Complexity Reduction in Massive-MIMO-NOMA SIC Receiver in Presence of Imperfect CSI

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Received: 28/Aug/2019 Revised: 01/Mar/2020 Accepted: 08/Apr/2020

Abstract

One of the main reasons for switching to the next generation of communication systems is the demand of increasing capacity and network connections. This goal can be achieved using massive multiple input - multiple output (massive-MIMO) systems in combination with Non-orthogonal multiple access (NOMA) technique. NOMA technology uses the successive interference cancellation (SIC) receiver to detect user's signals which imposes an additional complexity on the system. In this paper, we proposed two methods to reduce the system complexity. The proposed method despite imperfect channel state information (CSI) in the receiver, there is not significantly reduction in the system performance. Since the computation of matrices inverse has a high computational complexity, we used the Neumann series approximation method and the Gauss-Seidel decomposition method to compute matrices inverse in the SIC receiver. Simulation results are provided at the end of the paper in terms of bit error rate (BER) at the receiver which show, these methods have lower computational complexity in comparison with the traditional methods while they cause a slight performance reduction in the SIC receiver. Also, we examined the increasing and decreasing value of imperfect channel state information in the system performance which shows the increasing value of imperfect channel state information, cause a slight performance reduction in SIC receiver.

Keywords: Massive MIMO; NOMA; Complexity; SIC; Neumann; Gauss - Seidel.

1- Introduction

Reviewing and estimating the wireless networks traffic shows an increase in the networks traffic. Researchers are providing an overview for 5G systems that can increase the capacity of telecommunication cells, spectral efficiency and performance efficiency as well as decrease PAPR [1]. Multiple access techniques use the orthogonality principle in order to reduce the inter channel interference. A new non- orthogonal multiple access method has been introduced that in this method, with accepting a certain level of interference, we can remove the orthogonal principle and increase the number of sub-channels.

NOMA is one of the key techniques of multiple access methods, which is very promising for increasing the performance of the fifth generation, and in comparison, with FDMA, offer more favorable advantages that can be used to increase the spectral efficiency. This method uses a new field of work that called 'power'. For a certain level of interference to be accepted, all users should have a power limit. So, the main point in this method is the use of signals that have a different power level.

NOMA can support more connections than other multiple access techniques, which is important in the 5G systems. On the other hand, the use of NOMA enables users to access all available sub-carriers. Therefore, it can be said that NOMA can allocate channel capacity and bandwidth equally to all users. The combination of NOMA with other existing technologies, such as MIMO, effectively increases network bandwidth. So, more users can be used in the communications system. Reducing complexity in these systems is also an important point especially in downlink. Since the SIC receiver in the NOMA method imposes additional complexity on the system, solving this problem is particularly useful to reduce user equipment complexity. In this paper, we examine the massive MIMO transmission system combined with NOMA technique and use algebraic methods in the SIC receiver to reduce the receiver complexity. We have examined the performance of system

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with these methods and compared the results with the exact SIC receiver.

Many studies on NOMA technique and its combination with MIMO systems have been presented. An article[2] explains the challenges, theories and research that have been done for NOMA technique. In [3], by assuming that users are randomly deployed in a cell, the effect of path loss on the performance of NOMA in 5G systems has been characterized. Simulation results shows that NOMA achieves higher rates and better performance than the OMA technique. In [4] an optimal method for allocating power and maximizing ergodic capacity with low complexity has been proposed. Then a simulation has been carried out to examine the proposed method performance. By analyzing the numerical results, we can see significant increase in the interest of the NOMA technique in comparison with the OMA technique. Also, an article [5] is devoted to a new design of the detection matrix for MIMO-NOMA and its performance. In [6], the NOMA system was initially introduced, both of uplink and downlink. Simulations have also been performed to evaluate the rate of NOMA and OMA cells, which show that increasing the number of users, will increase the NOMA rate, but the OMA rate will go to saturation. In [7] a design for massive MIMO systems combined with NOMA has been developed that makes designing easier. To increase the efficiency of NOMA, the effect of the SIC receiver in ferroelectric mode is investigated in system [8]. In article[9] the user clustering scheme and optimization of precoding matrix for a NOMA system are investigated. The user selection plan and power plan for the NOMA system are based on ZF radiation to improve the capacity of the NOMA system in [10]. In [11], researchers have proposed a low complexity sub-optimal user-clustering method for Rayleigh fading channels by considering the effects of intra-cluster pilot contamination, inter-cluster interference, imperfect successive interference cancellation (SIC) and statistical downlink channel state information (CSI) at secondary users.

