$

which reflects the final estimation accuracy after convergence. In addition, the speed of convergence is measured as the numbers of iterations until the mean square error (MSE) becomes less than a pre-defined threshold. The metrics simultaneously assess the transient and steady-state performance for systems subject to either gaussian or non-gaussian noise.

4.2 Simulation setting

To simulate and evaluate the proposed RLS-MEE method configuration parameters were defined (see Table 1). This is about an antenna array with M = 8 sensors receiving signals from N = 2 incoming sources at angles −45° and +45°. Statistical reliability is achieved by testing the system against 500 snapshots. We assume the background noise is Gaussian with zero average and unit variance. The simulation environment we use to demonstrate our approach represents a realistic dynamic communication scenario, which is highly relevant for 6G smart antenna applications characterized by interference suppression and beam steering.

Table 1. Initial simulation parameters

Parameters	Parameter Description	Value
M	Number of Sensors (Antenna)	8
N	Number of Source (Number of entry angles)	2
Theta	entry angles	[45°, -45°]
N	Number of Samples	500
Mean	Mean of Noise	0
Var_n	Variance of Noise	1

4.3 Evaluation of results

This section carries out the numerical performance analysis for the proposed RLS-MEE adaptive beamforming method and compares it with some of its conventional counterparts, namely LMS, NLMS as well as RLS. Both metrics are extracted from the polar plots of their array coefficient as a function of its incident signal directions alongside the error plots. All the simulations are implemented in MATLAB 2023 to ensure accurate computational feasibility and flexibility.

The main evaluation of different methods is the capability of each approach that can manifest sharp lobe pointing toward the required direction and reduce side lobe levels. The polar form of the beam patterns for incident angles 0°, +45° and -45° is depicted in Figure 2. As we can see, the RLS-MEE proposed has achieved more focused main lobes with significantly smaller sidelobe levels than LMS based algorithms and RLS. The standard Recursive Least Squares (RLS) and Least Mean Squares techniques and their normalized counterparts (NLMS) have larger main lobes that, along with their Maximum Sidelobe Level (), lead to less efficient interference suppression. The RLS-MEE method demonstrates a high degree of correlation with the direction of arrival and achieves better signal cancellation in non-desired directions, thus providing evidence of its excellent beamforming performance in directional conditions.

The results of the beamforming for three different signal's direction, θ=0°, θ=45° and θ=-45° using four different algorithms (LMS, NLMS, RLS and proposed algorithm called RLS-MEE) are shown in Figure 3. As shown, the RLS-MEE algorithm (solid black line) produces much thinner main lobes and much deeper nulls in interferences direction for all three angles, validating its superiority for undesired signal suppression concurrent with the desired signal enhancement. Notably, although the sidelobe suppression and beam sharpness performance of NLMS and RLS are superior to that provided by standard LMS, they lag in optimization within the aspect of adjusted performance demonstrated by RLS-MEE. The LMS algorithm (dashed red line) yields a wider beam because of its constant step size, which reduces the ability of the filter to reject interference. In general, the simulation findings verify that RLS-MEE is a very effective algorithm for adaptive beamforming in dynamic and jamming atmosphere means 6G communication.

