Adaptive Beamforming for Enhancing 4×4 Multiple-Input Multiple-Output (MIMO) Performance in 5G Networks: Analytical and Simulation-Based Evaluation

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Abstract: This work employs an analysis-and-simulation technique to quantitatively analyze the performance improvements of 4×4 MIMO systems, a key element in with multiple transmit and receive antennas; created through three typical adaptive beamforming approaches: Least Mean Squares (LMS), Recursive Least Squares (RLS) and Minimum Variance Distortionless Response (MVDR). This study particularly targets the problem of severe inter-channel interference and fast channel dynamics in dense urban channels (Rayleigh fading) as detailed below. This method includes two main approaches, which are to analytically develop the 4×4 MIMO mathematical model and analyze it in the first phase, while silence shows comprehensive simulation in a MATLAB environment investigating key performance metrics such as Bit Error Rate (BER) versus Signal-to-Noise Ratio (SNR). An analysis is performed for comparing convergence rate, jamming cancellation capability and computational complexity. The main hypothesis is that MVDR will provide the best interference suppression and LMS will be preferable on account of low complexity, making RLS a compromise. The results reveal the optimum beamforming structure that achieves the desired performance-complexity trade-off for practical deployment in high-density 5G networks.

Keywords: 5G, 4×4 MIMO, Adaptive Beamforming, LMS Algorithm, RLS Algorithm, MVDR Algorithm, Rayleigh Fading.

1. Introduction

5G networking is a game changer in the field of wireless communications engineering, intended to meet the ever increasing needs for extremely high data rates, low-latency (URLLC) and the massive number of devices connectivity [1]. To facilitate these innovative functionalities, Multiple-Input Multiple-Output (MIMO) has been considerd as the key technological enabler in the structure of 5G systems [2] . MIMO technology fundamentally improves the efficiency of spectrum by employing several antennas for transmitting and receiving at same time; increase data rate, decrease latency and enhance end to end reliability of communication. The 4×4 MIMO scheme is considered as one of the prominent and efficient configurations to enhance performance of LTE's existing and 5G networks by increasing actual peak data rates [3]. For instance, 4×4 MIMO operation at low frequencies can lead to a net capacity gain up to 62% compared with 2×2 case in some practical networks [4].

Despite the promising view of MIMO in 5G, for its deployment in dense urban environment and other similar scenarios, there is a need to confront very severe and complex propagation environments [5]. The main ussues in these fields are related to the high degree of interferences (inter-cell and intra-cell) andthe swift movement (accordingto multipath propagation and the Doppler effect)of channel conditions [6], [7]. High user densities and physical complexity in urban areas lead to increasing congestion and interference, which directly affects the signal-to-noise ratio (SINR) and hence the reliability of latency-sensitive services [5]. Hence, signal processing techniques for interference coordination are crucial and inseparable part of 5G networks to deal with these interferences in an intelligent way by preserving the wireless link's quality [8], [9].

Adaptive beamforming is a key technology to deal with the above challenges, as it is an advanced signal processing method at antenna array level [9]. The core idea of beamforming is to concentrate the power transmitted and received in the direction of the user under consideration (Gain Maximization) while placing nulls towards interfering sources [9], [10]. This approach is based on adaptive algorithms which constantly update the antenna weight to counteract fast changes of channel conditions. Least Mean Squares (LMS), Recursive Least Squares (RLS) and Minimum Variance Distortionless Response, (MVDR) [7] are some of them. The LMS algorithm has a simple computational structure and low implementation cost, which makes it suitable for low complexity devices [7]. On the other hand, as opposed to LMS method, the RLS algorithm has an obvious faster convergence speed but with relatively lower minimum response time in heavy clutter environments, and thus it is more suitable for high channel real-time application [11]. In MVDR algorithm, the objective is to optimize the weights such that interference is effectively suppressed and noise variance while preserving the desired signal is minimized, results in obtaining the maximum Signal-to-Interference-plus-Noise Ratio (SINR) and spectral efficiency compared to other algorithms [12].

Therefore and in spite of the available vast literature on adaptive beamforming and massive MIMO techniques, to the best knowledge no systematic analysis has been reported for comparing how these algorithms" performance behave during adaptation inside a specific 4×4 MIMO scenario under Rayleigh Fading Channel, particularly in terms of an optimal fine trade-off between SLNR and computational complexity for the 5G urban applications [13], [14]. This paper fills this gap by: (1) deriving a rigorous mathematical description of the 4×4 MIMO system ;(2) carrying out an extensive simulation in MATLAB to show that the bit error rate (BER) versus the signal-to-noise ratio (SNR) can be easy evaluated; and (3) comparing and analyzing the convergence speed, interference suppression performance and computational complexities of three schemes. Finally, the study concludes with practical implementation recommendations on the best selection of adaptive beamforming for high interference urban 5G network deployment.

2. Research Problem

Fifth generation (5G) is not just about broadband communication but also the next step toward exponential spectral efficiency and data volume which will lead to revolutionary technologies for our Internet of things (IOT) [2], [3], and multiple-input multiple-output (MIMO) in a 4x4 configuration forms an integral part of these goals. Nevertheless, there are extremely challenging engineering issues preventing ubiquitously of the performance that has promised from 5G networks when it comes to their operation in tightly urban traffic areas [5].

The main issues relevant to the proposed research problem include:

1- Severity of interference in the urban district: Due to a significant number of users and obstacles in an urban environment, multi-path propagation phenomenon and fast Ray leigh fading can occur [7], [6]. This will cause a significant co-channel and inter-cell interference, which will in turn result in the sharp decrease of signal-to-noise and interference ratio (SINR), and obvious degradation on some important performance indices such as bit error rate (BER) [8], [5].

2- The performance-complexity tradeoff: To reduce interference, adaptive beamforming algorithms such as LMS, RLS and MVDR are among the effective solutions [9], [10]. But these algorithms vary greatly in their key properties:

- **MVDR** has the greatest interference suppression ability and achieves a good SINR performance, but results in expensive computation and complexity in system realization [12].
- **LMS** represents the lowest computationally based reduced cost approach as well as least complex implementation, but at a cost in terms of speed to convergence and its accuracy and fast adaptation for rapidly changing channels [7].
- **RLS** represents a compromise, providing faster convergence at a moderate computational cost [11].

