IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 10 March 2023, accepted 7 April 2023, date of publication 12 April 2023, date of current version 30 August 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3266476

RESEARCH ARTICLE

Low Complexity Signal Detection for Massive MIMO in B5G Uplink System

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ABSTRACT Massive Multiple Input Multiple Output (M-MIMO) is realized as a mandatory technique for Beyond Fifth Generation (B5G) wireless networks. In next-generation node B (gNB) uplink transmission, M-MIMO requires a low-complexity signal detection scheme with an increased number of antennas to attain high channel capacity and reliability. To attain close-optimal performance in these B5G systems, the Minimum Mean Square Error (MMSE) detection scheme is preferred at the gNB but it demands a complex matrix inversion concerning the number of users. Hence, this article proposes a Modified Weighted Two Stage (MWTS) iterative algorithm with an appropriate initial solution to realize MMSE detection at reduced complexity. MWTS detection algorithm is formulated by integrating the first half iteration phase of the weighted two-stage with the previous phase and ignoring the second half iteration. Further to improve the performance of the B5G system, a low-complexity soft decision Viterbi decoder is introduced at gNB. With K users, the proposed modifications display a reduction in computational complexity of $4K^2+16K$ as compared to the weighted two-stage algorithm of $7K^2+8K$. Simulation results confirm that the proposed MWTS algorithm yields lower complexity and near-optimal performance close to MMSE detection.

INDEX TERMS M-MIMO, MMSE, MWTS, complexity reduction, BER.

I. INTRODUCTION

In the wireless telecommunication communication industry, Massive Multiple Input Multiple Output (M-MIMO) technologies have gained a significant amount of attention. The M-MIMO system is equipped with a massive antenna at next-generation Node B (gNB), which can detect multiple users' data concurrently through identical frequency and time. Fig. 1 displays the conceptual diagram of M-MIMO uplink transmission. The K users are transmitting data simultaneously at the same time with identical frequency resources. After passing through the channel, M antennas at gNB receive the composite signal with K user data. The detection matrix is designed to separate the K user data without interference. The gNB has more antennas than the user equipment, such as M>K. The detection matrix is calculated in such a way that inter-user interference is suppressed. Detection is done at the base station to extract data for multiple users. There are two types of detection such as linear and non-linear detection. Linear detection has low complexity. Hence linear detection is preferred for achieving low complexity. Conventional linear detection techniques that have been extensively used include Zero Forcing (ZF) and Minimum Mean Square Error (MMSE).

Liu et al. [1] proposed a solution for low-complexity detection, which finds the approximate solution for matrix inversion using Neumann series expansion. The complexity is significantly reduced if the series is truncated with limited elements. However, it is observed that the Neumann series expansion increases the complexity for an increase in the number of elements. Also, the truncation of elements results in a low Bit Error Rate (BER). Lu et al. [2] proposed

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Jiang.

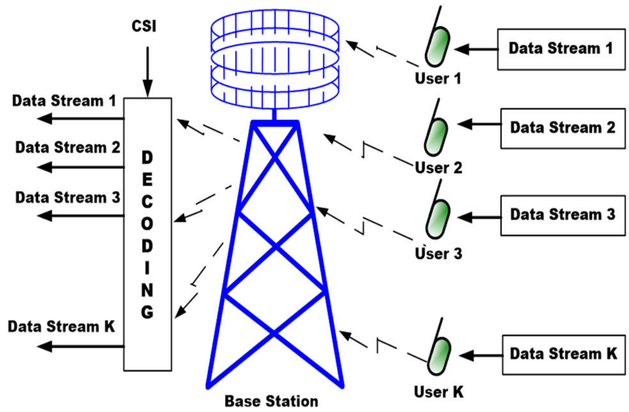

FIGURE 1. Conceptual Diagram of Massive MIMO (M-MIMO) Uplink.

a method for signal detection with reduced complexity using polynomial expansion, the same as Neumann series expansion. This method truncates the number of elements to reduce the complexity and yields low performance. Fang et al. [3] proposed a low-complexity signal detection method based on MMSE parallel interference cancellation. In this work, the Neumann series was employed to avoid matrix inversion calculation of high complexity. This method yields high BER.

Gao et al. [4] proposed a solution for low-complexity detection where the matrix inversion is not done, and the detection vector is formed directly by solving linear equations. A low-complexity iterative way of solving linear equations is proposed in this paper. The linear equation is solved using the Successive Over Relaxation (SOR) algorithm, and the complexity is reduced. However, it requires more iteration to get better BER performance. Dai et al. [5] proposed a low-complexity detection technique where the matrix inversion still needs to be done. The detection vector is formed directly by resolving a linear system of equivalences as that of the SOR method. A Gauss-Seidel-based iterative algorithm is proposed for finding a solution for linear equations. Nevertheless, the complexity upsurges with an increase in the iterations order.

Tang et al. [6] proposed a low-complexity detection technique based on the Newton repetition technique. It is derived from the Taylor series, which considers only the 1-order and improves the correctness by the iteration order with high computational complexity. Kong and Park [7] proposed a low-complexity detection technique based on an iterative algorithm called Jacobi. The matrix inversion problem is changed to a linear equation problem, and the complexity is reduced by solving linear equations with low complexity iterative algorithm called Jacobi. Nevertheless, Jacobi required more iterations to get better BER performance. Jiang et al. [8] proposed an algorithm with reduced complexity detection using the Jacobi method. However, this algorithm needs to provide better BER performance.

The main contribution has been highlighted as follows: Primarily, proposed the MWTS signal detection algorithm intends to reduce the intricacy of computations in the detection of the uplink M-MIMO system. Secondly, a mathematical model has been derived for it. Thirdly, the computational complexity of the MWTS and existing algorithms are analyzed. In addition, the BER performance is evaluated for MWTS with varying user equipment and gNB antennas. Finally, the computational complexity of MWTS and existing techniques with soft detection are analyzed. Moreover, the BER performance is assessed for the proposed algorithm with exact and approximate Log-Likelihood Ratio (LLR) calculations.

