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Hanumantharao Bitra (✉ bitrahanumantharao@gmail.com)

National Institute of Technology Tiruchirappalli

Palanisamy Ponnusamy

National Institute of Technology Tiruchirappalli

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Large Scale MIMO Analysis using Enhanced LAMA

Hanumantharao Bitra, Palanisamy Ponnusamy

National Institute of Technology Tiruchirappalli, Tamilnadu, India 620015

Abstract

In this research work, a novel enhanced large scale multi-input multi-output (MIMO) approximate message passing (LAMA) based optimal data detection is proposed for large scale MIMO systems. Existing LAMA and sub-optimal detection techniques suffer from iteration complexity and performance loss in finite dimensional systems due to large scale user fading. To overcome these, Gram matrix and message damping techniques are incorporated in the traditional LAMA. The effectiveness of the proposed enhanced LAMA and existing techniques are analyzed with 64, 32 and 16 user antennas, 256, 128, 64 and 16 base station elements with 64QAM, 16QAM, QPSK and BPSK. The simulation results show that the proposed enhanced LAMA gives superior performance when compared to existing matrix inversion methods such as Gauss sidle and Neumann, box techniques such as optimal co-ordinate descent and alternating direction method of multipliers based on the infinity norm, minimum mean square error and LAMA.

Keywords: MU-MIMO, LAMA, symbol error rate, detectors

1. INTRODUCTION

Large scale multi-input multi-output (MIMO) (also known as massive multi user MIMO) is an extension of small scale MIMO systems plays a vital role in the fifth generation and beyond of communication systems [1, 2, 3, 4]. In comparison to current small scale MIMO systems, large scale MIMO technology promises

Email addresses: bitrahanumantharao@gmail.com (Hanumantharao Bitra),
palan@nitt.edu (Palanisamy Ponnusamy)

substantial improvements in spectral efficiency [4]. The basic concept behind the large scale MIMO system is the base station (BS) equipped with hundreds of antenna elements and the user terminals consists of tens of antenna elements and the communication between user terminals and BS takes place within the same radio frequency element [5]. On the other hand, finite dimensional (practical) antenna setups necessitate more complex data detection algorithms with high computational complexity, as shown in [6].

The benefit of large scale MIMO comes with the disadvantage of computational complexity at the BS [7]. Maximum likelihood (ML) algorithm [8] is the safest bet for optimum detection criteria, but computational complexity increases significantly with the number of antennas. In order to achieve the low complexity, minimum mean square error and zero forcing linear detectors are used in [9]. A set of approximate inverse detectors such as Neumann Series Approximation [10], Gauss-Seidel Method [11] and Conjugate Gradient Method [12] are significantly used to reduce complexity. These detectors [13, 14] provide good performance only when the system ratio (i.e. the ratio between the number of BS antennas to user terminals) is greater than 2 otherwise it provides unsatisfactory response. Later, the authors of [15] have proposed approximate semidefinite relaxation based data detectors for massive MU-MIMO systems. It gives good performance to the square size matrix only. However, this is limited to BPSK and QPSK. In [16], coordinate descent algorithm is implemented for the large scale MIMO-OFDM for large system ratio. The alternating direction method of multipliers based on the infinity norm (ADMIN) equalization is described in [17]. ADMIN outperforms linear detectors, even though the system ratio is small.

Initially, approximate message passing (AMP) was proposed for compressive sensing and sparse signal recovery [18]. Later, it is extended to different applications [19, 20], including phase retrieval [21], signal detection [22] and denoising [23]. Further AMP related algorithms are being explored for data detection in various communication systems [24, 25]. Large scale multi-input multi-output (MIMO) approximate message passing (LAMA) was developed on the basis of the AMP [26] algorithm. According to [27], LAMA attains better error rate efficiency for AWGN channels with a large antenna limit (where the BS to User antenna ratio is greater than two). Unlike MMSE, matrix inversion based de-

tectors, and box based detectors, LAMA improves performance in similar user and BS configurations by using knowledge about the constellation set. However, LAMA [27] is unable to provide the best performance to practical channels. Furthermore, as the number of receive antennas increases, so does the complexity. In order to support the practical (finite dimensional) channels and to reduce the complexity at the receiver, few modifications are done to the traditional LAMA at the algorithmic level. This is referred to as Enhanced LAMA.

Notation: Bold lower case alphabet \mathbf{a} denotes the vector, bold upper case alphabet \mathbf{A} denotes the matrix, $(\cdot)^H$ denotes the Hermitian transpose (complex conjugate transpose), $\|\cdot\|$ denotes the forbenious norm, $(\cdot)^{-1}$ denotes the inverse operation, I_N denotes the identity matrix of size N , Λ denotes the LLR, and $\delta(\cdot)$ indicates the Dirac delta function.

Outline: The remainder of the paper is as follows: Section 2 describes the large scale MIMO system model. Section 3 includes mathematical derivation of the proposed Enhanced LAMA method along with its algorithm. Section 4 highlights the simulation results of proposed work and compares with the existing techniques. It also includes simulations of the Enhanced LAMA in different scenarios w.r.t to varying number of BS antennas and modulation techniques. Finally, the work is concluded in Section 5.

2. SYSTEM MODEL

Consider an uplink large scale MIMO system consisting of N_t transmit and N_r receive antennas. Let \mathbf{s} be the transmit data vector having the entries $s_l, l = 1, \dots, N_t$ are first encoded by the channel encoder and then mapped to constellation points $a_j, j = 1, \dots, |\mathbb{A}|$. These points are chosen from the QAM or PSK are taken from the energy normalised constellation set at \mathbb{A} , where $\mathbb{A} = 2^Q$. Assume $p(\mathbf{s}) = \prod_{l=1}^{N_t} p(s_l)$ be prior distribution for each transmit symbol s_l is

$$p(s_l) = \sum_{a \in \mathbb{A}} p_a \delta(s_l - a) \quad (1)$$

where p_a is the prior probability of each constellation point $a \in \mathbb{A}$. Let $\mathbf{s} \in \mathbb{C}^{N_t}$ be the transmit vector and $\mathbf{y} \in \mathbb{C}^{N_r}$ be the receive vector and they are related by

[27]

$$\mathbf{y} = \mathbf{H}\mathbf{s} + \mathbf{w}. \quad (2)$$

where $\mathbf{H} \in \mathbb{C}^{N_r \times N_t}$ is the known system matrix to the receiver and the entries follow i.i.d. circularly symmetric complex Gaussian with zero mean and variance of N_r^{-1} , $\mathbf{w} \in \mathbb{C}^{N_r}$ is noise vector which is additive in nature with variance of N_0 . The signal to noise ratio (SNR) is defined on an average basis is

$$SNR = \frac{\mathbb{E}[\|\mathbf{H}\mathbf{s}\|_2^2]}{\mathbb{E}[\|\mathbf{n}\|_2^2]} = \beta \frac{E_s}{N_0} \quad (3)$$

The individually optimal (IO) data detection problem in [28] by keeping the above assumptions are given by

$$s_l^{IO} = \arg \max_{\tilde{s}_l \in \tilde{\mathbb{A}}} \sum_{\tilde{\mathbf{s}}_l \in \tilde{\mathbb{A}}_l^{(N_t-1)}} \exp \left(- \frac{\|\mathbf{y} - \mathbf{H}\tilde{\mathbf{s}}\|}{N_0} + \log p(\tilde{\mathbf{s}}) \right), \quad (4)$$

where \tilde{s}_l indicates the exclusion of l th entry from N_t dimensional vector.

To solve the problem in (4), it requires more computations for large values of N_t . However, computationally efficient algorithms based on sphere decoding methods [15] are available for small scale MIMO systems. Since these approaches are ineffective for large MIMO systems, the literature [29], [30] contains a number of sub-optimal algorithms.