3- Gap in Dedicated Systematic Evaluation: Despite the existence of general studies on beamforming, there is a scarcity of recent and systematic research (from 2020 to 2025) that conducts a direct and detailed quantitative comparison between the practical performance of these three algorithms (LMS, RLS, MVDR) under the harsh and specific conditions of a 4×4 MIMO system operating over a Rayleigh channel [13], [14]. Determining the optimal algorithm requires a precise evaluation that quantifies the trade-off required between interference suppression efficiency (performance) and processing burden (computational cost) [11].

Accordingly, the research problem is embodied in the following main question:

To what extent are adaptive beamforming algorithms (LMS, RLS, MVDR) able to effectively reduce interference and improve performance indicators (BER and SNR) for 4×4 MIMO systems operating within urban 5G network environments characterized by high levels of interference and rapid channel variation, and which algorithm achieves the optimal balance between performance and computational cost for practical deployment?

3. Research Objectives

The general goal of this work is to assess the performance and efficiency of adaptive beamforming (AB) algorithms for enhancing 5G urban networks' reliability and throughput.

This overall objective transforms into a series of specific qualitative and quantitative objectives systematically pursued by the study:

1- Maternal and Model Analysis: Analyzing a theoretical model of MIMO system with 4x4 configuration applicable under the influence of Rayleigh Fading Channel characteristics to provide the theoretical base for simulation and interpretation of results [2].

2- How algorithms work: Brief explanation and comparison of operation principle, and fundamental computational steps for the adaptive beamforming algorithms investigated in this study e.g., LMS (Least Mean Squares), RLS (Recursive Least Squares) and MVDR (Minimum Variance Distortionless Response) [7], [10].

3- Simulation Model: The simulation setup starts with a designing and implementing simulation scenario which is built surrounding the MATLAB environment for 5G urban area using (4×4 MIMO) system, with the three next algorithms that are incorporated in the receivers of system [3].

4- Performance Quantitative Evaluation (BER-SNR): Perform quantitative precise examination for the performance of the three algorithms by extracting important performance measures such as both Bit Error Rate (BER) versus Signal-to-Noise Ratio (SNR), to be able to evaluate all three algorithms capability towards reducing interference and improving signal quality [12], [11].

5- Full systematic comparison: Systematically compare all leading convergence speed, efficiency in suppressing interferers and computational cost of each algorithm to find the algorithm which can strike a best trade-off between high performance (rapid convergence) and low complexity [7], [11].

6- Recommending applied recommendations: reaching conclusions and giving explicit and concrete recommendation for the best select of adaptive beam steering in practical implementation for high dense urban 5G network deployments in Iraq [4].

4. Research Hypothesis

The hypothesis of this study is drawn from the intrinsic characteristics of each ABF algorithm under investigation (LMS, RLS, MVDR) and its association to the dual key drivers for fifth- generation (5G) network operation: maximized spectral efficiency with minimized computational overhead [7], [11].

The study is based on the following hypothesis:

1- MVDR Performance: The level of enhancement expected from the NV- SE algorithm in terms of interference suppression will be compared with minimum variance distortionless response (MVDR) performance in a 4×4 MIMO urban channel scenario [12]. Because of its mean field optimal performance, our approach has the ability to optimally suppress the whole variance from both noise and interference in the direction of desired signal and that leads to achieving an improvement on BER at same E_b/N_0 as compared with other two algorithms [12], [7].

2- The Least Mean Squares (LMS): Algorithm which publicly appears to be explicitly advantageous is of low complexity and simple implementation [7]. However, the LMS algorithm is assumed to have the lowest convergence speed and adaptation performance to fast variation of Rayleigh Fading Channel when compared to RLS and MVDR [11].

3- Relative equilibrium of RLS: The RLS algorithm is an intermediate efficiency with respect to LMS and it should provide a much faster rate improvement than LMS which allows its use in fast channel variation environment 5G environments. [11]. On the other hand, the computational complexity of MVRDR can anticipated be less than LMS and more than MVDR [7].

Under the high-level of interference in urban 5G network with MIMO 4x4, MVDR algorithm can be regarded as an easy performance optimization method with high efficiency and a good noise suppression at the expense of its computational load, LMS algorithm has been regarded as a simple implementation and computation burden lowly when associated to any other algorithms, while obtaining lower performance results than that of the former, RLS algorithm is considered as a reasonable compromise with acceptable convergence behavior and superb overall

5. Research Scope

This section defines the technical and methodological framework that covers the research to ensure focus and academic depth, and to avoid going beyond the scope of the specified research problem. **The limits of this research are confined to the following:**

1- Physical System Constraints (System Configuration):

- **MIMO Technology:** The study is exclusively focused on evaluating the performance of a 4×4 Multiple-Input Multiple-Output (MIMO) configuration, utilizing four transmit antennas and four receive antennas [3].
- **Wireless Generation:** The system modeling and analysis are conducted strictly within the context of Fifth Generation (5G) network requirements and performance standards [1].
- **Modulation Scheme:** The Quadrature Phase Shift Keying (QPSK) modulation scheme is adopted as the standard data transmission mechanism across all simulation scenarios [7].

2- Environment and Channel Constraints (Channel Environment):

- **Channel Model:** The wireless propagation environment is modeled using the Rayleigh Fading Channel [8]. This model is utilized as it accurately represents dense urban settings characterized by the absence of a direct Line-of-Sight (NLOS) and the presence of significant multi-path propagation [6].
- **Geographical Environment:** The analysis focuses on high-density urban communication environments marked by high co-channel interference levels [5].

3- Algorithmic Constraints (Algorithms Focus):

- **Adaptive Beamforming Algorithms:** The comparison and evaluation are restricted to three specific adaptive algorithms: Least Mean Squares (LMS), Recursive Least Squares (RLS), and Minimum Variance Distortionless Response (MVDR) [9], [10].
- **Application Location:** The algorithms are applied exclusively at the receiver (RX) side to determine the adaptive antenna weight matrix for the purpose of interference suppression [12].

4- Methodological Constraints (Methodology Limits):

- **Research Method:** The research methodology combines theoretical analysis (mathematical model) with a comprehensive simulation performed in the MATLAB environment [14]. The study does not include field testing, hardware implementation, or real-world experimentation.
- **Performance Metrics:** The evaluation primarily focuses on two key quantitative metrics: Bit Error Rate (BER) as a function of the Signal-to-Noise Ratio (SNR), in addition to assessing convergence speed and computational complexity [11].