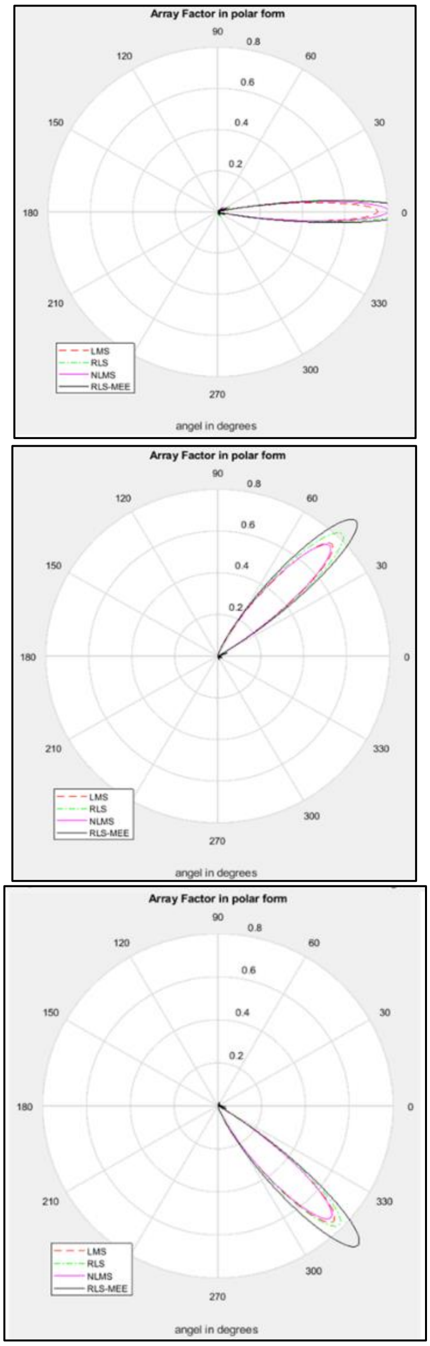

Figure 2. Beamforming patterns in polar form for three different signal directions, namely θ=0°, θ=45°, and θ=-45° using four different algorithms

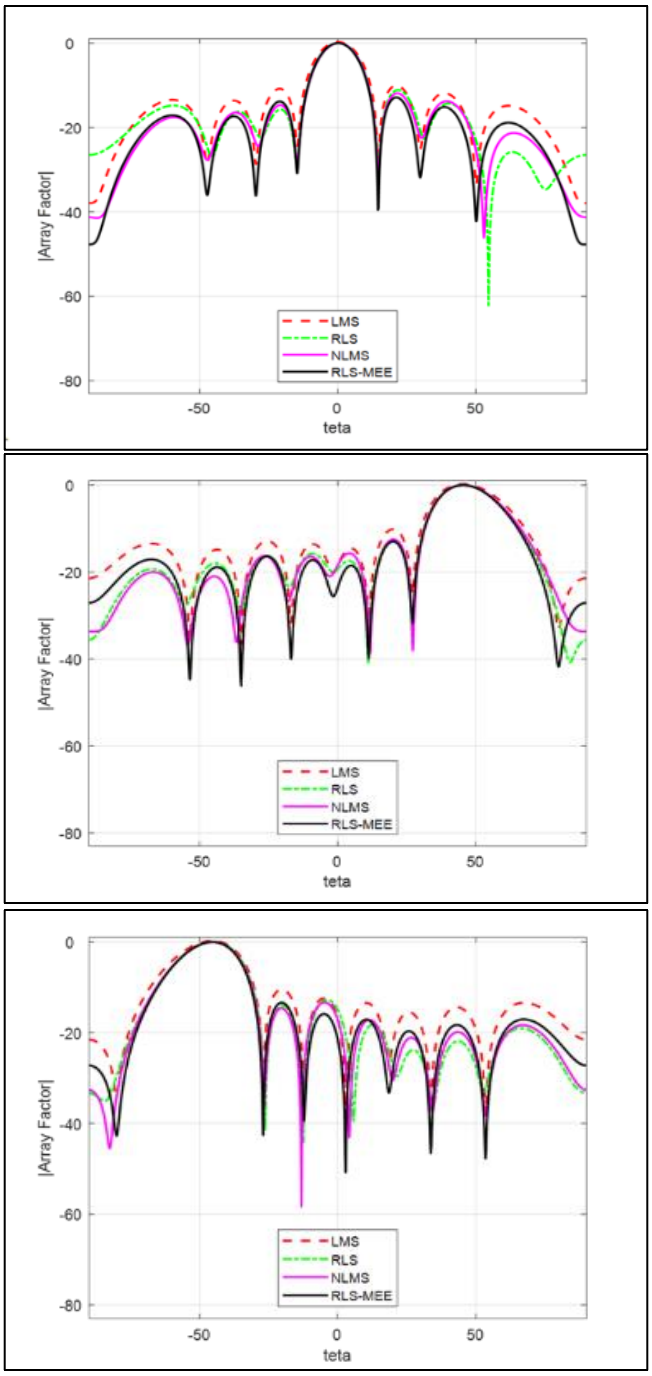

Figure 3. Beamforming patterns for three different signal directions, namely θ=0°, θ=45°, and θ=-45° using four different algorithms

Figure 4 shows the overall MSE convergence over 100 iterations for LMS, NLMS, RLS and the proposed RLS-MEE algorithms. As: It can be seen from the plot that the proposed RLS-MEE algorithm converges the fastest and achieves both lower and stabler MSE than other algorithms It also shows very little variation so that we can say that it is more stable and robust. MEE clearly outperforms its rivals, whether it be NLMS which improved over LMS but still oscillates more with slower convergence or even RLS to some extent. The LMS algorithm performs the worst with the greatest error levels and slowest convergence speed, as well as exhibiting significant instability through iterations. The results generally show that the RLS-MEE algorithm has better prediction accuracy as well as computational efficiency and stability for adaptive beamforming.