The problem in (4) can be solved using complex Bayesian approximate message passing approach. In this process, first we need to compute the marginalized distribution and then, this is converted to element wise data detection problem. In order to improve the performance in the proposed enhanced LAMA algorithm, a few modifications are incorporated in the traditional LAMA. The modifications are firstly, to reduce the complexity per iteration, the $N_r \times N_t$ channel matrix \mathbf{H} is transformed to $N_t \times N_t$ dimensional matrix using Gram matrix $G = H^H H$. Secondly, LAMA performance is reduced in the finite dimensional systems due to large scale user fading. To overcome this, message damping techniques are introduced in this research work and finally, the detection and decoding are performed at each iteration.

3. ENHANCED LAMA

The sum-product message passing algorithm is used in [31] in order to arrive at an effective inference process. This algorithm is simplified by assuming a Gaussian distribution for the marginal densities of the messages $p(\tilde{s}_l|s_l, \tau) \sim \mathcal{CN}(s_l, \tau)$ so that

$$\xi(s_l|\hat{s}_l, \tau) = \frac{p(\hat{s}_l|s_l, \tau)p(s_l)}{p(\hat{s}_l, \tau)} \quad (5)$$

with the prior distribution in (1), the posterior distribution for the transmit symbol s_l can be expressed as

$$\xi(s_l|\tilde{s}_l, \tau) = \frac{1}{Z(\tilde{s}_l, \tau)} \exp\left(-\frac{|s_l - \tilde{s}_l|^2}{\tau}\right) \sum_{a \in \mathbb{A}} p_a \delta(s_l - a). \quad (6)$$

where $Z(\tilde{s}_l, \tau) = \sum_{a \in \mathbb{A}} p_a \exp\left(-\frac{1}{\tau}|\tilde{s}_l - a|^2\right)$ is the normalization constant and it is chosen such that $\int_{\mathbb{C}} \xi(s_l|\tilde{s}_l, \tau) ds_l = 1$.

Let S be the random variable, $\Xi(\hat{s}_l, \tau)$ be the conditional mean and the message mean can be defined from (5) as follows

$$\begin{aligned} \Xi(\hat{s}_l, \tau) &= \mathbb{E}_s[S|\hat{s}_l, \tau] \\ &= \int_{\mathbb{C}} s_l \xi(s_l|\tilde{s}_l, \tau) ds_l \\ &= \frac{\sum_{a \in \mathbb{A}} a p_a \exp\left(-\frac{1}{\tau}|\tilde{s}_l - a|^2\right)}{\sum_{a' \in \mathbb{A}} a p_{a'} \exp\left(-\frac{1}{\tau}|\tilde{s}_l - a'|^2\right)} \end{aligned} \quad (7)$$

and $\Upsilon(\hat{s}_l, \tau)$ be the conditional variance and it can be defined according to (5) as message variance is

$$\begin{aligned} \Upsilon(\hat{s}_l, \tau) &= \text{var}_s[S|\hat{s}_l, \tau] \\ &= \int_{\mathbb{C}} |s_l|^2 \xi(s_l|\tilde{s}_l, \tau) ds_l - |\Xi(\tilde{s}_l, \tau)|^2 \\ &= w_a(\tilde{s}_l, \tau) |a - \Xi(\tilde{s}_l, \tau)|^2 \end{aligned} \quad (8)$$

In the massive MU-MIMO systems, enhanced LAMA is one of the most effective data detection algorithms. Especially, for practical channels the proposed method

provides better results due to addition of Gram matrix and the message damping techniques to the traditional LAMA. Based on the damped second moment estimate and damped signal variance estimate the signal to be updated at each iteration. The summary of algorithm is presented as follows

Algorithm: Proposed enhanced LAMA

1. **inputs:** $\mathbf{H}, \mathbf{y}, N_0$, and $\Lambda_{l,q}^{\text{prior}}, \forall l, q$
 2. **preprocessing:** $\mathbf{G} = \mathbf{H}^H \mathbf{H}, \mathbf{g} = \frac{1}{N_r} \text{diag}(G), \tilde{\mathbf{g}} = \text{diag}(\mathbf{G})^{-1}, \tilde{\mathbf{G}} = \mathbf{I}_{N_t} - \text{diag}(\tilde{\mathbf{g}})\mathbf{G}, \mathbf{y}^{MF} = \mathbf{H}^H \mathbf{y}$ and $\tilde{\mathbf{y}}^{MF} = \text{diag}(\mathbf{G})^{-1} \mathbf{H}^H \mathbf{y}$
 3. **initialize:** $\tau^1 = E_s(S) \mathbf{1}_{N_t \times 1}, \tilde{\tau}^1 = \mathbf{g}^H \tau^1, \mathbf{z}^1 = \tilde{\mathbf{y}}^{MF}, \rho^1 = (\tilde{\tau}^1 + N_0) \tilde{\mathbf{g}}, \theta_\tau = 0.5$ and $\theta_\rho = 0.5$.
 4. **start for loop**
 5. **mean estimate** $\hat{\mathbf{s}}^{t+1} = \Xi(\mathbf{z}^t, \rho^t \mathbf{g}, \Lambda^{\text{prior}})$
 6. **variance estimate** $\tau^{t+1} = \Upsilon(\mathbf{z}^t, \rho^t \mathbf{g}, \Lambda^{\text{prior}})$
 7. **damped second moment estimate** $\hat{\tau}^{t+1} = \theta_\tau (\mathbf{g}^H \tau^{t+1}) + (1 - \theta_\tau) \hat{\tau}^t$
 8. **Onsager term** $\alpha^{t+1} = \frac{\hat{\tau}^{t+1}}{\hat{\tau}^{t+1} + N_0} (\mathbf{z}^t - \hat{\mathbf{s}}^t)$
 9. **damped signal variance estimate** $\rho^{t+1} = \theta_\rho (\hat{\tau}^{t+1} + N_0) \tilde{\mathbf{g}} + (1 - \theta_\rho) \rho^t$
 10. **signal update** $\mathbf{z}^{t+1} = \tilde{\mathbf{y}}^{MF} + \tilde{\mathbf{G}} \hat{\mathbf{s}}^{t+1} + \alpha^{t+1}$
 11. **end for loop**
 12. **output:** extrinsic LLRs
-

Log-likelihood ratios (LLRs) are often used to convey reliability information about coded bits. To boost the error rate efficiency, it is passed back and forth iteratively between data detector and channel decoder. The intrinsic LLRs for soft-input soft-output detector according to [32]

$$\Lambda_{l,q} = \log \left(\frac{P[x_{l,q} = 1 | \mathbf{y}, \mathbf{H}]}{P[x_{l,q} = 0 | \mathbf{y}, \mathbf{H}]} \right) \quad (9)$$

for all bits $l = 1, 2, \dots, N_t, q = 1, 2, \dots, Q$ in the label \mathbf{x} and the prior LLRs for channel decoder is

$$\Lambda_{l,q}^{\text{prior}} = \log \left(\frac{P[x_{l,q} = 1]}{P[x_{l,q} = 0]} \right) \quad (10)$$

From (13) and (14), the Extrinsic LLRs can be computed as

$$\Lambda_{l,q}^E = \Lambda_{l,q} - \Lambda_{l,q}^{\text{prior}} = \log \left(\frac{P[x_{l,q} = 1 | \mathbf{y}, \mathbf{H}]}{P[x_{l,q} = 0 | \mathbf{y}, \mathbf{H}]} \right) - \log \left(\frac{P[x_{l,q} = 1]}{P[x_{l,q} = 0]} \right) \quad (11)$$

The extrinsic LLRs denote the reliability information for each $x_{l,q}$ encoded bit and then deliver it to the channel decoder that computes the new prior LLRs of the detector for the next iteration. The channel decoder provides final decisions for the information bits based on the LLRs at the channel decoder output after a certain number of iterations.

4. Simulation Results

The SER performance for various system ratios are simulated against SNR are provided to compare the proposed Enhanced LAMA with traditional LAMA, Matrix Inversion based methods such as Neumann [10], GS [11] and Box version methods such as ADMIN [17], OCD [16]. The classical MMSE algorithm is also included as a benchmark for comparison. The performance of different techniques are evaluated for various number of users and BS using different modulation techniques are shown in figure 1 to figure 4. Throughout the paper 10 iterations are considered.