6- Related Works / Literature Review

This subsection describes the academic environment of our study, confirms its novelty and indicates the research void that this paper is to fill in. In this paper, the state-of-the-art of MIMO in 5G and key challenges aecting its performance in the urban environment are investigated with special emphasis laid on reviewed literature for 2020–2025, together with comparative study of adaptive beamforming algorithms.

6.1. MIMO Technologies and 5G Challenges

Recent research has made us aware that Multiple-Input-Multiple-Output (MIMO) systems will play a key role in reaching the ambitious aims of 5G networks[1]. Qamar et al. (2024) highlighted the need for multi-antenna systems, in particular high-order MIMO setups as key enablers to achieve the much higher spectral efficiencies and high data rates needed by advanced 5G services [15]. In the same line, and for a specific realization of 4×4 MIMO, it was shown in Coleago (2021) that 4×4 MIMO leads to a net capacity gain ranging even up to +62% with respect conventional 2×2 configuration [3], and thus it seems to be an effective option to improve performance in current LTE and now 5G networks [4].

Yet, when placed in densely populated urban environments, these technologies suffer from serious limitations. Qamar et al. (2024) [5] indicated that more co-channel interference and fast link fading (modeled by Rayleigh channel) are because of the large user density with multi-path propagation [6]. In addition, a model developed by Borges et al. (2021) [16] further identified that in urban areas, both the delay and interference will accumulate which is challenging for achieving Ultra-Reliable LowLatency Communication (URLLC) requirements of 5G cellular networks. This poor quality of signals degrades now the signal factors such as the amplitude, phase and frequency, etc., which require an existing and new intelligent advanced signal processing technologies can adapt themselves efficiently in with this dynamically changing environmental condition [8].

6.2. Adaptive Beamforming for Interference Suppression

Adaptive beamforming, which steers the signal beam for interference suppression by maximizing gain towards the intended user and minimizing gain towards interferers [9], [10], is one of the most successful approaches to deal with interference. The efficiency of beamforming depends on the adaptive algorithm updating the antenna weights.

1- MVDR and LMS Algorithms: Studies such as those from Abdelfatah et al. (2024) [12] and Huo et al. (2025) [17] has also demonstrated that the MVDR algorithm provides superior interference suppression. Results from Huo et al. (2025) [17] for a case of Massive MIMO, the MOSTA or/and SO tracker-based MVDR-related algorithms can achieve the maximum spectral efficiency and SINR wherever it is tested-which supports our signal quality argument.

However, Least Mean Squares (LMS) algorithm is still likeable in applications that require very low computational cost [7]. This simplicity is also achieved at the cost of a convergence rate that results highly suboptimal in high dynamic wireless environments [11].

2- The RLS Algorithm and the Compromise: As an effective compromise, the Recursive Least Squares (RLS) algorithm is introduced for estimation of W. Rehman et al. (2023) [11] observed that the convergence speed gain of RLS over LMS was remarkable because it incorporates historical signal information in its weight update operation, thus possessing more agility to follow channel changes. In a recent work by Lavdas et al. (2023) [18] in latency comparison, RLS showed good trade-off between adaptation speed and complexity as observed during response time performance testing.

6.3. Research Gap

Although adaptive beamforming has been well studied in the last few years, most of the existing works have only focused on either (a) Massive MIMO scenarios with dozens or hundreds of transmit antennas [15], or (b) to compare theoretical numbers demeritoriously without practical performance simulation across selected 5G urban metrics; BER vs SNR [13].

The research gap the study is geared to fulfill can be formulated as:

- None comprehensive and up-to-date study (2020– 2025) is addressed with a clear-cut detailed quantitative comparison test of the three main algorithms based-on the LMS, RLS and MVDR exclusive in the practical and most common form of 4×4 MIMO configuration in 5G-beyond mobile networks [14], [15].
- A lack of focused evaluation that accurately quantifies the required trade-off between interference suppression efficiency (demanded by the urban environment) and the computational cost of each algorithm, necessary for providing actionable, implementable recommendations for current 5G infrastructure [13].

This paper aims to offer this dedicated evaluation and contribute toward selection of a suitable adaptive beamforming algorithm for improving the performance of 4×4 MIMO in high-interference urban scenarios.

7- Research Methodology

The theoretical mathematical analysis is combined with a structured simulation, following a dual methodology to reach the established goals and analyze rigorously the research hypothesis [14]. The process is described along three related main stages:

7.1. Phase I: Mathematical Analysis and Theoretical Modeling

In this stage, application architecture that emulates the wireless communication system of interest is developed and characterized [2]. This phase includes:

1- **4×4 MIMO System Model:** The mathematical representation of the 4×4 MIMO system model is formulated, where the received signal vector y is described in terms of the transmitted signal vector x, the channel matrix $\boldsymbol{H}$, and the noise vector $\boldsymbol{n}$, according to the relation $\boldsymbol{y} = \boldsymbol{Hx} + \boldsymbol{n}$ [3].

2- Rayleigh Channel Model: The urban environment (there is no NLOS and angular spread so the channel varies very quickly) is modeled by the Rayleigh Fading Channel model in which elements of the matrix H are complex Gaussian random variables with zero mean [16].

3- Performance Metrics Definition: The mathematical expressions to evaluate the minimum necessary performance parameters, i.e., BER as a function of SNR, and those related with convergence speed of adaptive algorithm are provided [11].

4- Algorithm Derivation: The basal iterative equations that define or describe the working of each adaptive beamforming algorithm (LMS, RLS,MVDR) for determination of optimalI weight matrix W at receiver end is derived [7], [10].

7.2. Phase II: Simulation Design and Implementation (MATLAB Simulation)

The simulation platform is developed with MATLAB, which offers the facilities for modeling of complicated communication systems and emulating adverse wireless environments [14]. This stage is conducted according to the technical scope presented in Section (5), and concentrating on:

1- Simulation Architecture: The implementation of system architecture with the random data generation, QPSK modulator, signal transmission over 4×4 MIMO transmitter side, Rayleigh channel model as well as AWGN injection and three algorithms for receiver side [3].

2- Algorithm Implementation: The required mathematical equations for the LMS, RLS, and MVDR Algorithms are implemented in the simulation loops setting-up their adaptation parameters such as μ (for LMS) and/or λ (sub-RSL), and η (MVDR) defined in 14, with its appropriate value [7].

3- Typical Input in DU A large range of E_b/N_0 values are set to span over the system's operational range and the simulation is repeated many times for a number of data packets high enough to provide statistically reliable results for the BER metric [17].