In this paper, we focus on the complexity reduction in massive-MIMO-NOMA SIC receiver in presence of imperfect channel state information. The concept of massive-MIMO-NOMA has been validated by using systematic implementation in [7]. Compared to these existing works, the contributions of this paper are as follows: we consider a general Massive-MIMO-NOMA system in which all users have a fixed set of power allocation coefficients. The interference between clusters has been removed by a precoder and the interference between the users in a cluster has been removed by the SIC receiver. We have used the Neumann series approximation method and the Gauss-Seidel decomposition method to compute matrices inverse in SIC receiver and a comparison between traditional LU decomposition method and Neumann series approximation and Gauss-Seidel decomposition methods have been investigated.

The rest of this paper is organized as follows: In Section.2, we present the system model of massive MIMO-NOMA. Section.3 examine complexity and discusses on algebraic methods to reduce computational complexity. Section.4 discuses on simulation results. Finally, Section.5 concludes the paper and offers suggestions to further works.

2- System Model

Consider a cellular downlink transmission scenario, in which the base station and receiver is equipped with M and N antennas, respectively. Channel between each transmit and receive antenna is flat fading with Rayleigh distribution. The modulation scheme is BPSK. In this system, user clustering is used, so that users' channels in a cluster have the same correlation matrix, and the channel matrix of the users in the different clusters is almost orthogonal. We divide the users into K clusters and each cluster has L user. The channel state information is imperfect in the receiver and the channel coefficients are summed with a random Gaussian variable Δ with the variance $\delta^2 = 10^{-4}$. The scheme used in this simulation is using a precoder at the BS and the SIC receiver at the user side.

Transmitted signal from the BS for k'th cluster is as follows

$$\mathbf{t_k} = \mathbf{w}_k \sum_{l=1}^{L} \sqrt{\alpha_{k.l}} \mathbf{S}_{k.l} \tag{1}$$

$\mathbf{S}_{k.l}$ is a signal that contains information of the l-th user in the k-th cluster. $\alpha_{k.l}$ is the power allocation coefficients for the l-th user in the k-th cluster. $\mathbf{w_k}$ is $k \times 1$ precoder vector. The received signal is as follows

$$\mathbf{Y}_{kl} = \mathbf{h}_{kl}\mathbf{t}_k + \mathbf{h}_{kl} \sum_{i=1; i\neq k}^{K} \mathbf{t}_i + \mathbf{N}_{kl} \tag{2}$$

for l=1, 2…, L.

$\mathbf{N}_{kl}$ is the receiver noise which is complex Gaussian random variable with zero mean and variance N_0.

As seen in Eq. (2), the first term of the equation is the useful signal for the l-th user in the k-th cluster. The second term shows the interference of the other clusters. In addition to the interference between the clusters in Eq. (2), in a cluster, each user interferes with other users, which is received by the SIC receiver. In this paper we have considered the SIC receiver with the use of the MMSE detector.

2-1- The Process of Removing Interference between Users with the SIC receiver

For eliminating interference between users with the nonlinear SIC receiver and the MMSE detector**,** we consider the allocation of power to users based on the SINR received by the users as follows

$$|\mathbf{h}_{11}|^2/_{N_{01}} < |\mathbf{h}_{12}|^2/_{N_{02}} < \cdots < |\mathbf{h}_{1L}|^2/_{N_{0L}} \qquad (3)$$

$$\alpha_{11} > \alpha_{12} > \cdots > \alpha_{1L}\,; \quad \sum_{l=1}^{L} \alpha_{1l}^2 = 1\ . \qquad (4)$$

According to the NOMA principles [6], the first user that has the best channel condition detects the signal of the other users with more allocated power and then removes their effects from the received signal. Then the first user can detect its corresponding signal with a slight amount of interference from the other users. Similarly, this process is will be done for other users to eliminate the interference between all users. Now we have to eliminate the inter clusters interference. We will do this with the use of precoder at BS.