II. RELATED WORKS

Mandloi and Bhatia [9] proposed a reduced complexity technique for M-MIMO detection. This algorithm uses an approximate inversion-based method to acquire a preliminary estimate and refine it iteratively. It requires more Signal Noise Ratio (SNR) to reach better BER. Xue et al. [10] proposed an algorithm with low complexity. This algorithm changes Maximum Likelihood (ML) detection as a sum of the convex function. The newly formulated problem is solved by iteratively using alternating minimization. Still, it requires more SNR for better BER performance. Qin et al. [11] projected a reduced complexity technique based on Jacobi and Steepest Descent algorithm. However, the complexity is increased for a given BER and SNR that demands complexity reduction techniques. Ren et al. [12] proposed a low-complexity MMSE Interference Rejection Combining (MMSE-IRC) signal detection technique using eigenvalue disintegration of interference and noise covariance matrix. Chen [13] proposed a method for data detection in an uplink M-MIMO system that carries out a coordinate descent method (CDM)-based system framework. Nevertheless, the SNR requirement for reaching good BER is more.

Costa and Roda [14] proposed a Richardson technique algorithm circumventing matrix inversion. It is an iterative algorithm whose complexity upsurges when the number of iterations is exaggerated. Liu et al. [15] projected a method for M-MIMO detection based on the weighted Neumann Series method. It requires more SNR to reach good BER performance. Ghacham et al. [16] proposed a method for soft-output detection using the steepest descent algorithm. This method uses the incomplete Cholesky factorization and the steepest descent process to find the approximate matrix inversion. Still, the complexity is more, and the complexity can be reduced further. Boukharouba et al. [17] proposed a low-complexity method called Neumann series approximation, the same as Liu et al. [1], but it is done for Zero forcing decoding. The complexity is reduced by truncating the series, but the BER performance needs to be improved. However, Boukharouba et al. [17] projected a technique for detection and precoding in uplink transmission with low complexity. It provides a solution for complex matrix inversion by QR decomposition.

Xie et al. [18] proposed a technique for directly finding the precoded vector in downlink by solving linear equations using an iterative Symmetric Successive Over Relaxation

(SSOR) method. This low-complexity scheme can be used in detection in uplink scenarios also. Still, there is scope for reducing computational complexity. Liu et al. [19] proposed a weighted two-stage technique where the precoded vector is found by solving linear equations using two iterations and combining the iteration using relation parameters, significantly reducing the complexity. This low-complexity algorithm can be used in detection in uplink scenarios also.

The requirement of a low complexity detector in Beyond Fifth Generation (B5G) Systems is increased in the number of Internet of Things (IoT) devices and massive Machine Type Communications (m-MTC) that operate in the interfering environment. The B5G system recommends full duplexing with two separate antenna panels for simultaneous transmission and reception. A deep learning-based symbol detector has been discussed for the B5G system for ultra-reliable connectivity by He et al. [20]. Here, amidst the correlated interferences, the multi-user M-MIMO detector effectively reduces the bit error rate with reduced complexity. The factors that influence the performance of m-MTC devices in Non-Orthogonal Multiple Access (NOMA) based B5G systems have been discussed by Yan et al. [21]. The factors include, the types of channel coding and decoding, multi-user detection schemes, repetition type and the number of receiver antennas are the major factor of B5G systems. The appropriate choice of the above factors improves the channel capacity and reduces the error rate in interference-limited scenarios.

The tradeoff between the computing resources and the complexity of signal detection in M-MIMO-based decentralized B5G systems has been discussed by Yang et al. [22]. The realization of a fusion center in edge computing has motivated the knowledge of decentralized baseband processing in B5G systems. This also enables massive connectivity of devices with optimum utilization of resources. Owing to the traffic density and latency of massive devices, there is a need for advanced physical layer technologies for B5G and Sixth Generation (6G) systems by Khalid et al. [23]. As the reliability of these systems demands a low error rate with a control plane latency of 1 ms, there is a need for artificial intelligence-based multiuser detection under the multi-ellipsoidal propagation model. The performance reduction in the B5G system due to inappropriate channel estimation techniques has been discussed by Vilas Boas et al. [24]. To improve the system performance amid various distortion and fading classes, the neural network and reinforcement-based channel state estimation and signal detection have been recommended for multicarrier B5G systems. The channel estimation with reduced overhead for improving the energy efficiency of the B5G system has been discussed by Khan et al. [25]. This motivates the development of the proposed signal detection algorithm with reduced complexity for B5G systems.

III. SYSTEM MODEL

M-MIMO scheme through gNB employs M antennas and K users. M is chosen such that it is much larger than K. The M-MIMO system is presented in Fig 1. The receiving vector gives the transmitted signal vector from users at the gNB, then y can be written as,

$$y = Hs + n \tag{1}$$

where $\boldsymbol{y} \in C^{M\times 1}$ refers to the received vector, $\boldsymbol{s} \in C^{K\times 1}$ refers to the signal vector transmitted by K users, $H \in C^{M\times K}$ denotes channel matrix, and $n \in C^{M\times 1}$ is noise which follows Complex Normal (CN) $(0,\sigma^2 I)$ distribution. The received vector y is detected using a detection matrix, and the detected vector s is approximately the transmitted vector. The ZF and MMSE linear detection techniques are less complex than nonlinear. However, the problem with this detection is complex matrix inversion. The computational complexity of M-MIMO is increased due to a massive number of arrays in gNB. Hence an optimal solution must be identified for having low complexity. We have implemented low-complex MMSE detection for massive MIMO in this work. The following performance parameters are analyzed: BER, computational complexity, and convergence. The performance of M-MIMO is investigated with varying users and gNB antenna. Also, the performance is monitored with channel coding at the transmitter section and low complex soft decoding at the receiver segment.