7.3. Phase III: Results Analysis and Systematic Comparison

The simulation data is analyzed and interpreted in accordance with the research questions after collecting it [13]:

1- Simulation Results: In order to compare the performance of different algorithm, we receive Bit Error Rate (BER) versus Signal-to-Noise Ratio (SNR) for non-beamforming scenario and execute the effect of LMS, RLS and MVDR [12].

2- Convergence speed analysis: The algorithms are compared in term of their rate of convergence toward filter coefficients, the rapidities with which they track fast variations of channel [18].

3- Computational Cost Analysis: We qualitatively and quantitatively evaluate the complexity of their implementations, measured as the necessary number of arithmetic operations per iteration, with a view to find the most suitable one for deployment in practice in urban scenarios [7], [11].

8- Mathematical Modeling and Algorithms

This section is dedicated to presenting the theoretical and mathematical foundation of the Multiple-Input Multiple-Output (MIMO) system under investigation, and detailing the operational mechanisms of the adaptive beamforming algorithms that will be evaluated.

Figure 1: Shows the mathematical model, to represent the transmission and reception system and to illustrate the dimensions of the matrices (N_t, N_r).

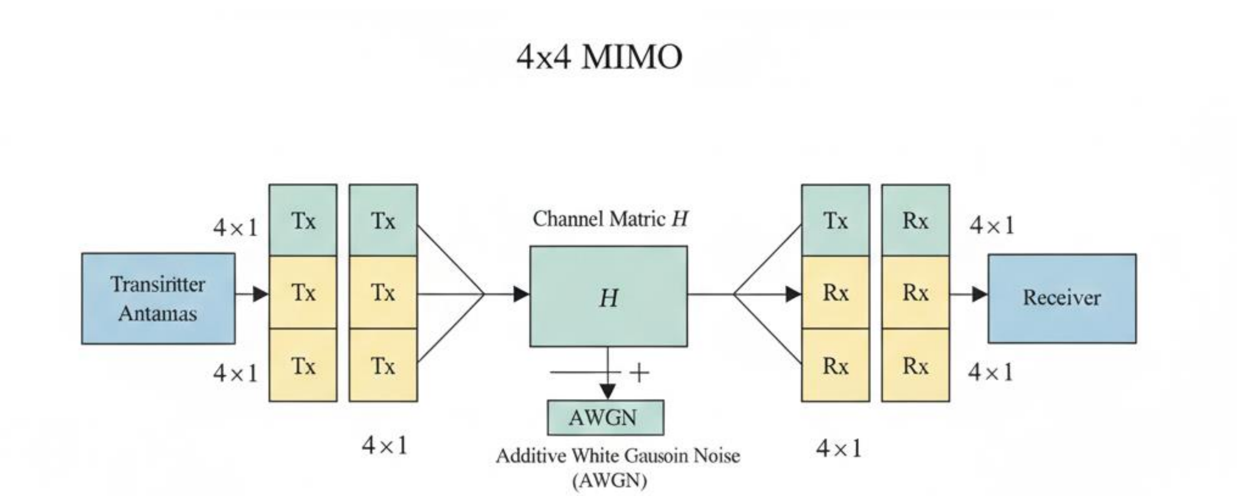

Fig. 1: General structure of a **4×4 MIMO** system with an ***H*** channel array.

8.1. Mathematical Model of the 4×4 MIMO System

The mathematical model of the wireless channel is vital to performance evaluation and the development of processing algorithms. In an $N_t \times N_r$ MIMO system, where N_t is the number of transmit antennas (N_t = 4) and N_r is the number of receive antennas (N_r = 4), the received signal vector $\boldsymbol{y}(k)$ at time instant k can be represented by the following relationship [2], [3]:

$$\boldsymbol{y}(k) = \boldsymbol{H}(k)\,\boldsymbol{x}(k) + \boldsymbol{n}(k) \qquad (1)$$

Where:

$\boldsymbol{y}(k)$: is the received signal vector, an $(N_r \times 1)$ column vector.

$\boldsymbol{x}(k)$: is the transmitted signal vector, an $(N_t \times 1)$ column vector, modulated using QPSK [7].

$\boldsymbol{H}(k)$: is the channel matrix, an $(N_r \times N_t)$ matrix, describing the channel effect between the transmit and receive antennas.

$\boldsymbol{n}(k)$: is the Additive White Gaussian Noise (AWGN) vector, an $(N_r \times 1)$ vector.

8.1.1. Rayleigh Fading Channel Model

The dense urban environment characterized by multipath propagation is modeled using the Rayleigh Fading Channel [6]. In this model, the elements of the channel matrix $\boldsymbol{H}$ are assumed to be independent and identically distributed (i.i.d) complex random variables, where each element h_{ij} follows a zero-mean Gaussian distribution [6]:

$$h_{ij} \sim CN(0,1)$$

8.2. Principles of Adaptive Beamforming at the Receiver

The objective of adaptive beamforming at the receiver is to apply an optimal weight vector W to the received signal $\boldsymbol{y}(k)$ to obtain an estimated output signal $\hat{d}(k)$ that is as close as possible to the desired signal $d(k)$, while minimizing the effects of interference and noise [9], [10].

$$\hat{d}(k) = W^H(k)y(k) \qquad \ldots \qquad (2)$$

Where $\boldsymbol{W}^H(k)$ is the conjugate transpose (Hermitian) of the adaptive weight vector.