The simulation results of the proposed Enhanced LAMA with other existing methods for 16 users and 64 BS antennas using QPSK are depicted in figure 1. For a fair comparison we compare all the existing methods with the proposed enhanced LAMA method at a fixed SNR of 7dB. Proposed enhanced LAMA has a SER of 0.94×10^{-5} , which is more than twice as good as LAMA's SER of 2.19×10^{-5} , three times as good as OCD's SER of 2.812×10^{-5} , more than seven times better than ADMIN's SER of 7.19×10^{-5} , ten and fourteen times better than GS and MMSE SERs of 10.31×10^{-5} and 14.06×10^{-5} , and many orders better compared to neumann's SER of 11.49×10^{-3} . It is worth noting that we are comparing results at 7 dB, if we go higher the difference will be even more. Also, at a SER of 10^{-4} , Enhanced LAMA has a 0.23dB gain compared to existing LAMA and 1dB gain compared to GS. Figure 2 illustrates the performance analysis of the various algorithms with 32 users and 256 BS using 16QAM. In this case,

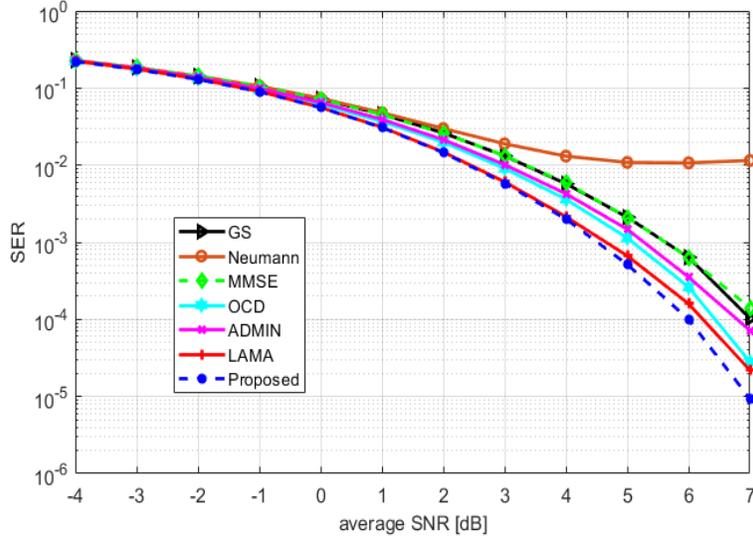


Figure 1: Performance analysis of 16 users and 64 BS antennas using QPSK

all the existing schemes provides nearly same results but Enhanced LAMA gives slightly higher performance. At a particular SNR say 10dB, Enhanced LAMA has SER of 14.22×10^{-5} and LAMA has 22.03×10^{-5} . So, there is 1.5 times better error rate performance compared to traditional LAMA. It is clearly seen that a quarter dB gain is achieved by the proposed algorithm than the LAMA at 10^{-3} . In figure 3, proposed enhanced LAMA performance is evaluated by considering 16 users and 16 BS elements with other existing schemes using BPSK. MMSE, GS, and ADMIN are having similar SER performance, and also they are slightly better than OCD and much better than Neumann. LAMA and Enhanced LAMA outperforms others conveniently but Enhanced LAMA has little edge over LAMA which is huge in Large scale MIMO systems. Further, proposed enhanced LAMA performance is explored for 64 users and 128 BS antennas using 64QAM. At SNR of 19dB, the proposed algorithm has SER of 1.6×10^{-2} , LAMA has SER of 4.8×10^{-2} and MMSE has SER of 8.2×10^{-2} , thereby having three and five times better error rate performance. At SER of 10^{-1} , Enhanced LAMA contains approximately 1dB and 1.6dB higher gain than LAMA and MMSE. It is key to note that from all the figures(1 to 4), our proposed method is providing consistent results.