In the case of using a precoder at the BS, it is necessary for the channel matrix to be perfect at the BS. We have also assumed that the channel matrix **H** is perfect at BS, and it is used to construct the MMSE precoder vector, **w**, to eliminate the inter clusters interference. The vector **w** is constructed based on the stronger user-channel vector that eliminates inter clusters interference. To remove the inter clusters interference, the following condition should be met

$$\mathbf{H}^{\mathrm{H}}\mathbf{P} = 0 \qquad (5)$$

$$\mathbf{h}_{il}\mathbf{w}_k = \begin{cases} 0 & i \neq k \\ 1 & i = k \end{cases} \ . \qquad (6)$$

As seen in Eq. (6), the inter clusters interference can be removed.

3- Computational Complexity

Computational complexity is one of the important criteria for implementing communications system. This important criterion examines the amount of resources needed to implement the algorithms. The most commonly used resources are the calculation time and computational complexity. In this section, the computational complexity of the system is examined. Since the purpose of this paper is to reduce the computational complexity, two methods used to reduce matrix inverse calculations will be introduced.

One of the algebraic methods to calculate the matrix inverse is the Neumann series approximation method. In this method, with the order of n, the matrix inverse is calculated in the following order[12]

$$\mathbf{X^{-1}}_L = \left(\sum_{n=1}^{L} (\mathbf{I} - \mathbf{AX})^{n-1}\right)\mathbf{A} \quad , (\mathbf{A}=\mathbf{X}^{-1})\ . \qquad (7)$$

For this approximation method, the complexity is as follows

If **A** is a matrix with dimensions $N \times N$, then the complexity of calculation the matrix $\mathbf{A^{-1}}$ is as shown in Table 1[13].

Table 1: Complexity of Neumann method with different orders for calculating the inverse of matrix $\mathbf{A}_{N\times N}$ [13]

Neumann-Series Method	***Complexity***
Order of one	N
Order of two	$3N^2$-$2N$
Order of three	$16N^3$+$3N^2$-$4N$

It is noteworthy that we use 'order of two' for the above approximation method, because the first order with the lowest complexity does not provide a good performance for the system. Also, the third order with best performance, provide higher complexity, so we use the second order to ensure that, along with an appropriate complexity, the system performance dose not reduce significantly.

Another method to iteratively compute matrix inverse is 'gauss-seidel' decomposition method. In this method. we decompose matrix **A** as follows

$$\mathbf{A} = \mathbf{L}_* + \mathbf{U} \qquad (8)$$

where $\mathbf{L}_*$ is lower triangular component and **U** is strictly upper triangular component given by[14];

$$\mathbf{L}_* = \begin{bmatrix} a_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ \mathrm{a}_{\mathrm{n}1} & \cdots & \mathrm{a}_{\mathrm{nn}} \end{bmatrix} \qquad \mathbf{U} = \begin{bmatrix} 0 & a_{12} \cdots & \cdots a_{1n} \\ \vdots & \ddots & \vdots \\ 0 & \ldots & 0 \end{bmatrix} \qquad (9)$$

If $\mathbf{A}^{-1}$= **X**, and

$$\mathbf{AX} = \mathbf{I} \qquad (10)$$

According to the multiplication properties of matrices, we know

$$\mathbf{A}x_i = e_i \quad ; i = 1.2. \ldots . n\ . \qquad (11)$$

In the above relation x_i is the *i* th column of matrix **X** and e_i is *i* th column of matrix **I**.