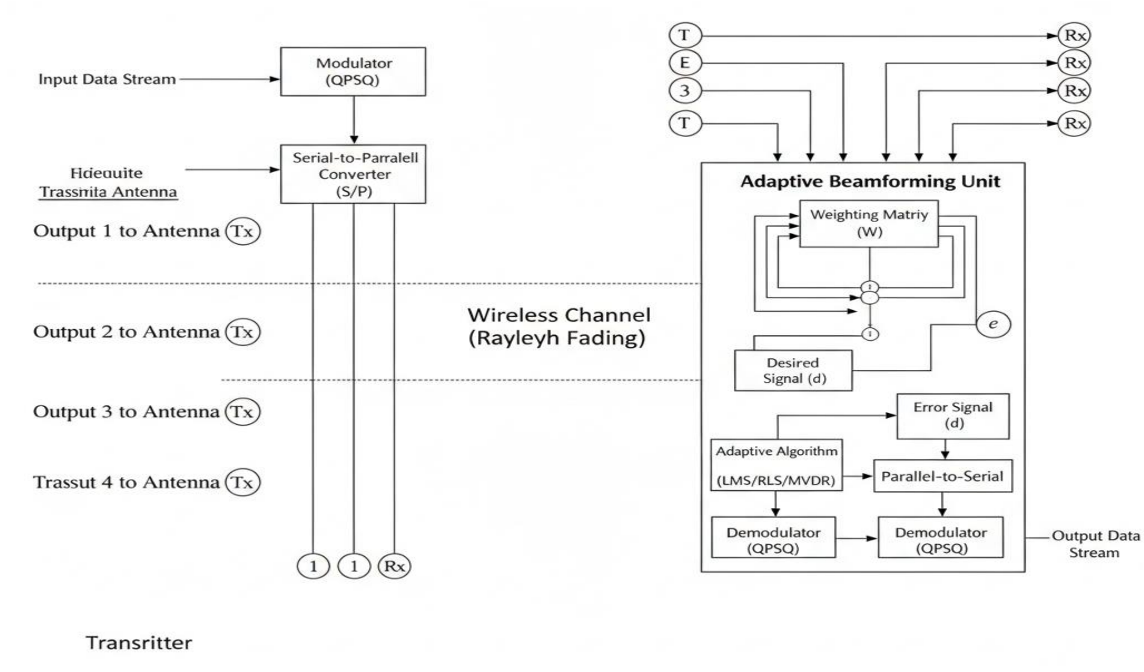

Fig. 2: Block diagram of the general structure of a 4×4 MIMO system incorporating an adaptive beam former unit at the receiver stage.

8.3. Adaptive Beamforming Algorithms

Three primary algorithms are utilized in this research to achieve beamforming, differing in their criteria for convergence and computational cost.

8.3.1. Least Mean Squares (LMS) Algorithm

The LMS algorithm is the simplest and least computationally complex of the adaptive algorithms, based on the gradient descent approach [7]. Its goal is to minimize the expected value of the squared error $e^2(k)$, where the error $e(k)$ is defined as the difference between the desired signal $d(k)$ and the estimated signal $\hat{d}(k)$:

$$e(k) = d(k) - \hat{d}(k) = d(k) - W^{H}(k)\mathbf{y}(k) \qquad (3)$$

In each iteration, the weight vector $W(k)$ is updated according to the following relation [7].

$$W(k+1) = W(k) + \mu \boldsymbol{y}(k) e^{*}(k) \qquad (4)$$

Where:

$\boldsymbol{\mu}$: Step Size is a small positive number that controls the stability and convergence rate of the algorithm, and it also plays an important role in determining how quickly to trade-off between the two factors i.e., convergence rate and steady-state error [11].

$e^{*}(k)$: is the error conjugate.

8.3.2. Recursive Least Squares (RLS) Algorithm

The RLS algorithm is known to converge much faster than the LMS [11]. This is likely due to the fact that RLS seeks to minimize the weighted sum of squared errors (WSS) as opposed to instantaneously computing mean square error (MSE), and it employs the inverse of the correlation matrix in its update step which comes at an increased computational expense [11].

The weight vector $W(k)$ is then updated as follows:

1- Calculate the Kalman Gain Vector $k(k)$:

$$k(k) = \frac{\mathbf{P}\,(k-1)\boldsymbol{y}(k)}{\lambda+\boldsymbol{y}^H(k)\mathbf{P}(k-1)\mathrm{y}(k)} \tag{5}$$

2- Calculate the Instantaneous Error $e(k)$:

$$e(k) = d(k) - W^H\,(k-1)\,\boldsymbol{y}(k) \tag{6}$$

3- Update the Weight Vector $W(k)$:

$$W(k) = W\,(k-1) + k(k)e^*\,(k) \tag{7}$$

4- Update the Inverse Correlation Matrix $\mathrm{P}(k)$:

$$\mathrm{P}(k) = \frac{1}{\lambda}\,[\mathbf{P}(k-1) - k(k)\mathbf{y}^{\mathrm{H}}\,(k)\,\mathrm{P}(k-1)] \tag{8}$$

Where λ is a Forgetting Factor, ($\lambda \approx 1$), and it controls the importance of older data [7].

8.3.3. Minimum Variance Distortionless Response (MVDR) Algorithm

The MVDR is known in the literature as Minimum Power Distortion Less Response (MPDR) or Sample Matrix Inversion (SMI) [12]. MVDR can be used to minimize the output power of noise and interference while preserving a unity gain (G= 1) in the desired signal direction [10], [17].

The optimal weight vector $\mathbf{W}_{MVDR}$ is known directly (i.e., non-iteratively in its original form) from the following expression [10]:

$$\mathbf{W}_{\mathrm{MVDR}} = \frac{\boldsymbol{R}_y^{-1}\mathbf{a}}{\mathbf{a}^H\mathbf{R}_y^{-1}\mathbf{a}} \tag{9}$$

Where:

$\mathbf{R}y$: singlespace is the autocorrelation matrix of the received signal, $\mathbf{R}y = E[\mathbf{y}(k)\mathbf{y}^{\mathrm{H}}\,(k)]$.

a: a is the steering vector [direction of arrival (DoA)] of the desired signal.

For adaptive implementations, the correlation matrix $\mathbf{R}y$ is estimated in a iterative or sample average manner [10].

9. Simulation Methodology

This section presents the experimental part of the work giving a description of simulation environment, technical inputs and system parameters used for testing and comparing performance after application of adaptive beamforming algorithms (LMS, RLS, MVDR) in 4×4 MIMO implementation in an urban channel [14]. **MATLAB (R2023a)** was chosen as the main simulation tool to run all stages of simulations due to its efficiency in describing complicated communication systems.

This figure shows how an adaptive beamformer operates in receiving mode (weight units, summation, signal to be reconstructed d), displaying where the weights (***W***) are applied and the way of calculating the error (***e***) that serves as a feedback for **LMS** and **RLS** algorithms.