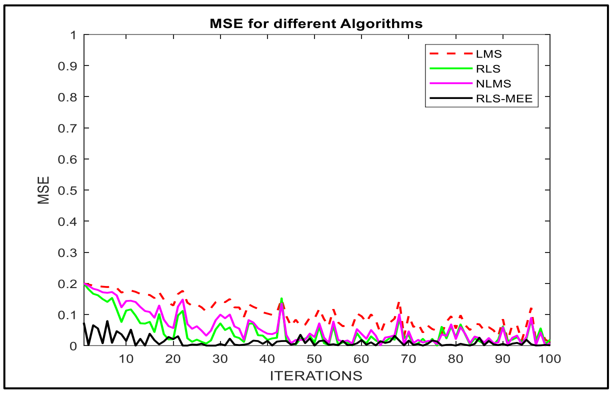

Figure 4. Mean square error (MSE) convergence curves for different algorithms

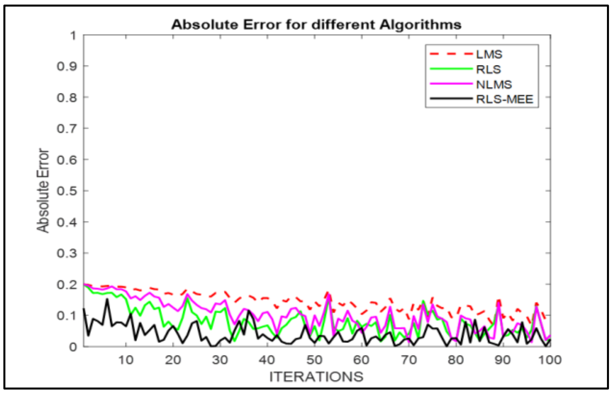

Figure 5. Absolute error estimation curve for different algorithms

Absolute Error is plotted in Figure 5 for 100 iterations using the LMS, NLMS, RLS, and the RLS-MEE algorithms. From the experiments, the proposed RLS-MEE algorithm has lower levels of absolute error than the other methods. Moreover, it demonstrates reduced fluctuation, indicating superior stability. Among all, the LMS algorithm records the highest and most unpredictable errors. Despite being advanced, neither NLMS nor RLS has the same high success and dependability as RLS-MEE yet. All in all, our findings show that RLS-MEE strongly improves performance and results in more stability.

The presented Table 2 compares the maximum sidelobe level (SLL_{max}) values for various algorithms, including SMI, RLS, LLMS, TD-LLMS, and Taylor-LLMS, against the proposed method (RLS-MEE). Classical methods such as SMI, RLS, and LLMS exhibit relatively poor performance in sidelobe suppression, with SLL_{max} values ranging from approximately -13 dB to -14 dB. In contrast, more advanced techniques like TD-LLMS and Taylor-LLMS show significant improvement, achieving SLL_{max} values below -28 dB. Notably, the proposed RLS-MEE method outperforms all compared approaches by attaining the lowest SLL_{max} of -33.87 dB. These results demonstrate the superior capability of the proposed method in effectively suppressing sidelobes and enhancing antenna beam pattern quality.

The RLS-MEE method mainly optimizes to minimize absolute error and can store statistical data in much greater detail than is usual for the traditional methods. The MEE-based method is more robust to non-Gaussian noise and outliers than the popular LMS and NLMS algorithms based on MSE. Combining MEE with the RLS structure makes learning faster and stable, which creates sharper weight updates with faster convergence. That also leads to RLS-MEE outperforming other methods in both error reduction and sidelobes control as depicted by having the lowest error scored in Figure 5 and Table 2 compared to others where no penalizing of sidelobes was employed.