IV. PROPOSED METHODOLOGY

The computational complication of conventional MMSE detection is more because of the composite matrix inversion required. To lessen the complexity, two techniques have been proposed so far. The first method approximates matrix inversion by series expansion by Liu et al. [1], while the other method rearranges the detection vector into a linear equation problem and solves the detection vector directly without the matrix inversion. The approximate matrix inversion using series expansion includes the Neumann series by Liu et al. [1] and truncated polynomial expansion. Iteratively solving linear equations includes symmetric successive over-relaxation and weighted two-stage (WTS) methods. This section explains the techniques compares all the methods and proposes a near-optimal solution for the low-complexity detection for M-MIMO systems.

A. M-MIMO UPLINK TRANSMISSION

Fig. 2 gives the block representation of the uplink M-MIMO system model. The binary data of K users are 64 Quadrature Amplitude Modulation (64-QAM) modulated, and the symbols $\mathbf{s}_1$ to $\mathbf{s}_k$ are transmitted simultaneously using identical time and frequency possessions. A gNB with M antennas receives the signal and performs MMSE detection to retrieve the symbols $\mathbf{s}_1$ to $\mathbf{s}_k$. It is QAM demodulated to get the binary data from respective users.

B. NEUMANN SERIES APPROXIMATION AND SYMMETRIC SUCCESSIVE OVER-RELAXATION

The detection vector of the MMSE detector is given as,

$$G_{MMSE} = \left(H^H H + \sigma^2 I_k\right)^{-1} H^H \tag{2}$$

where $W = \left(H^H H + \sigma^2 I_k\right)$

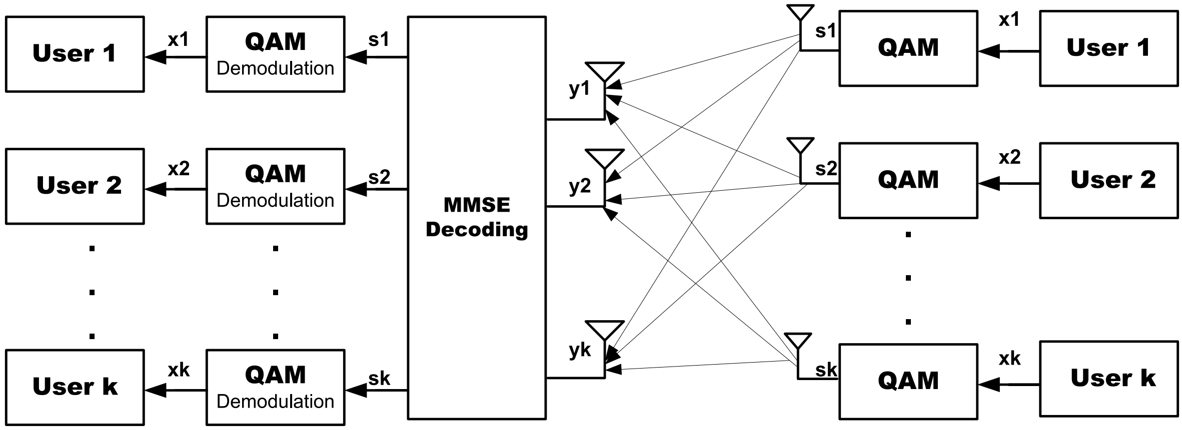

FIGURE 2. Block diagram of M-MIMO scenario.

The Neumann series (NS) for matrix inversion by Liu et al. [1] is written as,

$$W^{-1} = \sum\nolimits_{n=0}^{L} (I_k - DW)^n D \tag{3}$$

where D is the inverse of the diagonal matrix W.

The detection vector $\hat{s}$ can be written as,

$$\hat{s} = W^{-1}H^H y = W^{-1}\bar{y} \tag{4}$$

where$\bar{y} = H^H y$.

This can be rewritten by $W\hat{s} = \bar{y}$.

The Symmetric Successive Over Relaxation (SSOR) method can manipulate the vector $\hat{s}$ using the iterative method without the matrix inverse. The SSOR detection is done through the following three steps.

1) First, the W is disintegrated as $W = L + U + D$

Here, U, L, and D represent strictly upper triangular, lower triangular, and W's diagonal factor, correspondingly.

2) The first half iteration is computed as below,

$$(D + \Omega L)\, s^{\frac{k+1}{2}} = (1 - \Omega)\, Ds^k - \Omega Us^k + \Omega y \tag{5}$$

where k denotes the repetition factor and Ω is the relaxation constraint.

3) The second half repetition is carried out by taking the SSOR method in the reverse order as below,

$$(D + \Omega U)\, s^{k+1} = (1 - \Omega)\, Ds^{\frac{k+1}{2}} - \Omega Ls^{\frac{k+1}{2}} + \Omega y \tag{6}$$

After several iterations based on the above two, the obtained vector is multiplied with H^H to obtain the detection vector 's'.

C. WEIGHTED TWO-STAGE METHOD

Two half-iterations are used in the weighted two-stage (WTS), and the relaxation parameter is used to weigh and combine the two iterations. This situation differs from SSOR by Xie et al. [18] because it computes the iterations without including the relaxation parameter and then combines the iterations value with a relaxation parameter that further reduces the complexity. The two half iterations for WTS are written by letting $\omega = 1$ in the SSOR method, and it is written as below,

$$\begin{aligned} (L + D)\, s^{k+1/2} &= y - Us^k \\ (U + D)\, s^{k+1} &= y - Ls^{k+1/2} \end{aligned} \tag{7}$$

where k is the iteration number. And to further speed up the convergence, the two half iterations are combined

$$\hat{s}^{k+1} = (1 - \omega)\, s^{k+1} + \omega s^{(k+1)/2} \tag{8}$$

where ω denotes the relaxation parameter. The weighted coefficient is given by $\omega = \left({}^{K}/_{M}\right)^2$. After several iterations, the obtained vector 's' is the detection vector.