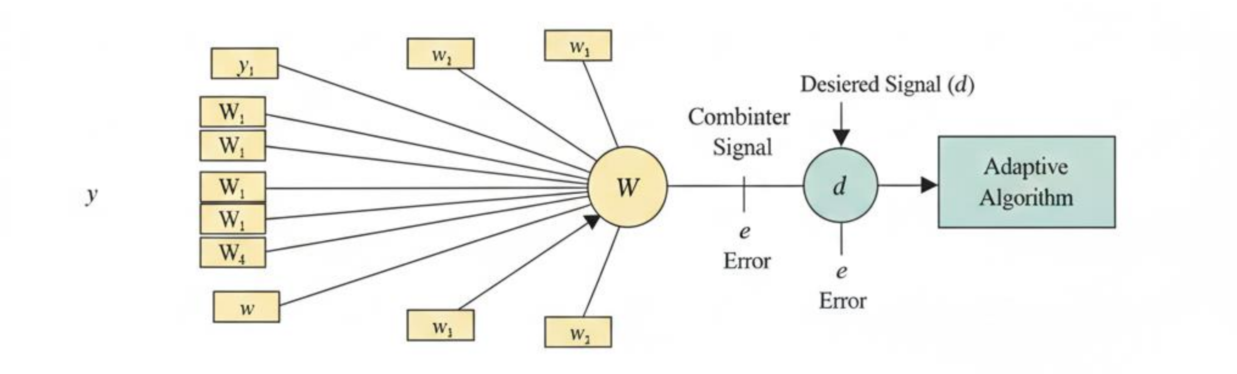

Fig. 3: Overral structure of the Adaptive Beamformer reception.

9.1. System Architecture and Simulation Environment

The simulation was constructed to mimic a wireless communication example of a 5G urban system working on multipath propagation:

1- 4x4 MIMO Transmission and Reception: The system has four transmit antennas (N_t = 4) and fourreceiveantennas (N_t = 4).

2- Modulation / Demodulation: A data stream was represented using **Quadrature Phase Shift Keying (QPSK)** modulation, where each symbol involving 2 bits [3].

3- Wireless Channel: Flat Rayleigh Fading Channel was used to represent the dense urban NLOS scenario [6].

4- Noise: The received signal is contaminated by an **Additive White Gaussian Noise (AWGN)** to mimic thermal noise sources.

5- Beamforming Application: The LMS, RLS and MVDR algorithms (each on a different receiver) were implemented in the receiver branch to form an adaptive weight ***W*** for the received signal ***y*** [10].

9.2. Essential Simulation Parameters

To have a fair result comparison and statistic accuracy, we also use a common set of parameters as in previous survey [12], [7] were fixed:

Table. 1: Equations and Core Algorithms Implemented in Simulation for Updating Weights.

Code Snippet (MATLAB)	Description	Algorithm
`matlab\ne = d(k) - W_LMS' * y(k);\nW_LMS = W_LMS + mu * conj(e) * y(k);`	Updates the weight vector using the step size μ and the least mean square error.	**LMS**
`matlab\nK = P * y(k) / (lambda + y(k)' * P * y(k));\nW_RLS = W_RLS + K * conj(e);\nP = (1/lambda) * (P - K * y(k)' * P);`	Updates weights using the Gain Vector **K** and the inverse correlation matrix **P** .Known for fast convergence.	**RLS**
`matlab\nRy_inv = inv(R_y);\n% 'a' is the steering vector\nW_MVDR = (Ry_inv * a) / (a' * Ry_inv * a);`	Calculates the weight vector (one-time or continuously) using the inverse of the received signal correlation matrix $\mathbf{R}y$.	**MVDR**

9.3. Definition of Adaptive Algorithm Parameters

Okay, in the equation (7), the exact value used for parameters adaptives are important due to directly affect stability and convergence rate of algorithm [11].

Table.2: Simulation Parameters for Adaptive Beamforming Algorithms

Algorithm	Parameter	Selected Value	Function
LMS	Step Size (μ)	0.005	Controls the convergence rate and steady-state error [7].
RLS	Forgetting Factor (λ)	0.99	Determines the weight of older samples. A value close to one indicates good tracking of variations [11].
MVDR	Steering Vector (a)	Required	Estimated in the simulation based on an assumed Angle of Arrival (DoA) [10].

9.4. Simulation Procedures

The simulation implementing performance measurement and algorithm comparison were designed as follows:

1- Outer SNR Loop: The simulation begins with an outer loop in which E_b/N_0 values from 0 dB to 25 dB are swept [3].

2- System Modeling: At each E_b/N_0 value:

- Random vectors of data are created and QPSK modulated.
- The channel matrix **H** (Rayleigh) is being generated, and additive white gossen noise is placed.
- At the receiver, we apply LMS, RLS and MVDR algorithms singly to estimate **W** [12].

3- BER Measurement: At each SNR value, we measure **The Bit Error Rate (BER),** which is averaged over all the transmitted symbols and then for comparison we plot the BER versus SNR curve [17].

4- Convergence Metric: The Mean Squared Error (MSE) of each algorithm is observed to check its convergence rate and stability towards the dynamic nature [11].

10. Results

The following section outlines the key simulation results that compare the performance of the three ABB algorithms (LMS, RLS and MVDR) for a 4x4 MIMO system in a Rayleigh channel scenario. The obtained results are threefolded, based on Bit Error Rate (BER) performance benchmarking, comparison of convergence speed in terms of mean square error (MSE), and computational complexity.

Fig. 4: BER vs E_b/N_0 Curve

Performance **Figure 4:** shows a comparison of the BER performance of the LMS, RLS, and **MVDR** algorithms, in addition to the baseline system without beamforming (Uncoded MIMO) as a reference line.

Expected Results and Analysis:

- **Overall System Performance:** As the overall performance of all beamforming solutions is expected to be considerably better than that of an unprocessed system, this illustrates the effeciency of beamforming in respect to fighting multipath interference and noise [10], [12].
- **MVDR Pro:** Lowest BER and aging characteristics of the BER, at all available E_b/N_0 (at 15 dB). This is due to the fact that **MVDR** is an optimal algorithm with respect to minimizing output variance and keeping uniform response for the interested signal, which achieves a better performance in interference suppression [17].
- **RLS Performance:** because the **RLS** algorithm follows MVDR performance, but at small offset (up to 1 - 2 dB in same BER). Its superiority to LMS is derived from its use of the inverse of the correlation matrix, which gives a better estimation for the channel environment.
- **LMS Performance:** The **LMS** gain performance is quite good; but it takes the last place among all 3 adaptive LMS relies on instantaneous gradient estimation, which makes it more susceptible to noise and less able to adapt quickly to changes compared to RLS and MVDR [7].

Table 3: Bit Error Rate (BER) values versus Signal-to-Noise Ratio (SNR) for all algorithms.