So according to Eq. (8) and (10), and with *m* iterations, we have.

$$(\mathbf{L}_* + \mathbf{U})\mathbf{X} = \mathbf{I} \quad (12)$$

$$\mathbf{L}_*\mathbf{X} = \mathbf{I} - \mathbf{UX} \quad (13)$$

$$\mathbf{X}^{(k+1)} = \mathbf{L}_*^{-1}\left(\mathbf{I} - \mathbf{UX}^{(k)}\right) \quad (14)$$

$$x_i^{(k+1)} = \frac{1}{a_{ii}}\left(e_i - \sum_{j>i} a_{ij}\, x_j^{(k)} - \sum_{j<i} a_{ij}\, x_j^{(k+1)}\right)$$

$$i = 1,2,3,\dots,n \ \ and \ \ k = 1,2,\dots,m \quad (15)$$

Table 2: Complexity of Gauss-Seidel decomposition method with *m* iterations for calculating of matrix inverse $\mathbf{A}_{N\times N}$ [14]

Method	***Complexity***
Gauss-Seidel	$m\times O(N^2)$

In Table 3 we compare the complexity of SIC receiver using three methods of matrix inverse calculation.

Table 3: Comparison complexity of three methods of inverse matrix $\mathbf{A}_{N\times N}$ for entire system with *L* users

Methods	***Complexity***
LU	$\frac{L(L+1)}{2}O(N^3)$
Neumann	$\frac{L(L+1)}{2}O(N^2)$
Gauss-Seidel	$\frac{L(L+1)}{2}mO(N^2)$

4- Simulation Results and Discussions

In this section, computer simulations are used to study the performance of the proposed Massive-MIMO-NOMA scheme. The BS is equipped with M = 50 antennas and the receiver is equipped with one antenna. In Fig. 1 the BER performance of the Massive-MIMO-NOMA scheme, in the case of traditional LU decomposition method for calculating the matrices inverse is studied. In Fig. 2 and Fig. 3 the impact of using of Neumann series method and gauss-seidel decomposition method for calculating the matrices inverse are illustrated, respectively. Fig. 4 shows a comparison between three methods. As can be seen from these figures, the use of the Neumann series method and gauss-seidel decomposition method for calculating matrices inverse in Massive-MIMO-NOMA scheme, reduce the system performance slightly.

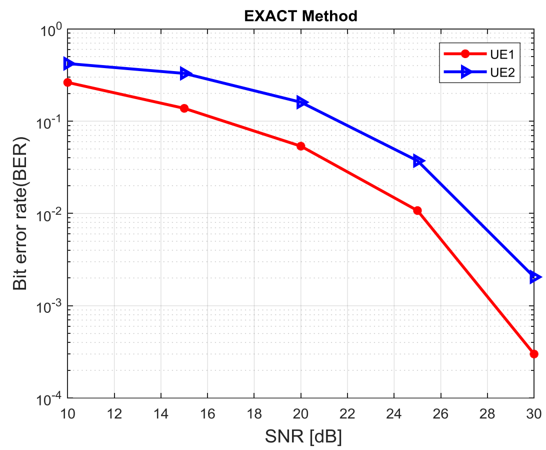

Fig. 1 The BER curve of the scheme in the matrix inverse calculation for 2 users and 2 clusters ($a_1{}^2$ =6/7, $a_2{}^2$ =1/7) for exact method.

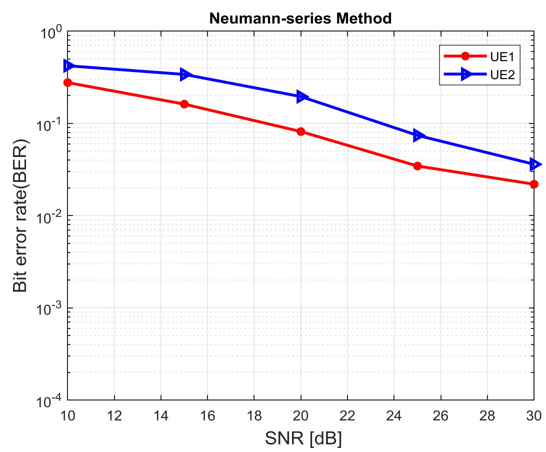

Fig. 2 The BER curve of the scheme in the matrix inverse calculation for 2 users and 2 clusters ($a_1{}^2$ =6/7, $a_2{}^2$ =1/7) for Neumann series method.