D. PROPOSED METHODOLOGY: MODIFIED WEIGHTED TWO-STAGE METHOD

In the proposed weighted two-stage algorithm. The first half iteration of WTS is taken,

$$(L + D)\, s^{k+1} = y - Us^k \tag{9}$$

The first half and the previous iteration are combined in two levels to speed up the convergence as below

$$\mathrm{s}^{k+1} = (1 - \mathrm{a})\, \mathrm{s}^{k+1} + \mathrm{a}\mathrm{s}^{k}$$

where $\mathrm{a} = 1 + (\mathrm{K/M})$

$s^{k+1} = (1 - \omega)\, s^k + \omega s^{k+1}$

Here $\omega = \left(\frac{K}{M}\right)^2$. Where k is the iteration number.

Since the second half iteration in the WTS is not used in the modified WTS, the computational complexity is narrowed. Further to improve the performance the realistic initial solution is introduced as $\mathrm{s}^{(0)} = \mathrm{D}^{-1}\mathrm{y}$. In addition to that channel encoding is introduced at the transmitter and soft decision Viterbi decoding is done at the receiver to improve the BER performance. Fig. 3 shows a block diagram of M-MIMO with channel coding, in which the max-log approached Log-Likelihood Ratio (LLR) of bit b for the user k can be

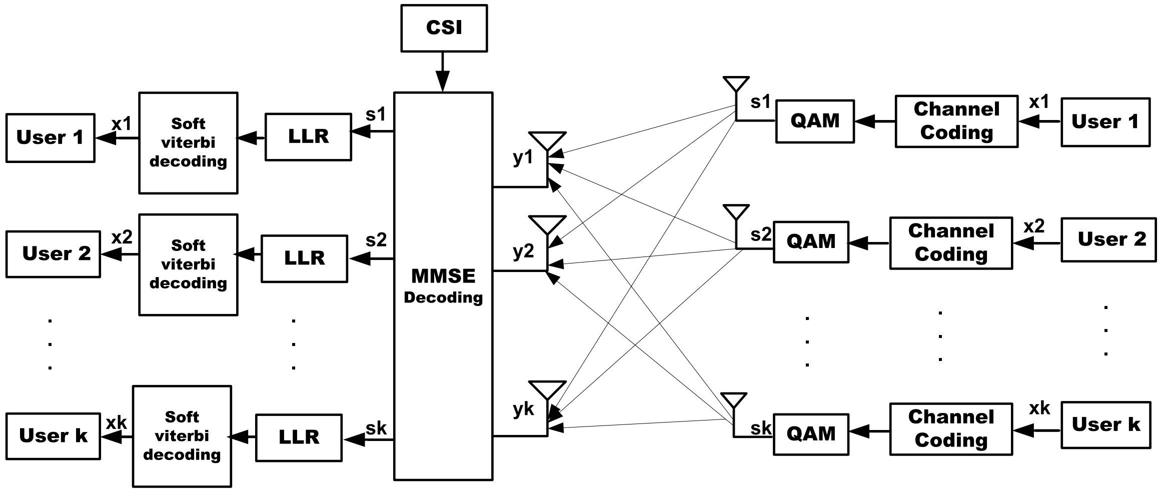

FIGURE 3. Block diagram of M-MIMO scenario with channel coding.

stated as

$$\mathrm{L}_{\mathrm{k,b}} = \gamma_{\mathrm{k}} \left\{ \min_{\mathrm{q}\in \mathrm{S}_{\mathrm{b}}^{0}} \mathrm{xe}^{-\mathrm{x}^2} \left| \frac{\mathrm{s}_{\mathrm{k}}}{\mu_{\mathrm{k}}} - \mathrm{q} \right|^2 - \min_{\mathrm{q}'\in \mathrm{S}_{\mathrm{b}}^{1}} \mathrm{xe}^{-\mathrm{x}^2} \left| \frac{\mathrm{s}_{\mathrm{k}}}{\mu_{\mathrm{k}}} - \mathrm{q}' \right|^2 \right\} \tag{10}$$

where γ_k is the SINR and $\mathrm{S}_{\mathrm{b}}^{0}$, $\mathrm{S}_{\mathrm{b}}^{1}$ are the sets containing the symbols with b^{th} bit equal to 0 and 1. Also, μ_{k} is the equivalent channel gain and $\mathrm{v}_{\mathrm{k}}^{2} = \sum_{\mathrm{m}\neq \mathrm{k}}^{\mathrm{K}} |\mathrm{E}_{\mathrm{mk}}|^2 + \mathrm{U}_{\mathrm{kk}}\sigma^2$, is the signal variance in which $\mathrm{U} = \mathrm{W}^{-1}\mathrm{G}\mathrm{W}^{-1}$ and $\mathrm{E} = \mathrm{W}^{-1}\mathrm{G}$. Hence in LLR, the matrix inversions lead to high computations. As discussed, a low-complexity LLR method is recommended for the uplink M-MIMO system with targeted BER. Wherever W^{-1} is required, an approximate solution of D^{-1} is proposed. Here, D = diag(W). With the approximate LLRs, soft-input Viterbi decoding is done to extract the transmitted data.

V. RESULTS AND DISCUSSION

This module compares the computational complexity of the modified WTS method with existing techniques. Also, the BER performance is analyzed for various scenarios and compared with the existing algorithms. The simulation is performed in MATLAB.