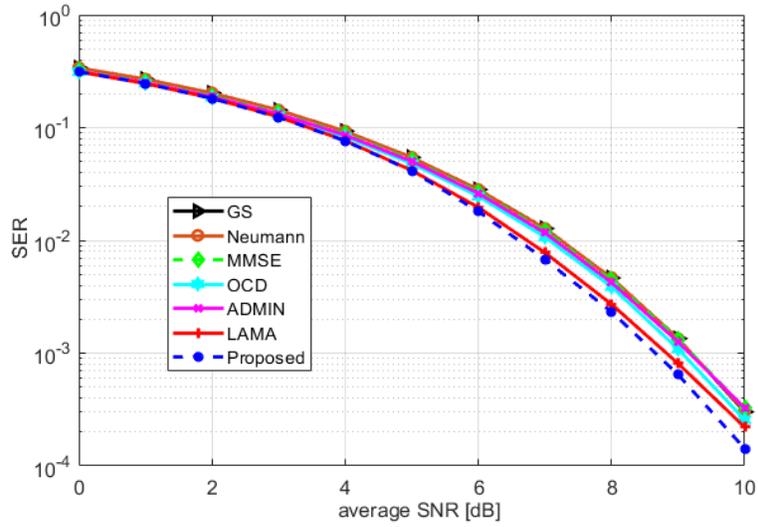


Figure 2: Performance analysis of 32 users and 256 BS antennas using 16QAM

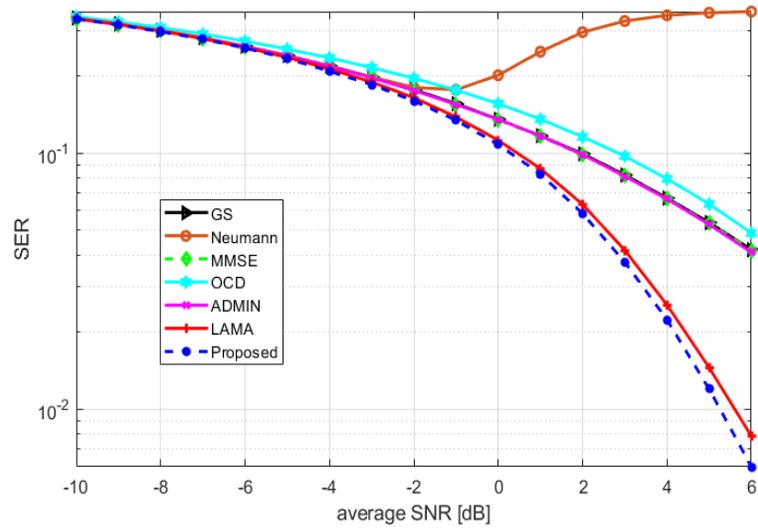


Figure 3: Performance analysis of 16 users and 16 BS antennas using BPSK

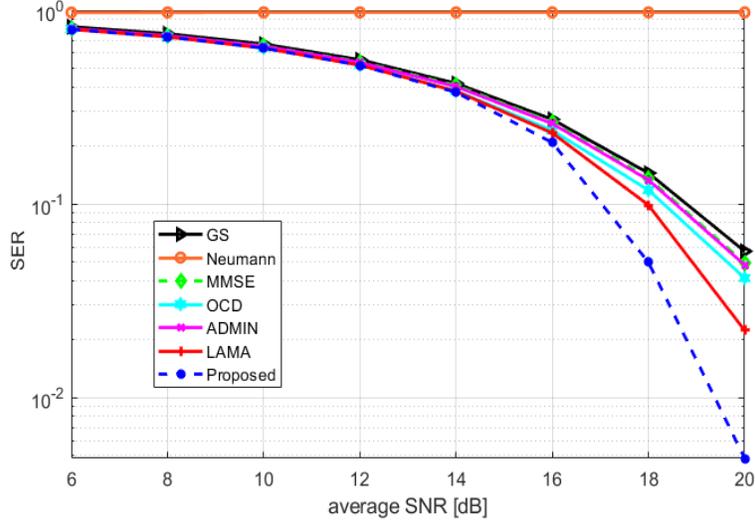


Figure 4: Performance analysis of 64 users and 128 BS antennas using 64QAM

Proposed enhanced LAMA performance is evaluated over different number of BS antennas with corresponding modulation schemes are shown in figure 5 to 7. The simulation results of 32 users using QPSK modulation scheme is exploited for our proposed method are shown in figure 5. The SER of 10^{-3} is achieved at 11.12dB when $N_r = 32$, whereas it obtained at 7.60dB when $N_r = 64$, 4.29dB for $N_r = 128$, 1.18dB and -1.76dB for $N_r = 256$ and $N_r = 512$ respectively. We can notice a significant gain of 3.52dB by doubling N_r from 32 to 64, also a gain of 3.31dB by augmenting N_r to 128, a 3.11dB of gain is achieved by increasing N_r to 256 and finally, a gain of 2.94dB is obtained by using 512 receiver antennas. We have also seen that a whopping gain of 12.88dB by varying receiver antennas from 32 to 512. A consistent gain is observed by increasing number of receiver antennas which is feasible at BS. From figure 6, when number of receivers are 16 and 32, the SER is large due to low system ratio and it reduces exponentially for different BS antennas of 64,128 and 256 respectively due to higher system ratio. The performance analysis of proposed enhanced LAMA with 64 users using QPSK is shown in figure 7. For a fair comparison, we consider a particular SNR say 4dB, SER of 2.35×10^{-1} is obtained for $N_r = 64$, by doubling to 128 SER falls 10 times i.e., 3.76×10^{-2} , again increasing to 256 SER reduces 10 times

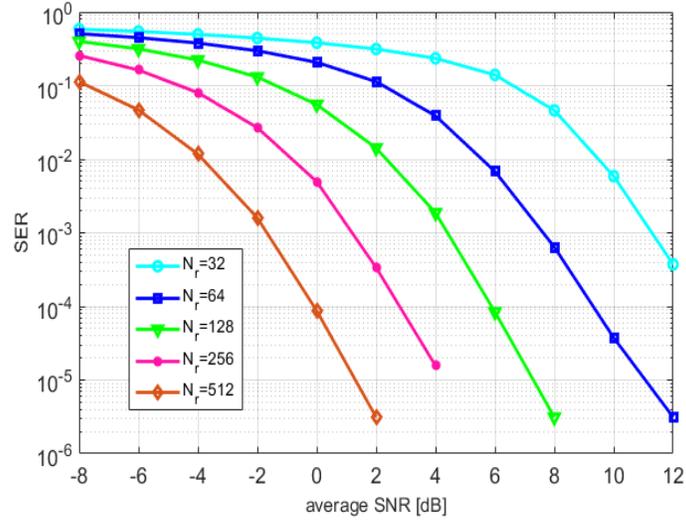


Figure 5: SER of proposed enhanced LAMA with 32 users using QPSK for various BS antennas

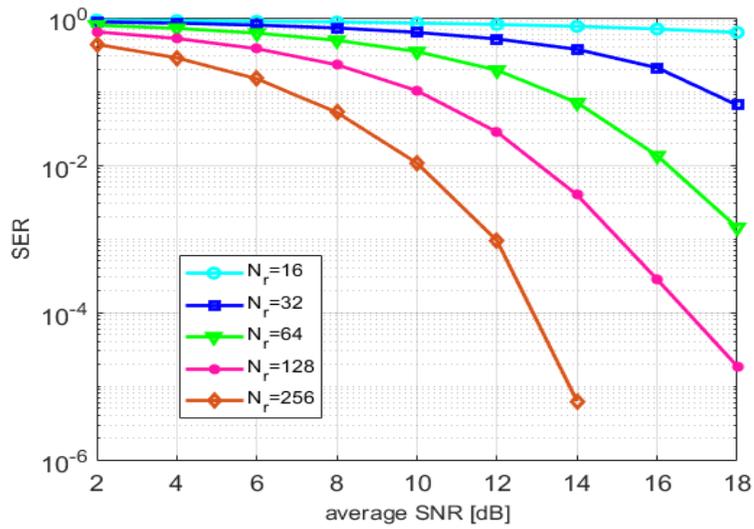


Figure 6: SER of proposed enhanced LAMA with 16 users using 64QAM for various BS antennas

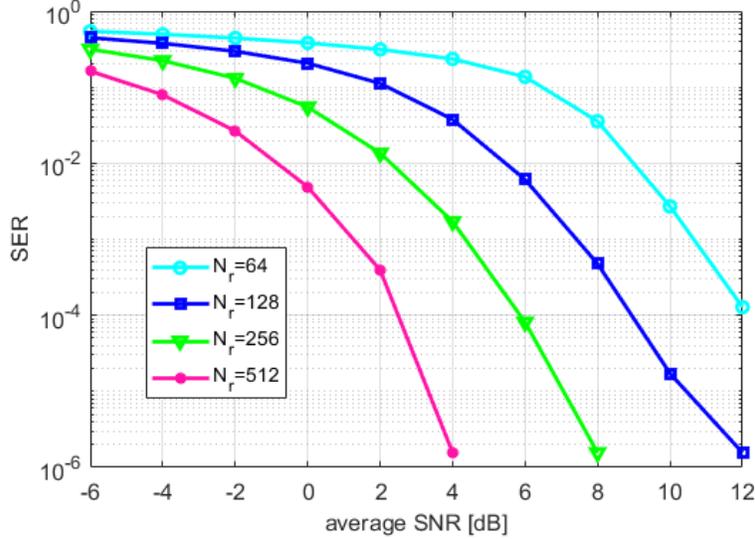


Figure 7: SER of proposed enhanced LAMA with 64 users using QPSK for various BS antennas

i.e., 1.71×10^{-3} and now just by doubling to 512, SER has decreased drastically to 1.56×10^{-6} . one can notice that until and unless system ratio is greater than two, SER is large for all the algorithms. SER falls significantly for higher system ratios, hence it is advised to maintain optimal system ratio to reap the benefits of the proposed enhanced LAMA algorithm.

Finally, the performance of our proposed algorithm is evaluated with 16 UE and 128 BS antennas for various modulation schemes are shown in figure 8. It is worth noting that the SER of 10^{-3} is achieved at 14.60dB for 64QAM, 8.56dB for 16 QAM, 1.09dB and -2.67dB for QPSK and BPSK respectively. So, even for higher modulation schemes tolerable SER is achievable at low SNR values.

5. CONCLUSION

Large Scale MIMO technology plays a crucial role in the upcoming wireless systems. In this research work, the Enhanced LAMA algorithm is proposed to get the better spectral efficiency in large scale MIMO systems. In the proposed enhanced LAMA, the Gram matrix is used instead of the channel matrix to reduce the per iteration complexity and also deployed the message damping techniques to eliminate the large scale user fading for practical channels. The simulation results

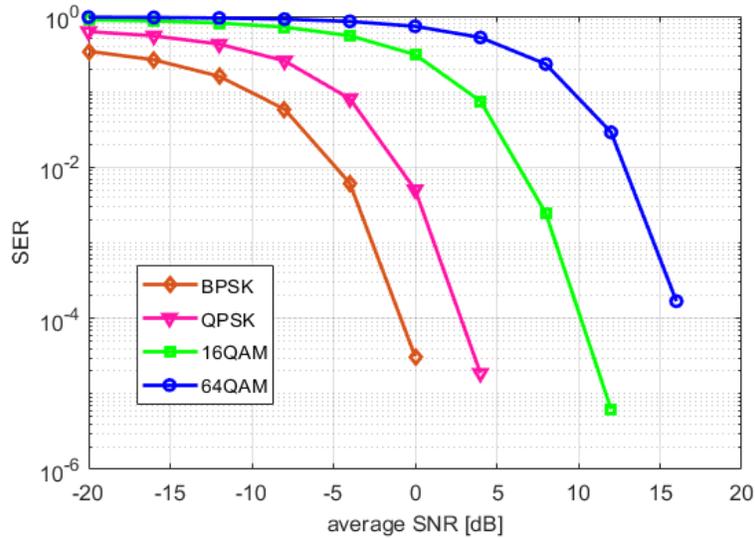


Figure 8: SER of proposed enhanced LAMA with 16 users and 128 BS antennas

show that the proposed enhanced LAMA outperforms the existing schemes such as Gauss side, Neumann, optimal co-ordinate descent, ADMIN, minimum mean square error and traditional LAMA.