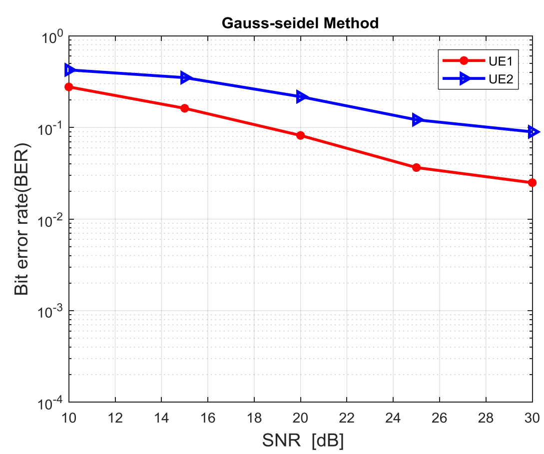

Fig.3 The BER curve of the scheme in the matrix inverse calculation for 2 users and 2 clusters ($a_1{}^2$ =6/7, $a_2{}^2$ =1/7) for Gauss-Seidel decomposition method.

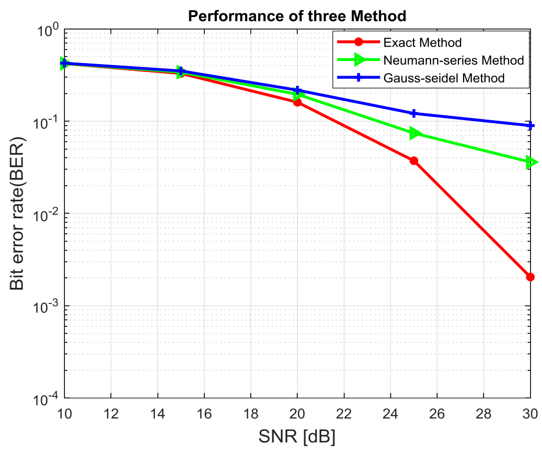

Fig. 4 Comparison the BER curve of the scheme in the matrix inverse calculation between three methods for 2 users and 2 clusters ($a_1{}^2$ =6/7, $a_2{}^2$ =1/7)

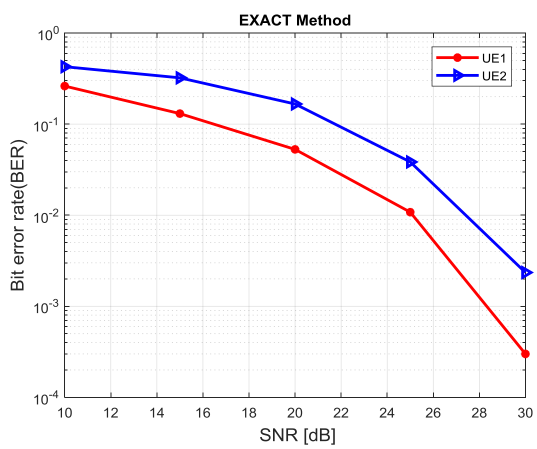

Fig. 5 The BER curve of the scheme in the matrix inverse calculation for 2 users and 2 clusters ($a_1{}^2$ =4/5, $a_2{}^2$ =1/5) exact method

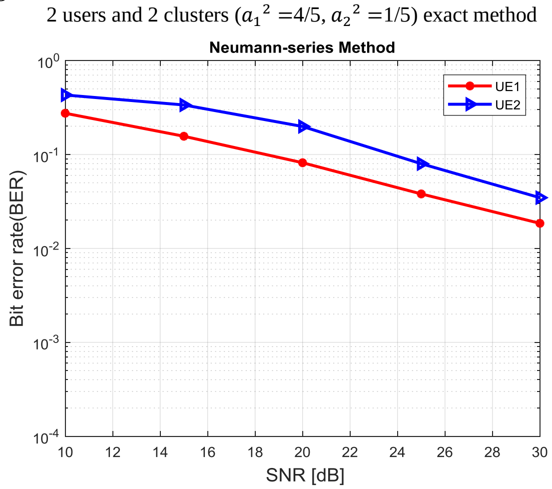

Fig. 6 The BER curve of the scheme in the matrix inverse calculation for 2 users and 2 clusters ($a_1{}^2$ =4/5, $a_2{}^2$ =1/5) for Neumann series.