A. COMPUTATIONAL COMPLEXITY ANALYSIS

Table 1 presents the computational complexity comparison for the detection methods discussed, including Neumann series approximation, SSOR detection by Xie et al. [18], WTS detection, and modified WTS method. The complexity of the Neumann series increases if the number of iterations increases and it reaches the same complexity as MMSE; hence there are better solutions than this one. However, in the SSOR method, the complexity is less than in the Neumann method. Nevertheless, compared to SSOR and WTS, Modified WTS has much lower complexity; hence, Modified WTS is the low complexity algorithm compared to other methods discussed. The improved WTS scheme has reduced computational complexity, as the detector vector has three sections. The primary section is resolving s utilizing the following equivalence,

$$S_m^{j+1} = 1/w_{mm}(y_m - \sum\nolimits_{n<m} w_{mn} s_n^{j+1} - \sum\nolimits_{n>m} w_{mn} s_n^{j} \tag{11}$$

where m, n = 1,2,…K. Here s_m^{j+1} and y_m denote m^{th}elements of s and y vectors, correspondingly. The set of multifaceted multiplications needed is K^2 for each iteration. Hence, resolving s needs jK^2 times of complex multiplications.

The second part is the combining process. For the combining procedure, the set of composite multiplications needed is 4jK. The third section is the initial solution part. The initial calculation part requires 2K complex multiplications. Hence the combined complexity is $jK^2 + 4jK + 2K$.

B. COMPLEXITY ANALYSIS WITH CHANNEL CODING

Table 2 also presents the computational complexity comparison for the detection methods such as Neumann series approximation, SSOR detector by Xie et al. [18], WTS detector, and modified WTS detector but with channel coding. Based on the literature, the approximate LLR require K^2+2K as in Dai et al. [5] complex multiplications. This shows that the computational complexity depends upon the quantity of serving equipment.

C. BER ANALYSIS

The BER is evaluated for the modified WTS technique and compared with the existing algorithms. Fig. 4 displays the error rate in Rayleigh fading with the B5G channel condition. The simulation is executed with 64-QAM, 128 gNB antennas, and 16 users with varying SNR. Further, a code rate of 1/2, a maximum constraint length of 7, and a code word length of 128 bits are considered for system analysis. It is found that Neumann decoding has less significant performance as

TABLE 1. Comparison of computational complexity.

No. of Iterations	Neumann Based Detection [1]	SSOR based detection [18]	WTS based detection [19]	Modified WTS detection (Proposed)
2	$12K^2 - 4K$	$6K^2 + 3K$	$4K^2 + 2K$	$2K^2 + 10K$
3	$8K^3 + 4K^2 - 2K$	$8K^2 + 3K$	$6K^2 + 4K$	$3K^2 + 14K$

TABLE 2. Comparison of computational complexity with soft detection.

No. of Iterations	Neumann Based Detection [1]	SSOR based detection [18]	WTS based detection [19]	Modified WTS detection (Proposed)
2	$13K^2 - 6K$	$7K^2 + 5K$	$5K^2 + 6K$	$3K^2 + 12K$
3	$8K^3 + 5K^2 - 4K$	$9K^2 + 5K$	$7K^2 + 8K$	$4K^2 + 16K$

compared to other conventional algorithms. It is also found that the BER of the modified WTS-based detection is similar to WTS detection techniques. Further, it yields near-optimal performance as MMSE detection with reduced complexity. These observations display that the modified WTS-based detection is the near-optimal detection technique in terms of error rate analysis. Fig. 5 compares the error rate of the modified WTS algorithm with various initial solutions. It is observed that the WTS with zero initial condition of i=1 displays a high error rate as compared to the modified WTS algorithm. Further, as the number of iterations increases the modified WTS (i=3) attains the optimal error rate of MMSE with reduced SNR.

Fig. 6 displays the BER curves for a varying number of users. It is observed that Neumann and SSOR detection have limited performance than conventional algorithms as the number of users increases. However, it is also found that the bit error rate performance of modified WTS-based detection (with i=3) performs similarly to WTS optimal techniques. It is also observed that for a number of users equal to 16, the existing detection techniques display a bit error rate of less than 10^{-3} as compared to WTS and modified WTS algorithms. However, as the number of users increased beyond 16, the modified WTS display a better error rate as compared to WTS with reduced complexity. It gives a near-optimal performance as MMSE detection. Fig. 7 displays the bit error rate comparison for varying gNB antennas. It is found that the Neumann detection does not improve with BER for varying gNB antennas. With an increase in gNB antennas from 110 to 120, the modified WTS attains the optimal performance as that of MMSE. With further increase of the gNB antennas, the slope of the curve is at most flat and attains a BER between 10^{-3} to 10^{-4}.

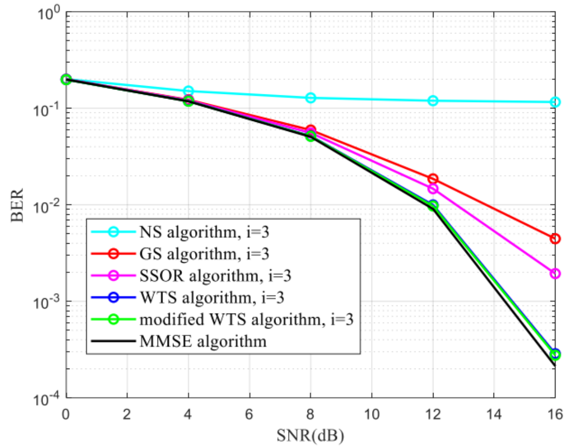

FIGURE 4. BER comparison of 64 QAM low complexity algorithms.