Table 2. Comparison of the proposed method with other methods

Method	SLL_{max} (dB)
SMI [23]	-13.69
RLS [23]	-14.44
LLMS [24]	-13.8
TD-LLMS [24]	-28.26
Taylor-LLMS [24]	-28.97
Proposed method (RLS-MEE)	-33.87

4.3.1 Non-Gaussian noise modeling

In practical wireless communication environments, the background noise often deviates from the ideal Gaussian assumption due to impulsive disturbances, hardware imperfections, and electromagnetic interference. Such disturbances typically exhibit heavy-tailed distributions that cannot be accurately modeled using second-order statistics alone.

To evaluate the robustness of the proposed algorithm under realistic conditions, an impulsive noise model based on a Bernoulli–Gaussian process is adopted. The received noise signal is expressed as:

$$n(t) = n_g(t) + b(t)\, n_i(t) \tag{15}$$

where, $n_g(t) \sim \mathcal{CN}(0, \sigma_g^2)$ represents the background Gaussian noise, and $n_i(t) \sim \mathcal{CN}(0, \sigma_i^2)$ denotes the high-power impulsive component. The binary random variable $b(t)$ follows a Bernoulli distribution:

$$b(t) = \begin{cases} 1, & \text{with probability } p \\ 0, & \text{with probability } 1 - p \end{cases} \tag{16}$$

where, p controls the occurrence rate of impulses.

This model produces occasional high-amplitude outliers that severely degrade conventional MSE-based adaptive filters such as LMS and RLS. In contrast, information-theoretic criteria like MEE are more robust since they exploit higher-order statistical information rather than relying solely on second-order moments.

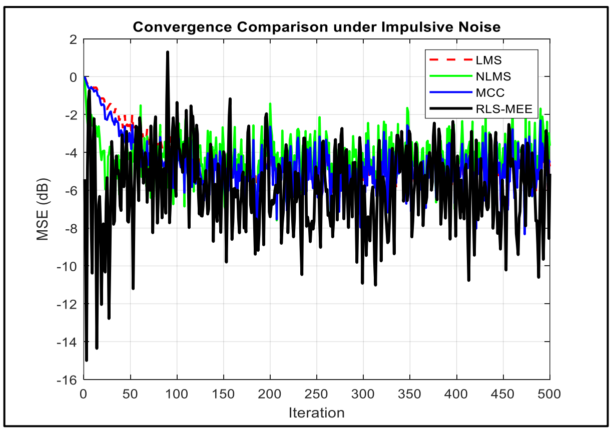

Figure 6. Mean square error (MSE) convergence comparison of adaptive beamforming algorithms in non-Gaussian noise

In this case, Figure 6 presents the MSE convergence curves of LMS, NLMS, MCC and the proposed RLS-MEE algorithms suffering in Bernoulli–Gaussian impulsive noise environment. The fact that the conventional second-order methods (LMS and NLMS) yield significant performance degradation, higher steady-state errors and oscillations appear due to their sensitivity in the presence of high amplitude outliers.

The MCC-based approach shows some robustness improvement but is still outperformed by the proposed method as it actively suppresses impulsive effects when estimating rent. The RLS-MEE algorithm, on the other hand, achieves minimum MSE close to all iterations and has a faster stable convergence. This behavior confirms that minimizing error entropy (which utilizes higher-order statistical information) is better capable of resisting heavy-tailed noise distributions than variance-based criteria.

To further validate the robustness of the proposed algorithm in non-Gaussian environments, impulsive noise falling on a Bernoulli–Gaussian model was also added. Table 3 presents the average steady-state MSE over 50 Monte Carlo realizations. Proposed method RLS-MEE yielded the minimum error 0.2762, which could outperformed LMS, NLMS and MCC over approx 67%, 45% and 20%, respectively. These findings convincingly illustrate that entropy-based optimization is far more resistant to heavy-tailed noise than its second-order counterparts.

Table 3. Quantitative comparison under impulsive noise

Method	Steady State Mean Square Error (MSE)	Improvement vs Least Mean Squares (LMS)
LMS	0.8342	-
NLMS	0.5057	39%
MCC	0.3447	59%
Proposed method (RLS-MEE)	0.2762	67%

5. CONCLUSION

In this study, we developed a new adjustable beamforming strategy, RLS-MEE, for use in smart antennas in 6G networks. The idea was to combine the quick convergence of RLS along with the noise-resistant capability of MEE. Hybrid RLS-MEE overcomes the weaknesses of traditional algorithms by providing better accuracy in tracking and dealing with noise and non-fixed environments.