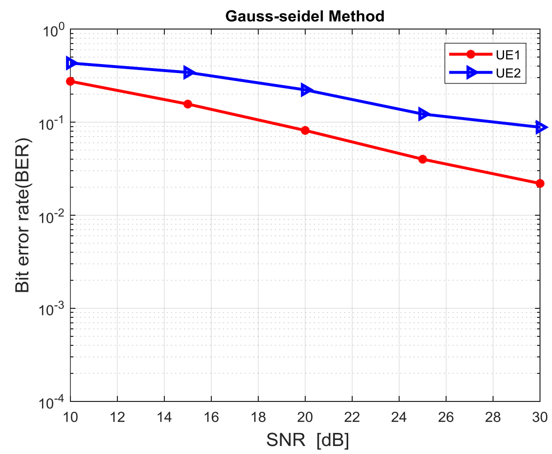

Fig. 7 The BER curve of the scheme in the matrix inverse calculation for 2 users and 2 clusters ($a_1{}^2$ =4/5, $a_2{}^2$ =1/5) for Gauss-Seidel decomposition method

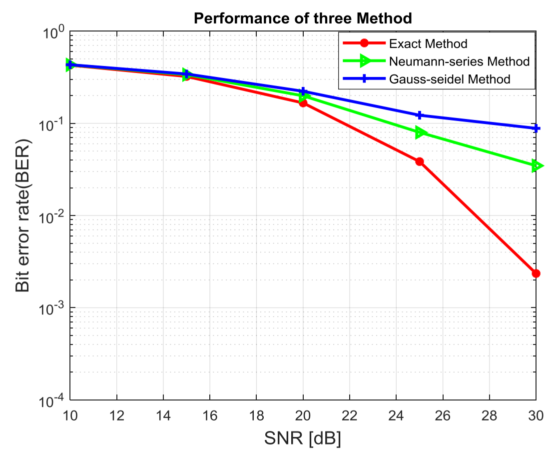

Fig. 8 Comparison the BER curve of the scheme in the matrix inverse calculation between three methods for 2 users and 2 clusters($a_1{}^2$ =4/5, $a_2{}^2$ =1/5)

Now we change the power allocation coefficients and repeat the simulation with $a_1{}^2$ =4/5, $a_2{}^2$ =1/5 values. The effect of increasing power allocation coefficients can be seen in the Fig. 5 to Fig. 8.

Then we increase the amount of variable power that indicates imperfect channel state information in the receiver and set it to $\delta^2=10^{-3}$ and observe its effect on system performance.

As it can be seen in Fig. 9 to 12, increasing the amount of δ^2 for channel state information in the receiver, reduce the system performance slightly. So, we can conclude that these methods are not so sensible to imperfect channel state information.

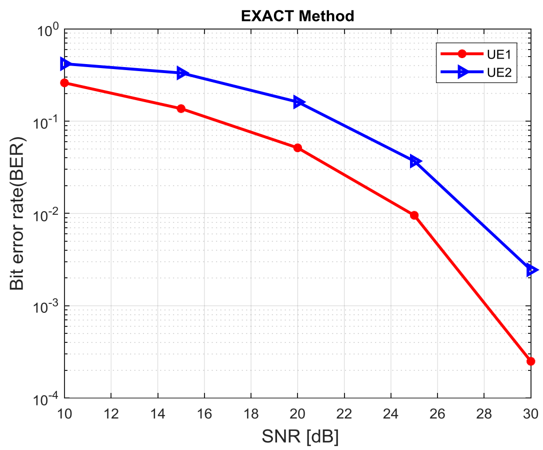

Fig. 9 The BER curve of the scheme in the matrix inverse calculation for 2 users and 2 clusters ($a_1{}^2$ =6/7, $a_2{}^2$ =1/7) for exact method