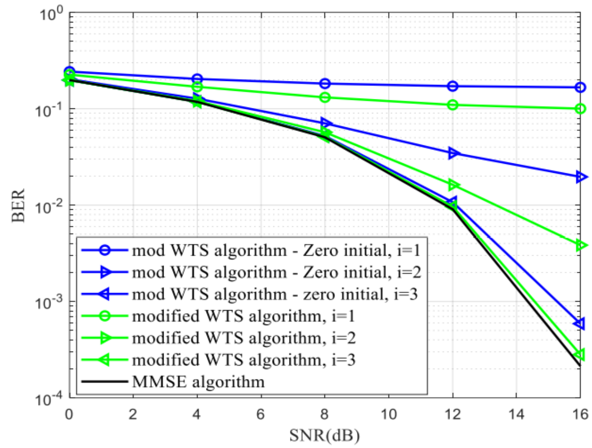

FIGURE 5. BER of modified WTS with zero and proposed initial solution.

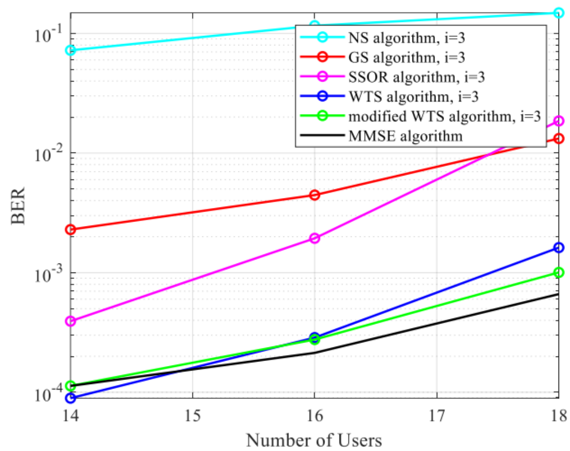

FIGURE 6. BER comparisons of reduced complexity scheme by varying number of users.

D. BER PERFORMANCE ANALYSIS WITH CHANNEL CODING

The effect of channel coding on BER performance is evaluated for the aforementioned low-complexity detection techniques. Fig. 8 exhibits the BER performance of

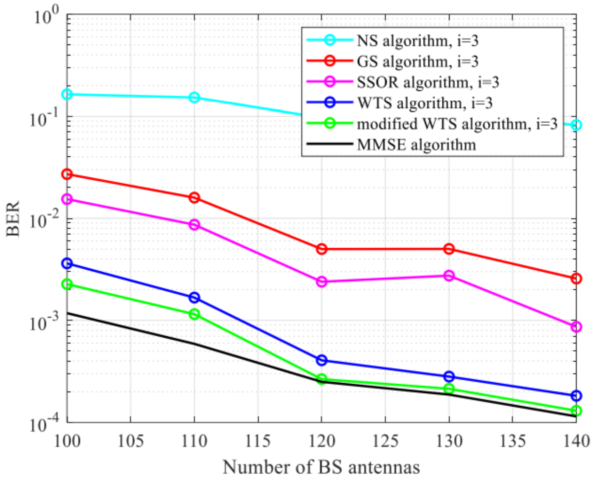

FIGURE 7. BER comparisons of low complexity algorithms by varying gNB antennas.

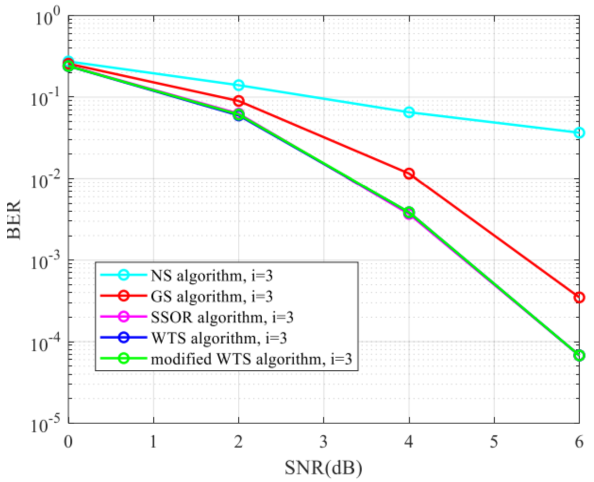

FIGURE 8. BER Performance comparison of soft decoding with exact LLR.

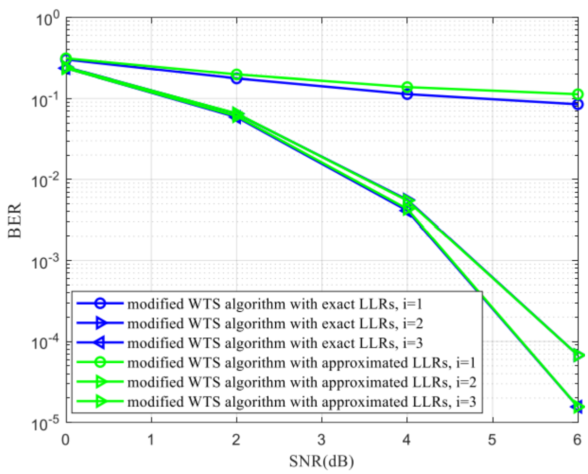

FIGURE 9. BER comparisons with exact and approximate LLR.

low-complexity algorithms with channel coding with exact LLR. As the channel coding is carried out at the transmitter's

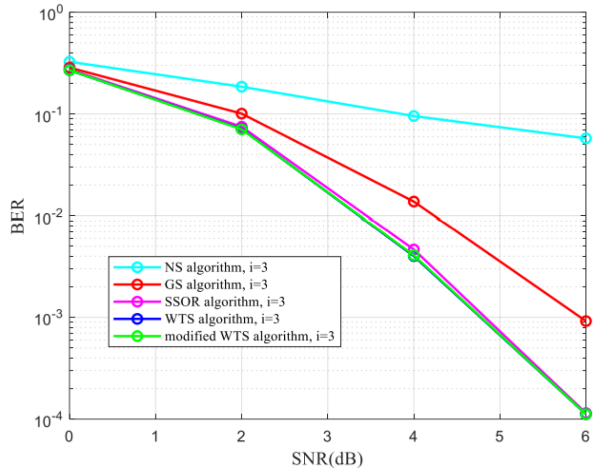

FIGURE 10. BER performance of soft decoding with approximated LLR.