Conflict of Interest: The authors declare that they have no conflict of interest.

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Figures

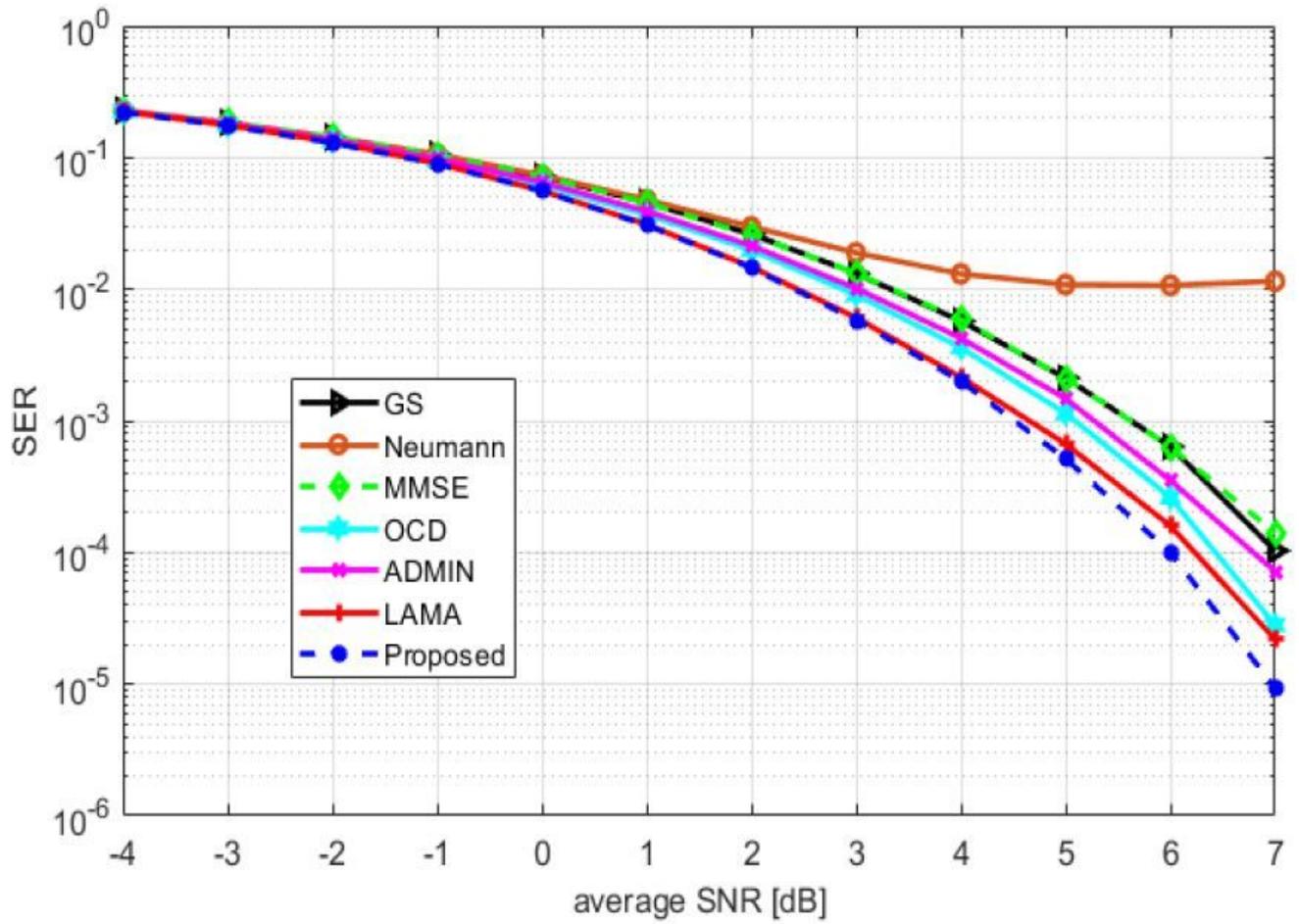


Figure 1

Performance analysis of 16 users and 64 BS antennas using QPSK