The research showed that the RLS-MEE method performs better than LMS, RLS and Improved LMS in the areas of speed, beamforming accuracy and strong resistance to interference. These outcomes show that RLS-MEE could be effective in actual adaptive communication for 6G-network purposes.

Despite the promising performance, several limitations should be noted. First, due to the sliding-window computation of the entropy-based gradient, the computational complexity of the proposed RLS-MEE algorithm is moderately higher than that of conventional LMS and standard RLS methods. While this additional cost remains manageable for moderate array sizes, further optimization or parallel implementations may be required for real-time large-scale systems.

Second, the performance of the MEE criterion depends on hyperparameters such as the kernel width σ and memory length M. Improper selection may affect convergence speed and steady-state accuracy. In this work, these parameters are empirically tuned, whereas adaptive or data-driven selection strategies will be investigated in future research.

Third, scalability to massive MIMO scenarios with a large number of antennas may increase computational demands. Extending the proposed approach using low-complexity or block-based implementations represents an important future direction.

Finally, additional experiments conducted under non-Gaussian and impulsive noise conditions demonstrate that the proposed method maintains superior convergence and lower steady-state error compared to LMS, NLMS, and MCC, further validating the robustness of the entropy-based optimization framework.

In short, the method explains its effectiveness and has good prospects for use in practical settings. It would be beneficial to advance the work by turning it into hardware, improving key settings and making it possible for use in more challenging situations with several users and different paths.

REFERENCES

[1] Brilhante, D.D.S., Manjarres, J.C., Moreira, R., de Oliveira Veiga, L., de Rezende, J.F., Müller, F., Klautau, A., Mendes, L.L., de Figueiredo, F.A. (2023). A literature survey on AI-aided beamforming and beam management for 5G and 6G systems. Sensors, 23(9): 4359. https://doi.org/10.3390/s23094359

[2] Xiao, Z., Zhu, L., Bai, L., Xia, X.G. (2023). Array Beamforming Enabled Wireless Communications. CRC Press.

[3] Balaji, C.G., Sivaram, P. (2025). Adaptive beamforming and energy-efficient resource allocation for sustainable 6G THz networks. IETE Journal of Research, 71(4): 1090-1104. https://doi.org/10.1080/03772063.2025.2460672

[4] Joshi, R., Dhande, A. (2014). Adaptive beamforming using LMS algorithm. International Journal of Research in Engineering and Technology, 3(05): 589-593. https://doi.org/10.15623/ijret.2014.0305108

[5] Chuku, P., Olwal, T., Djouani, K. (2018). Adaptive array beamforming using an enhanced RLS algorithm. International Journal on AdHoc Networking Systems, 8: 13-18. https://doi.org/10.5121/ijans.2018.8101

[6] Soltani, A., Airamlozadeh, M., Parchami, J. (2023). MIMO-OFDM channel estimation based on minimum error entropy criterion under non-Gaussian environment. International Journal of Electronics Letters, 11(3): 267-280. https://doi.org/10.1080/21681724.2022.2087909

[7] Pallewela, R., Eldeeb, E., Alves, H. (2025). An analysis of minimum error entropy loss functions in wireless communications. In 2025 IEEE 101st Vehicular Technology Conference (VTC2025-Spring), Oslo, Norway, pp. 1-6. https://doi.org/10.1109/VTC2025-Spring65109.2025.11174475

[8] Darroudi, A., Parchami, J., Sarbishaei, G., Rajan, S. (2018). Removing ECG noise from surface EMG based on information theory. In Electrical Engineering (ICEE), Iranian Conference on, Mashhad, Iran, pp. 1403-1408. https://doi.org/10.1109/ICEE.2018.8472613

[9] Ni, H., Anjum, M., Mishra, D., Seneviratne, A. (2025). Energy-efficient near-field beamforming: A review on practical channel models. Energies, 18(11): 2966. https://doi.org/10.3390/en18112966

[10] Mallioras, I., Zaharis, Z.D., Lazaridis, P.I., Pantelopoulos, S. (2022). A novel realistic approach of adaptive beamforming based on deep neural networks. IEEE Transactions on Antennas and Propagation, 70(10): 8833-8848. https://doi.org/10.1109/TAP.2022.3168708