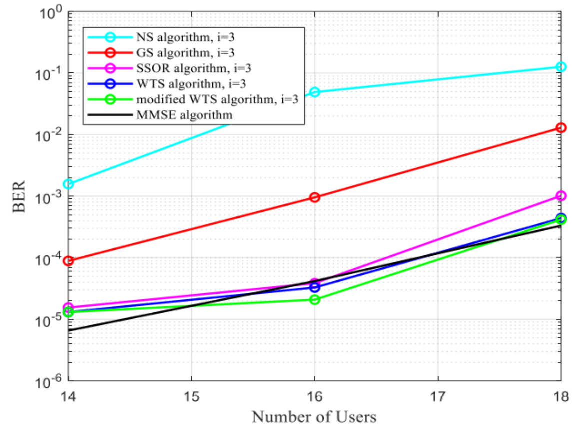

FIGURE 11. BER comparisons of reduced complexity methods with channel coding by varying the users.

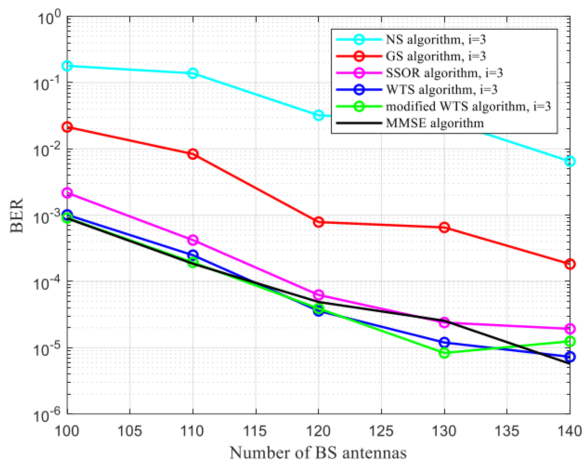

FIGURE 12. BER of low complexity algorithms with channel coding by a varying number of gNB antennas.

section, the soft decoding is performed at the receiver side with a target BER of 10^{-4} at 6 dB. The curves display that the proposed modified WTS exhibit an improved performance with reduced complexity and coding gain as compared to the NS algorithm. Moreover, the significance of exact and approximate LLRs for a varying number of iterations is displayed in Fig. 9. Hence, the exact and approximated LLR display optimal performance for an error rate of 10^{-4} for increased number of users in B5G system.

Fig. 10, Fig. 11, and Fig. 12 illustrate the BER performance of low-complexity algorithms for soft decoding techniques with approximate LLR, varying number of users, and gNB antennas, respectively. It is observed that the modified WTS algorithm attains an error rate of 10^{-3} at 4.7 dB. Nevertheless, the GS algorithm attains a similar error rate at 6 dB. Hence, the proposed WTS displays a coding gain of 1.3 dB as compared to the conventional GS algorithm. Interestingly, the WTS and SSOR also attain similar error rate with increased complexity as displayed in Table 1 and Table 2. Similar performance improvement can be observed with an increased number of users. The modified WTS attains an error rate between 10^{-3} and 10^{-4} in a cluster of 18 users with IoT connectivity. Further, as the number of gNB (BS) antennas is increased to 130, the error rate of 10^{-5} is obtained with the proposed WTS algorithm. However, due to the approximation of LLR, it is observed that the error rate is increased with the rise of the number of gNB (BS) antennas. This tradeoff in the number of gNB (BS) antennas and BER is rewarded with the reduced complexity of the proposed WTS algorithm.

VI. CONCLUSIONS AND FUTURE WORK

In this article, a low-complexity MWTS detection scheme is proposed for the M-MIMO system by modifying the WTS iteration and initial solution. In addition to that, a low complexity soft decision Viterbi channel decoding is also introduced at gNB for giving better BER performance. Numerical studies confirm that the proposed MWTS algorithm and the soft decision decoding provide a reduction in computational complexity. The BER performance analysis shows that the proposed algorithms perform better than various low-complexity algorithms such as NS, GS, and SSOR &WTS and are also close optimal to the classical LMMSE detector with reduced computational complexity. The BER performance investigation was also carried out by increasing the user equipment and gNB antennas. Investigation results concluded that the proposed algorithm performs better in all scenarios than the existing algorithms. Though MWTS detection performance is good, to achieve outstanding results MWTS requires a favorable initial solution. In this article, the effectiveness of the proposed work was investigated merely on a simulation basis. The future work of this article is the implementation of the proposed detector on a Universal Software Radio Peripheral (USRP) and exploring its practical performance Further this method can also be extended for mmWave massive MIMO uplink scenarios in B5G wireless networks

REFERENCES

[1] X. Liu, Z. Zhang, X. Wang, J. Lian, and X. Dai, "A low complexity high performance weighted Neumann series-based massive MIMO detection," in *Proc. 28th Wireless Opt. Commun. Conf. (WOCC)*, May 2019, pp. 1–5.

[2] A.-A. Lu, X. Gao, Y. R. Zheng, and C. Xiao, "Low complexity polynomial expansion detector with deterministic equivalents of the moments of channel Gram matrix for massive MIMO uplink," *IEEE Trans. Commun.*, vol. 64, no. 2, pp. 586–600, Feb. 2016.

[3] L. Fang, L. Xu, and D. D. Huang, "Low complexity iterative MMSE-PIC detection for medium-size massive MIMO," *IEEE Wireless Commun. Lett.*, vol. 5, no. 1, pp. 108–111, Feb. 2016.