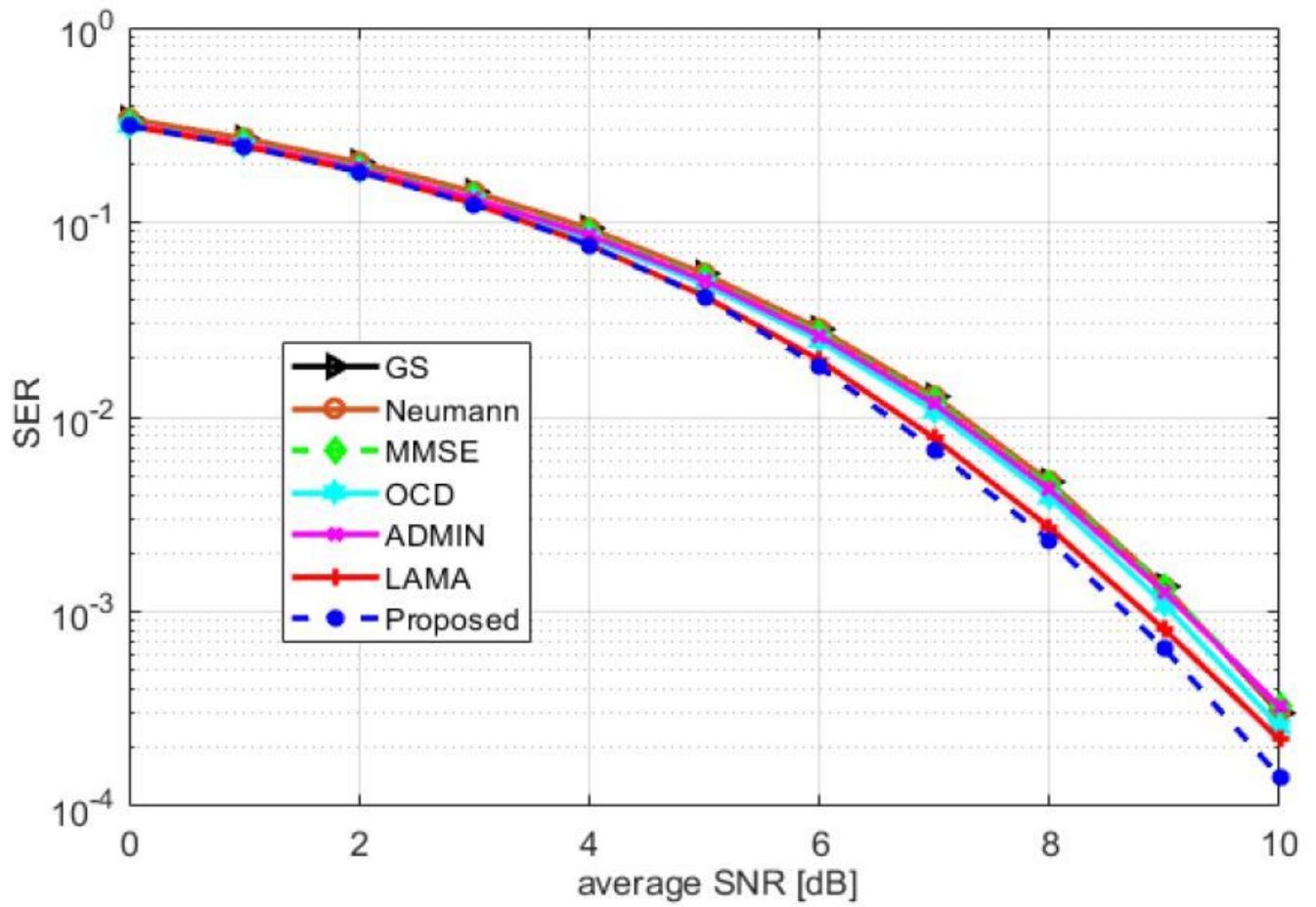


Figure 2

Performance analysis of 32 users and 256 BS antennas using 16QAM

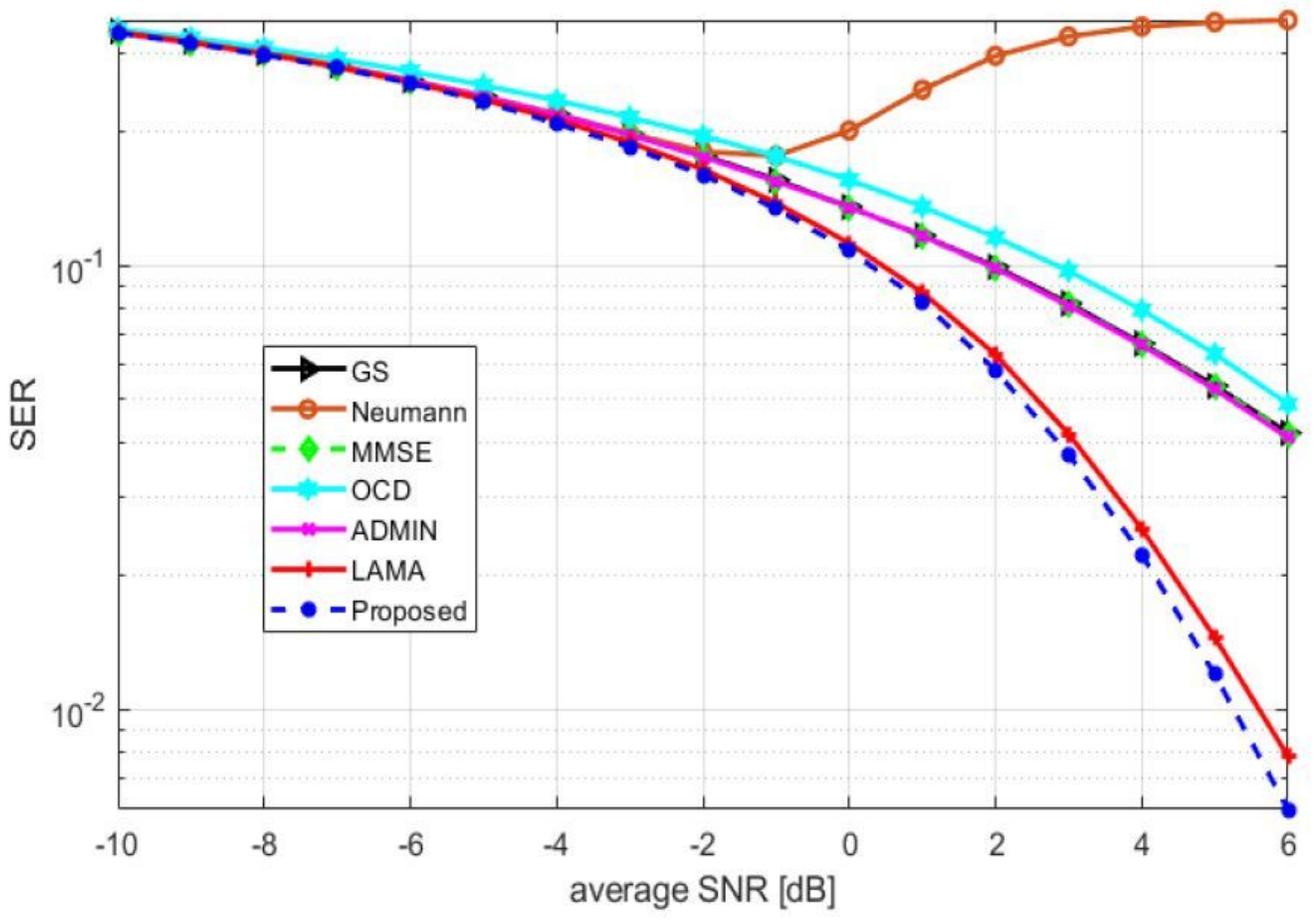


Figure 3

Performance analysis of 16 users and 16 BS antennas using BPSK

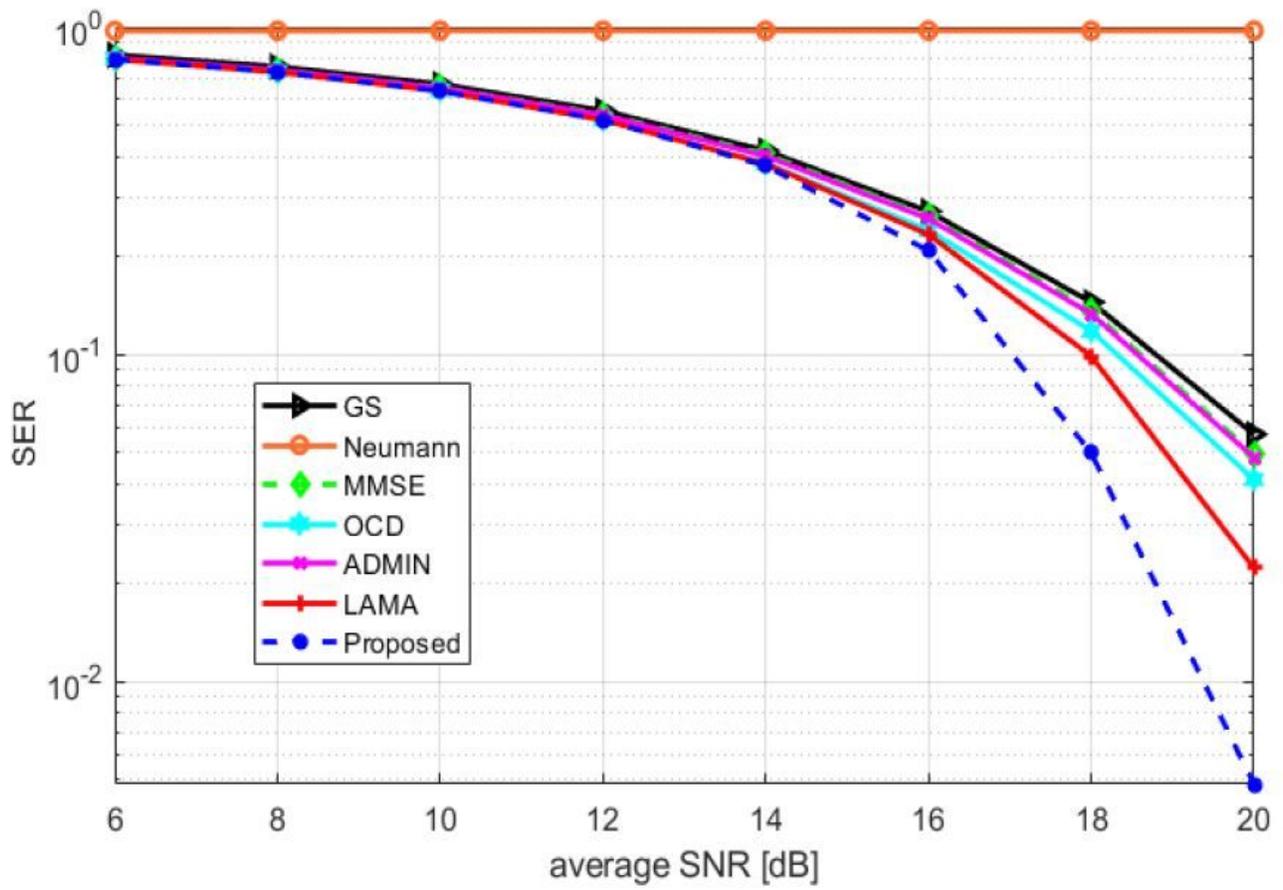


Figure 4