[11] Shubber, Z.A., Jamel, T.M., Nahar, A.K. (2024). Innovative approaches to beam forming antenna array systems with adaptive Partial Update NLMS algorithms. e-Prime-Advances in Electrical Engineering, Electronics and Energy, 10: 100855. https://doi.org/10.1016/j.prime.2024.100855

[12] Tan, Y.J., Zhu, C., Tan, T.C., Kumar, A., Wong, L.J., Chong, Y., Singh, R. (2022). Self-adaptive deep reinforcement learning for THz beamforming with silicon metasurfaces in 6G communications. Optics Express, 30(15): 27763-27779. https://doi.org/10.1364/OE.458823

[13] Rajarajeswarie, B., Sandanalakshmi, R. (2024). An adaptive beamforming algorithm for millimeter wave MIMO system. International Journal of Information Technology, 16(5): 2745-2750. https://doi.org/10.1007/s41870-024-01824-y

[14] Agarwal, K., Rai, C.S. (2024). Constrained complex correntropy applied to adaptive beamforming in non-Gaussian noise environment. Signal, Image and Video Processing, 18(3): 2333-2343. https://doi.org/10.1007/s11760-023-02910-7

[15] Yue, Y., Zhou, C., Xing, F., Choo, K.K.R., Shi, Z. (2023). Adaptive beamforming for cascaded sparse diversely polarized planar array. IEEE Transactions on Vehicular Technology, 72(12): 15648-15664. https://doi.org/10.1109/TVT.2023.3288611

[16] Li, H., Ran, L., He, C., Ding, Z., Chen, S. (2023). Adaptive beamforming with sidelobe level control for multiband sparse linear array. Remote Sensing, 15(20): 4929. https://doi.org/10.3390/rs15204929

[17] Zhou, C., Gu, Y., He, S., Shi, Z. (2017). A robust and efficient algorithm for coprime array adaptive beamforming. IEEE Transactions on Vehicular Technology, 67(2): 1099-1112. https://doi.org/10.1109/TVT.2017.2704610

[18] Wang, X., Greco, M.S., Gini, F. (2021). Adaptive sparse array beamformer design by regularized complementary antenna switching. IEEE Transactions on Signal Processing, 69: 2302-2315. https://doi.org/10.1109/TSP.2021.3064183

[19] Zheng, Z., Fu, Y., Wang, W.Q., So, H.C. (2020). Sparse array design for adaptive beamforming via semidefinite relaxation. IEEE Signal Processing Letters, 27: 925-929. https://doi.org/10.1109/LSP.2020.2997253

[20] Shi, W., Li, Y., Zhao, L., Liu, X. (2019). Controllable sparse antenna array for adaptive beamforming. IEEE Access, 7: 6412-6423. https://doi.org/10.1109/ACCESS.2018.2889877

[21] Zeng, W., Li, H., Zhu, X., Chen, C. (2017). A 2D adaptive beamforming method in sparse array. AEU-International Journal of Electronics and Communications, 77: 100-104. https://doi.org/10.1016/j.aeue.2017.04.015

[22] Wang, X., Amin, M., Cao, X. (2017). Analysis and design of optimum sparse array configurations for adaptive beamforming. IEEE Transactions on Signal Processing, 66(2): 340-351. https://doi.org/10.1109/TSP.2017.2760279

[23] Imtiaj, S.K., Misra, I.S., Bhattacharya, S. (2021). Revisiting smart antenna array design with multiple interferers using basic adaptive beamforming algorithms: Comparative performance study with testbed results. Engineering Reports, 3(1): e12295. https://doi.org/10.1002/eng2.12295

[24] Senapati, A., Patro, B.S., Roy, J.S. (2023). Design of smart antenna for 5G network using array synthesis methods and leaky LMS algorithm. Wireless Personal Communications, 129(4): 2829-2841. https://doi.org/10.1007/s11277-023-10260-3

[25] Singh, U.K., Alaee-Kerahroodi, M., Shankar, M.B., Thipparaju, R.R. (2024). MEE-based adaptive state estimator for non-Gaussian radar measurement. In 2024 IEEE Radar Conference (RadarConf24), Denver, CO, USA, pp. 1-6. https://doi.org/10.1109/RadarConf2458775.2024.10548434

[26] Eweda, E., Macchi, O. (1987). Convergence of the RLS and LMS adaptive filters. IEEE Transactions on Circuits and Systems, 34(7): 799-803. https://doi.org/10.1109/TCS.1987.1086206