[4] X. Gao, L. Dai, Y. Hu, Z. Wang, and Z. Wang, "Matrix inversion-less signal detection using SOR method for uplink large-scale MIMO systems," in *Proc. IEEE Global Commun. Conf.*, Dec. 2014, pp. 3291–3295.

[5] L. Dai, X. Gao, X. Su, S. Han, C.-L. I, and Z. Wang, "Low-complexity soft-output signal detection based on Gauss–Seidel method for uplink multiuser large-scale MIMO systems," *IEEE Trans. Veh. Technol.*, vol. 64, no. 10, pp. 4839–4845, Oct. 2015.

[6] C. Tang, C. Liu, L. Yuan, and Z. Xing, "High precision low complexity matrix inversion based on Newton iteration for data detection in the massive MIMO," *IEEE Commun. Lett.*, vol. 20, no. 3, pp. 490–493, Mar. 2016.

[7] B. Y. Kong and I.-C. Park, "Low-complexity symbol detection for massive MIMO uplink based on Jacobi method," in *Proc. IEEE 27th Annu. Int. Symp. Pers., Indoor, Mobile Radio Commun. (PIMRC)*, Sep. 2016, pp. 1–5.

[8] F. Jiang, C. Li, and Z. Gong, "A low complexity soft-output data detection scheme based on Jacobi method for massive MIMO uplink transmission," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2017, pp. 1–5.

[9] M. Mandloi and V. Bhatia, "Low-complexity near-optimal iterative sequential detection for uplink massive MIMO systems," *IEEE Commun. Lett.*, vol. 21, no. 3, pp. 568–571, Mar. 2017.

[10] Y. Xue, C. Zhang, S. Zhang, Z. Wu, and X. You, "Steepest descent method based soft-output detection for massive MIMO uplink," in *Proc. IEEE Int. Workshop Signal Process. Syst. (SiPS)*, Oct. 2016, pp. 273–278.

[11] X. Qin, Z. Yan, and G. He, "A near-optimal detection scheme based on joint steepest descent and Jacobi method for uplink massive MIMO systems," *IEEE Commun. Lett.*, vol. 20, no. 2, pp. 276–279, Feb. 2016.

[12] B. Ren, Y. Wang, S. Sun, Y. Zhang, X. Dai, and K. Niu, "Low-complexity MMSE-IRC algorithm for uplink massive MIMO systems," *Electron. Lett.*, vol. 53, no. 14, pp. 972–974, Jul. 2017.

[13] J.-C. Chen, "A low complexity data detection algorithm for uplink multiuser massive MIMO systems," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 8, pp. 1701–1714, Aug. 2017.

[14] H. J. Costa and V. O. Roda, "A scalable soft Richardson method for detection in a massive MIMO system," *Networks*, vol. 2, p. 3, Aug. 2016.

[15] X. Liu, Z. Zhang, X. Wang, J. Lian, and X. Dai, "A low complexity high performance weighted Neumann series-based massive MIMO detection," in *Proc. 28th Wireless Opt. Commun. Conf. (WOCC)*, May 2019, pp. 1–5.

[16] S. Ghacham, M. Benjillali, and Z. Guennoun, "Low-complexity detection for massive MIMO systems over correlated Rician fading," in *Proc. 13th Int. Wireless Commun. Mobile Comput. Conf. (IWCMC)*, Jun. 2017, pp. 1677–1682.

[17] A. Boukharouba, M. Dehemchi, and A. Bouhafer, "Low-complexity signal detection and precoding algorithms for multiuser massive MIMO systems," *Social Netw. Appl. Sci.*, vol. 3, no. 2, pp. 1–7, Feb. 2021.

[18] T. Xie, L. Dai, X. Gao, X. Dai, and Y. Zhao, "Low-complexity SSOR-based precoding for massive MIMO systems," *IEEE Commun. Lett.*, vol. 20, no. 4, pp. 744–747, Apr. 2016.

[19] Y. Liu, J. Liu, Q. Wu, Y. Zhang, and M. Jin, "A near-optimal iterative linear precoding with low complexity for massive MIMO systems," *IEEE Commun. Lett.*, vol. 23, no. 6, pp. 1105–1108, Jun. 2019.

[20] K. He, Z. Wang, D. Li, F. Zhu, and L. Fan, "Ultra-reliable MU-MIMO detector based on deep learning for 5G/B5G-enabled IoT," *Phys. Commun.*, vol. 43, Dec. 2020, Art. no. 101181.

[21] C. Yan, W. Liu, and H. Yuan, "Numerous factors affecting performance of NOMA for massive machine type communications in B5G systems," *Frontiers Commun. Netw.*, vol. 2, Aug. 2021, Art. no. 689530.

[22] Q. Yang, J. Yan, X. Zhang, and H. Zhang, "Decentralized detection for B5G massive MIMO: When local computation meets iterative algorithm," *Phys. Commun.*, vol. 51, Apr. 2022, Art. no. 101554.

[23] W. Khalid, H. Yu, R. Ali, and R. Ullah, "Advanced physical-layer technologies for beyond 5G wireless communication networks," *Sensors*, vol. 21, no. 9, p. 3197, May 2021.

[24] E. C. V. Boas, J. D. S. e Silva, F. A. P. de Figueiredo, L. L. Mendes, and R. A. A. de Souza, "Artificial intelligence for channel estimation in multicarrier systems for B5G/6G communications: A survey," *EURASIP J. Wireless Commun. Netw.*, vol. 2022, no. 1, pp. 1–63, Dec. 2022.

[25] I. Khan, M. Zafar, M. Jan, J. Lloret, M. Basheri, and D. Singh, "Spectral and energy efficient low-overhead uplink and downlink channel estimation for 5G massive MIMO systems," *Entropy*, vol. 20, no. 2, p. 92, Jan. 2018.

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Open Access funding provided by 'Università degli Studi di Enna ''KORE''' within the CRUI CARE Agreement