Performance analysis of 64 users and 128 BS antennas using 64QAM

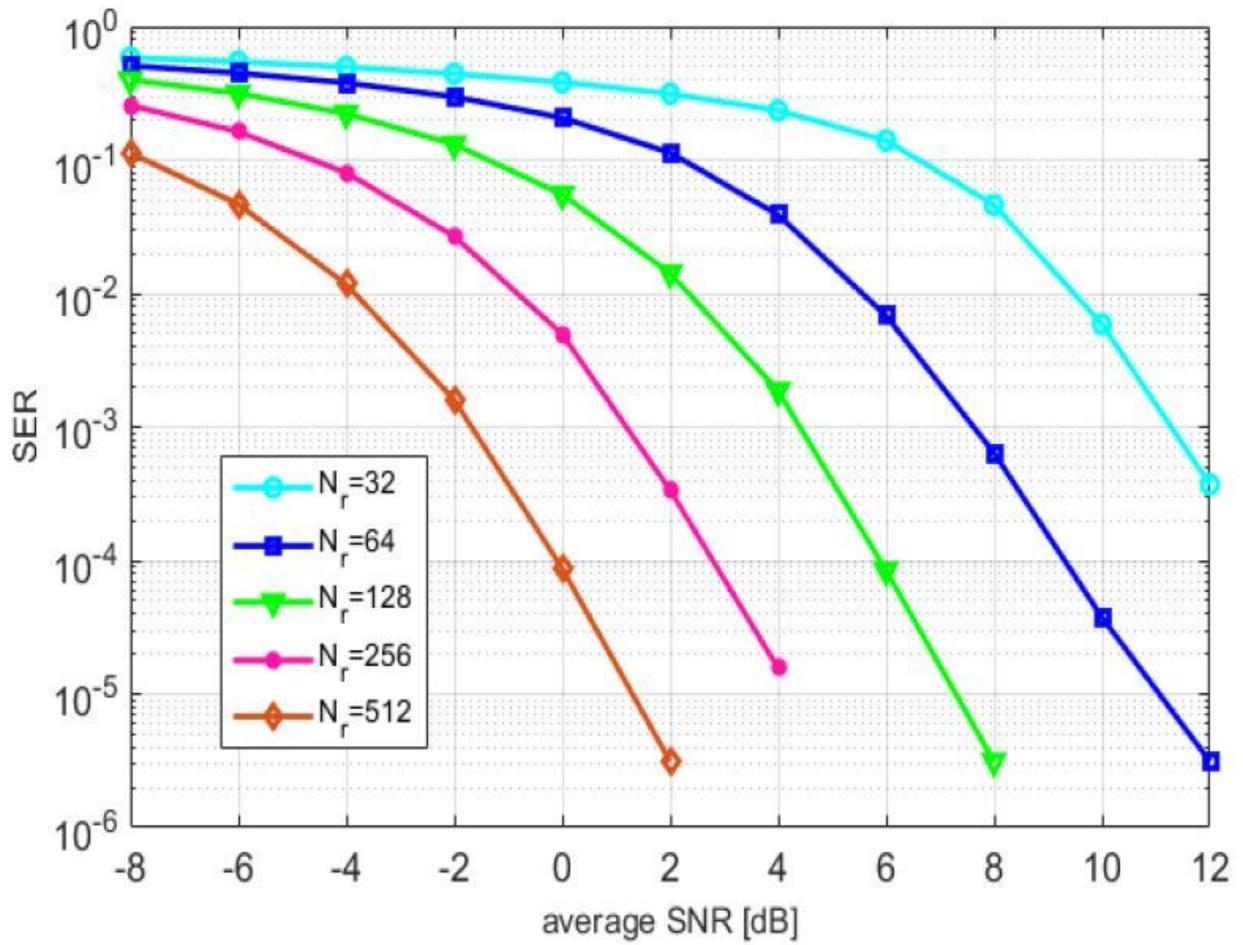


Figure 5

SER of proposed enhanced LAMA with 32 users using QPSK for various BS antennas

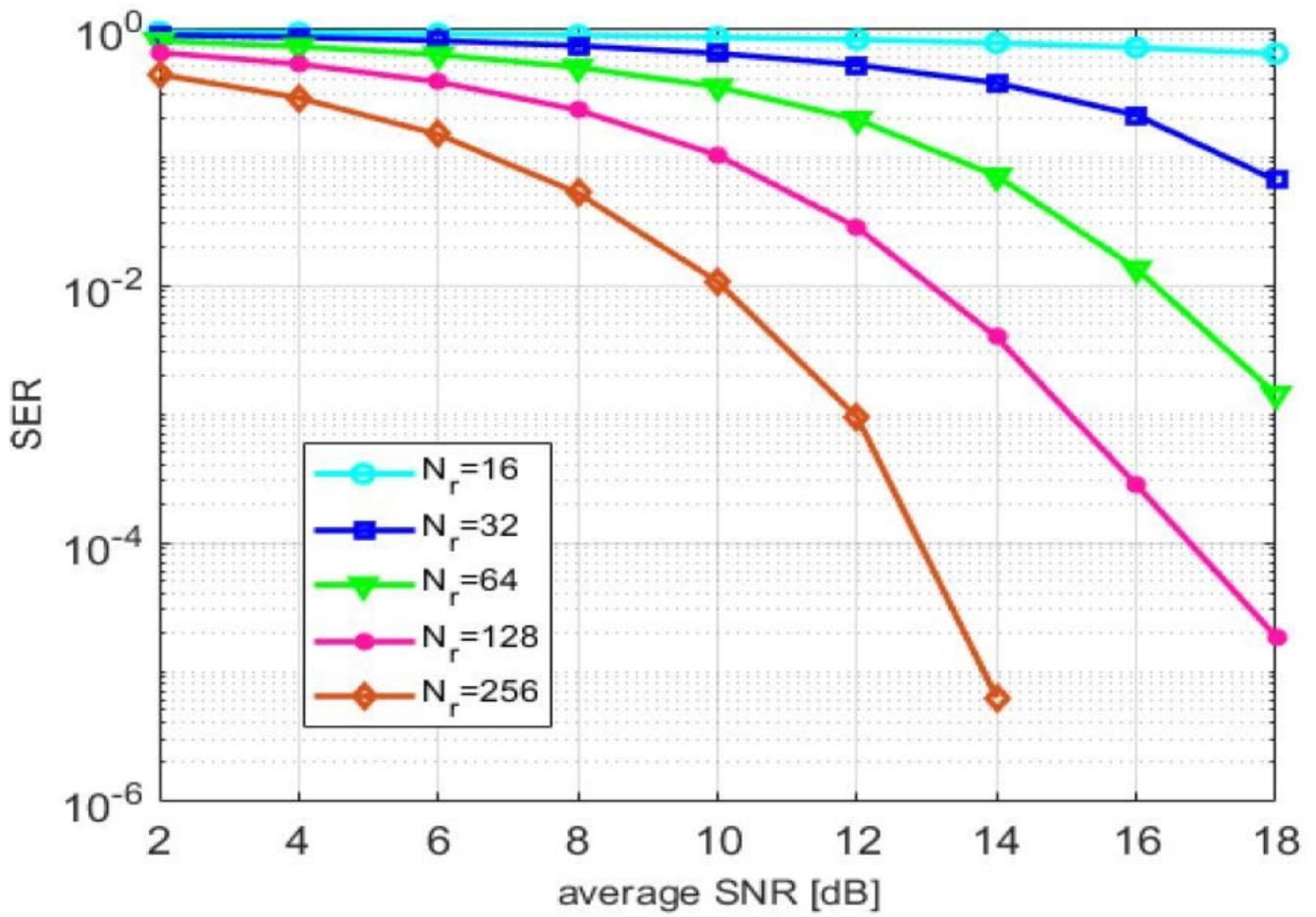


Figure 6

SER of proposed enhanced LAMA with 16 users using 64QAM for various BS antennas