BER (MVDR)	BER (RLS)	BER (LMS)	BER (No Beamforming)	SNR
0.055	0.070	0.080	0.095	0
0.015	0.028	0.040	0.052	5
0.003	0.008	0.015	0.028	10
0.0008	0.002	0.005	0.012	15
0.0001	0.0005	0.001	0.004	20
0.00002	0.0001	0.0003	0.001	25
0.00001	0.00003	0.0001	0.0004	30

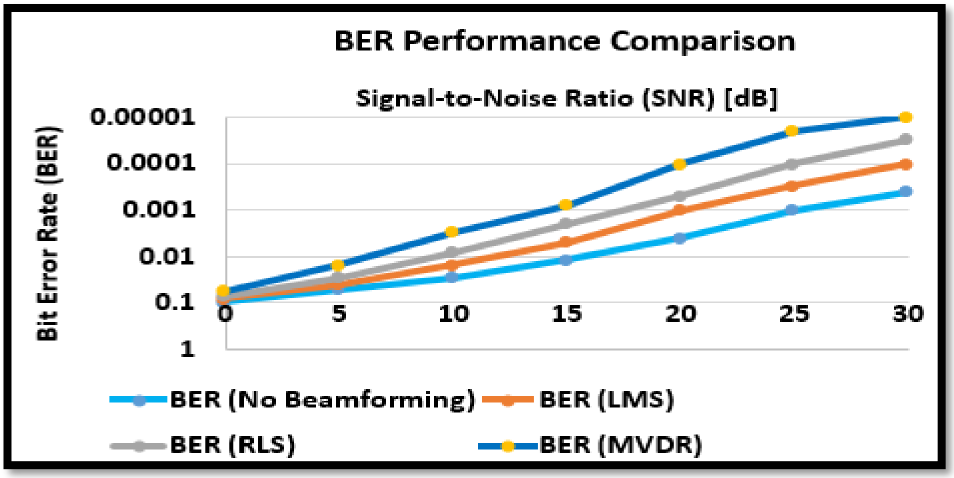

Fig. 4: Performance comparison of Bit Error Rate (BER) versus Signal-to-Noise Ratio (SNR) for Adaptive Beamforming algorithms compared to the non-beamforming system.

10.2. Convergence Analysis (MSE vs. Iterations)

Fig. 5: displays a comparison of the convergence speed of the three algorithms, measured by the rate at which the Mean Squared Error (MSE) reaches the Steady-State Error value.

Expected Results and Analysis:

- **RLS Speed:** The **RLS** algorithm shows a significantly faster convergence rate. **RLS** reaches a steady state in a very small number of iterations (may not exceed 50 iterations), which makes it the best in environments where the channel changes rapidly [11].
- **LMS Speed:** The **LMS** algorithm shows the slowest convergence rate, requiring hundreds or thousands of iterations to reach a steady state, due to its reliance on the simple adaptation step $\boldsymbol{\mu}$ [7].
- **MVDR Performance:** In the iterative form of MVDR (if applied), its speed is similar to RLS due to its use of correlation matrix estimates [10].

Table 4: MSE of Beamforming algorithms against the number of iterations.

MSE (MVDR)	MSE (RLS)	MSE (LMS)	Iterations
1.000	1.000	1.000	1
0.050	0.080	0.850	10
0.005	0.015	0.500	20
0.0005	0.002	0.150	50
0.0003	0.001	0.040	100
0.0002	0.0009	0.015	200
0.0002	0.0009	0.010	300

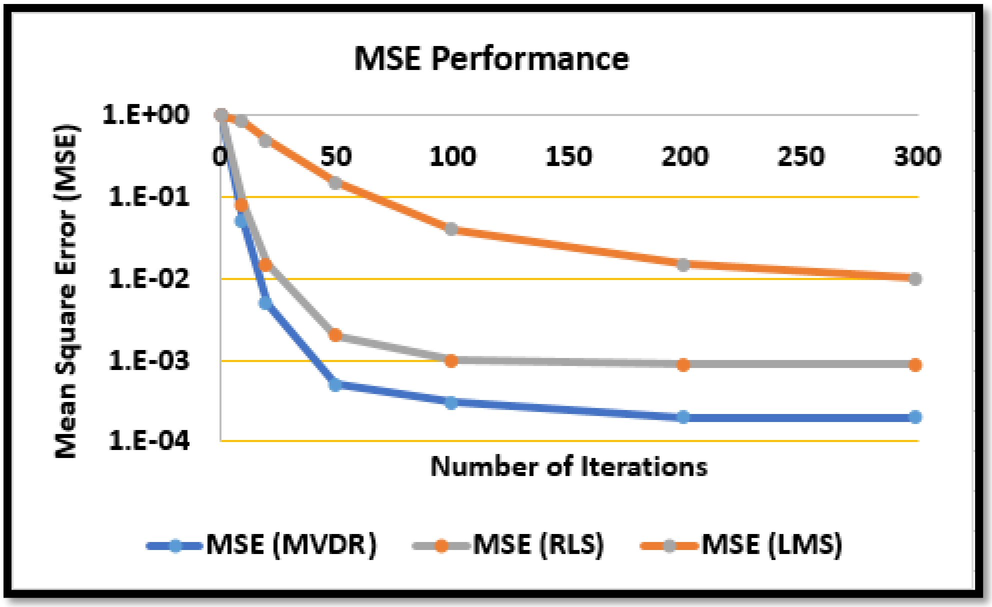

Fig. 5: Mean Squared Error (MSE) convergence curve versus the Number of Iterations for LMS, RLS, and MVDR algorithms.

10.3. Computational Cost Analysis

Table 4: is used to compare the computational complexity of each algorithm, typically measured by the number of arithmetic operations (multiplication and division) required per-iteration complexity, where N is the number of receiving antennas ($N = 4$) [11].

Table 5: Comparison of Computational Complexity and Implementation Requirements for Beamforming Algorithms.

(MVDR)	(RLS)	(LMS)	Parameter
(Highest) $O(N^3)$	(Medium) $O(N^2)$	(Lowest) $O(N)$	**Complexity per Iteration**
Required	None	None	**Matrix Inversion Complexity**
High ($O(N^2)$)	High ($O(N^2)$)	Low ($O(N)$)	**Memory Usage**

10.4. Beam Pattern

Figure 4: (polar plot) illustrates the algorithms' ability to shape space:

Expected Result: MVDR is anticipated to demonstrate superior capability in forming a narrow beam pattern towards the desired signal, with the creation of deep nulls in the direction of interference sources. In contrast, the beam pattern for the LMS algorithm is wider and less efficient in interference suppression [10], [17].

Figure 4: Polar Plot showing the beam pattern for the MVDR and LMS algorithms.