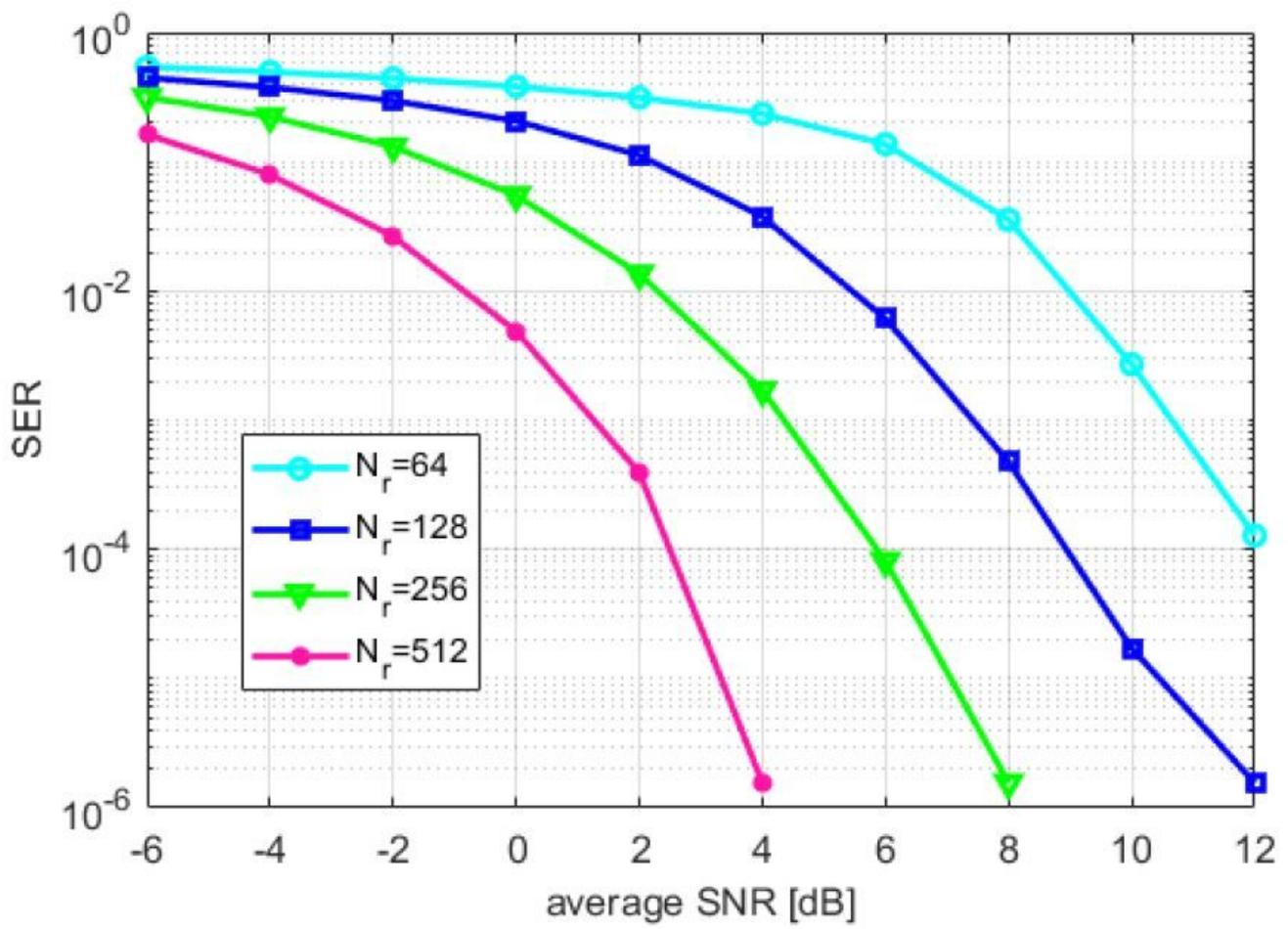


Figure 7

SER of proposed enhanced LAMA with 64 users using QPSK for various BS antennas

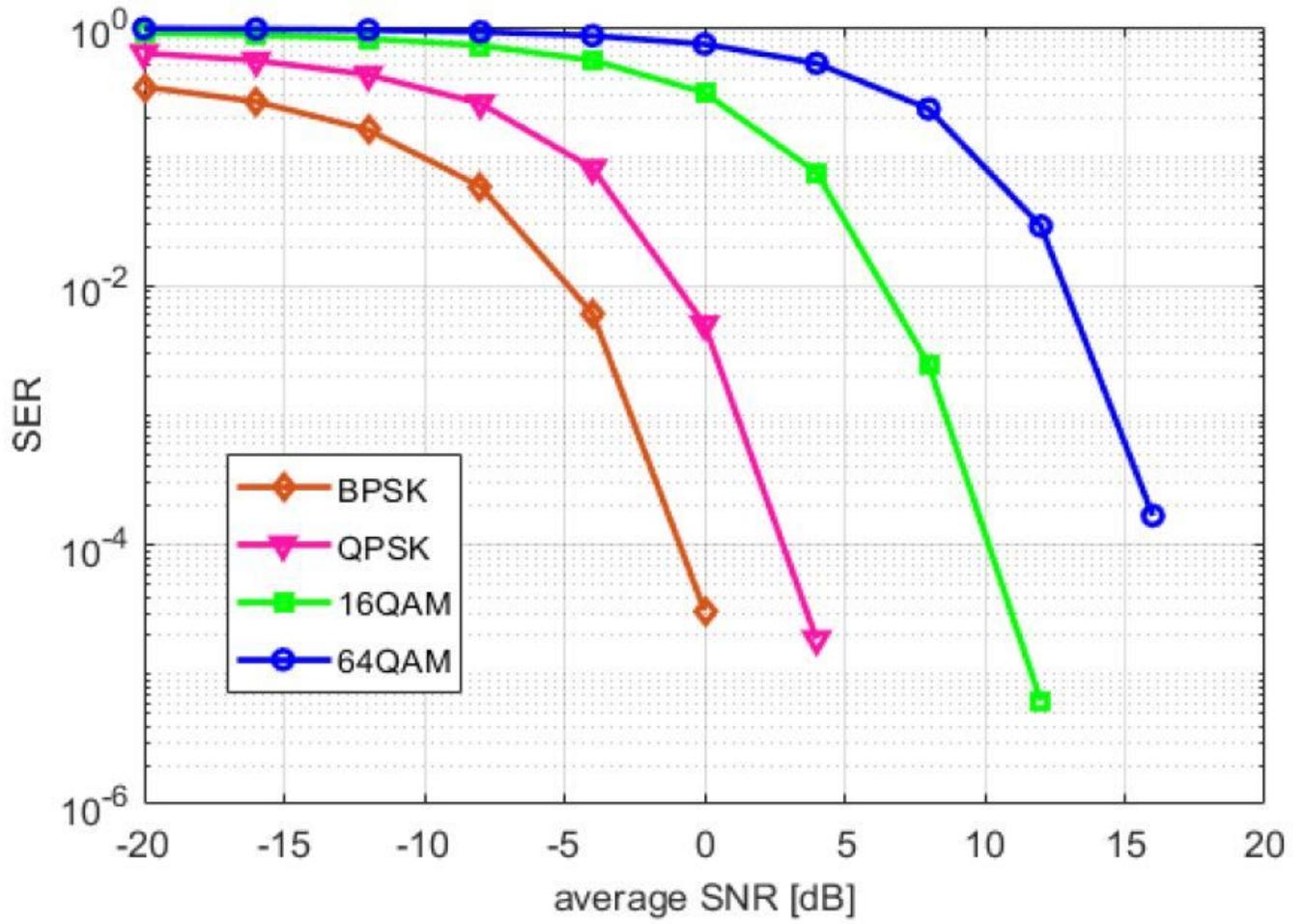


Figure 8

SER of proposed enhanced LAMA with 16 users and 128 BS antennas