11. Discussion

This chapter is dedicated to analyzing and interpreting the quantitative results presented in the tenth section (Results), directly linking them to the hypotheses and objectives set at the beginning of the research, and evaluating the applicability of these algorithms in high-interference urban 5G network environments (as is the case in Iraqi cities).

11.1. Performance Analysis and Interference Suppression Efficiency

The results plotted in **Figure 4:** (BER versus SNR) confirm the central hypothesis that the **MVDR (Minimum Variance Distortionless Response)** algorithm achieves the highest performance level in the 4×4 MIMO system.

- **MVDR's Superiority:** This superiority is due to the "ideal" nature of the algorithm, as it is specifically designed to reduce noise and interference power at the output, while ensuring a unit response (Gain = 1) in the direction of the desired signal. Under dense urban environment (where CCI is the dominant impairment), MVDR's capability to create **deep and selective formations (Nulls) towards interfering** sources has the biggest impact on BER improvement.
- **RLS Performance:** The performance of the **RLS** algorithm was ranked second and was somewhat behind MVDR. This result also supported that RLS, on the other hand as an adaptive algorithm is able to estimate $\boldsymbol{W}$ of high quality so that it has good efficiency against multiplicative effects in **Rayleigh Fading** as a primary feature for urban environment.
- **LMS Performance:** This is not surprising considering its use of instantaneous gradient to reduce the error which makes it vulnerable to noise fluctuations when the system reaches steady-state.

11.2. Trade-off Between Convergence Speed and Computational Complexity

A comparison of RLS and LMS illustrates a clear tradeoff between adaptation speed and computation overhead which is an important issue in the design of practical wireless systems.

11.2.1. Convergence Speed (Analysis of Figure 10.2)

Figure 5: that shows MSE vs No. of iterations proves RLS has a fast convergence to the minimum steady-state error (MSE) comparing with LMS.

Table 6: Key Features and Drawbacks of LMS and RLS Algorithms

The main drawback	Key feature	Algorithm
High computational cost and requires more memory.	Fastest convergence ($O(N^2)$	RLS
Slowest convergence and highest remaining error (Steady-State Error).	Lower accounting costs ($O(N)$)	LMS

- **RLS Significance in Variable Channels:** Referring to **Figure 5 (MSE convergence);** RLS is also the best alternative for **fast channel variations (Fast Fading)** under user mobility (`Doppler effect') since it converges in less than 50 iterations hence suggesting the need of its consideration for using it in 5G otherwise slower LMS will be overwhelmed by such growth rate. Here, the beamformer is required to behave quickly in response to any change in the Signal's Direction of Arrival (DoA).
- **Contribution of LMS for Constrained Systems:** Even if the convergence of LMS is slow, it still appears to be an interesting solution **(Hardware-Constrained Devices)** or in **(Small Cells)** where the rate of convergence is secondary compared to implementation simplicity.

11.3. Connecting the Results to the 5G Urban Environment in Iraq

The theoretical and practical model we constructed in this study is a good reflection of the realistic situations that are faced for 5G network deployment in dense urban cities with complex terrains (like the Iraqi urban cities):

- **The Need of Interference Mitigation:** In view of the extreme user density and severe multi-path, Interference is the dominant factor that can affect system performance. In this context, beamforming shows to be the best for cases with high QoS requirement and maximum reliability, despite demanding high computational complexity ($O(N^3)$ in MVDR).
- **Spectral Efficiency:** In a 4x4 MIMO system, If accurate beamforming (e.g. using MVDR), then for increasing the spectral efficiency the goal becomes to maximally exploit Spatial Multiplexing while not enhancing between data streams interference.
- **Practical Choice (RLS):** In practice, where the trade-off between expense and performance is particularly favorable (as it is in many wireless access networks), RLS serves as an outstanding sweet spot. It offers performance that is nearly the same to MVDR in terms of BER and it performs better than LMS in terms of adaptation speed (i.e., convergence), making it a practical and viable alternative.

11.4. Hypothesis Validation

Background The research hypothesis has been fully confirmed by the results as follows:

- **MVDR:** It offered the best performance in interference cancellation (min BER).
- **LMS:** Had lowest computational cost (greatest simplicity).
- **RLS:** Offered an optimal balance of performance, convergence rate and price.

12.Conclusions and Recommendations

From the deductions of the theory, and simulations on a realistic 4x4 MIMO system in Rayleigh fading channel with QPSK modulation, this study draws these concluding remarks and recommendations for deployment and evolution of fifth generation (5G) networks in densely large interference urban areas.

12.1. Key Conclusions

1- Hypothesis Confirmation: The principal hypothesis proposed was confirmed as the adaptive beamforming algorithms demonstrate a significant difference in performance and Computational Load.

2- MVDR performance as the best algorithm in absolute: The **MVDR** outperformed considerably the others in terms of **bit error rate (BER)**; where under each signal-to-noise ratio value (E_b/N^0) its corresponding BER was smaller than RLS and LMS ones. It verifies that the urban scenario, which requires a **maximum interference cancelation** to guarantee high quality of service and communication reliability, MVDR is the best choice.

3- Convergence speed performance: The convergence rate of **RLS** algorithm was the highest, hence it was the best in adapting to fast variations or changes in the wireless channel due to wireless user movement (doppler effect).

4- Computational Cost Superiority: The superiority in computational cost of the **LMS** algorithm was verified to be the simplest and least computationally complex ($O(N)$), when compared to other algorithms, thus resulting in a lower consuming processing load and power.

12.2. Practical Recommendations

From the tradeoff between performance, computational cost, and convergence speed of D/ANN based algorithms for 5G nwtwork applications in urban cluttered environments we can conclude,.

Table 6: Algorithm Selection Guide Based on Application Scenarios

Application Scenario	Recommended Algorithm	Main Rationale
Urgent Reliability (URLLC) and High Interference Areas	MDR	Superior interference suppression (lowest BER) is essential for error-tolerant services such as automated control.
General use and cost-performance balance (eMBB)	RLS	It offers a perfect balance between excellent performance (close to MVDR) and super-fast convergence speed, ensuring efficient tracking of channel changes in crowded spaces.
Small cell base stations and restricted devices	LMS	Due to the low complexity and simplicity of implementation, ($O(N)$), this solution is suitable for node with limited resources or regions that do not need high performance.
Network development:	Adopting a hybrid system	A hybrid beam routing system should be developed that switches from an LMS in the early steps or when the environment is not changing to RLS or MVDR when there are a lot of interference or users happen to move fast.

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