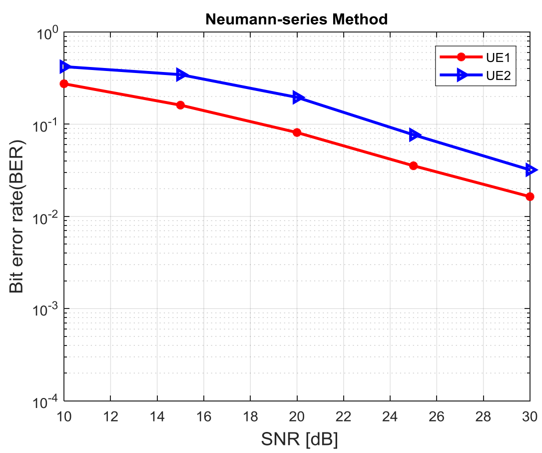

Fig. 10 The BER curve of the scheme in the matrix inverse calculation for 2 users and 2 clusters($a_1{}^2$ =6/7, $a_2{}^2$ =1/7) for Neumann series method

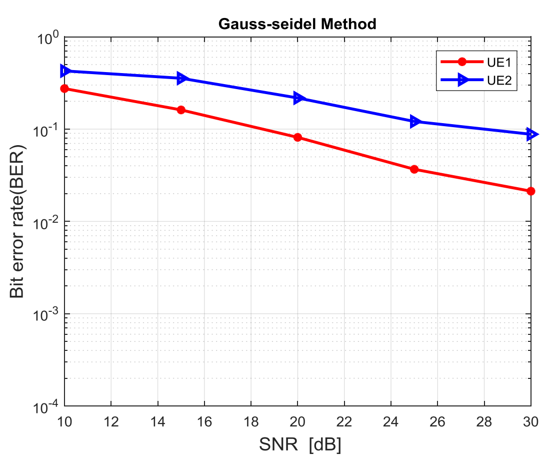

Fig. 11 The BER curve of the scheme in the matrix inverse calculation for 2 users and 2 clusters($a_1{}^2$ =6/7, $a_2{}^2$ =1/7) for gauss-Seidel decomposition method

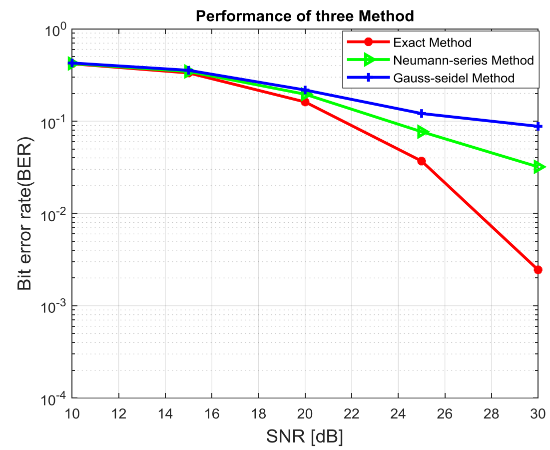

Fig. 12 Comparison the BER curve of the scheme in the matrix inverse calculation between three methods for 2 users and 2 clusters($a_1{}^2$ =6/7, $a_2{}^2$ =1/7)

As we know, performance of the SIC receiver is dependent on the matrix inverse accuracy. Better accuracy of matrix inverse results better performance of SIC receiver. In the Gauss-seidel method, there is a factor *m* that indicates the number of iterations in the algorithm and affects the accuracy of matrix inverse. The larger the factor *m*, the better approximation of matrix inverse be. In this work we have chosen *m*=10 to have the complexity order of Gauss-Seidel method not so larger than that of Neumann series method. So, on the other hand we have a lower accuracy of matrix inverse than that of Neumann series method because of low convergence rate of Gauss-Seidel method [14]. So, using Gauss-Seidel method to approximate matrix inverse, causes a lower performance of SIC receiver in comparison to that of using Neumann series method. The LU decomposition method performs better than two other methods in SIC receiver, because it exactly calculates the matrix inverse. To better illustration of the results comparisons, in Table 4, we have examined the three methods mentioned in terms of complexity and performance.

Table 4: A numerical example for comparison the complexity and performance of three methods of inverse matrix $\mathbf{A}_{N\times N}$ for entire system with *L* users in 25dB SNR

Methods	***Complexity***	***Approximate BER***
LU	$\frac{\boldsymbol{L(L+1)}}{\boldsymbol{2}}\boldsymbol{O}(\boldsymbol{N^3})$	4×10^{-2}
Neumann	$\frac{\boldsymbol{L(L+1)}}{\boldsymbol{2}}\boldsymbol{O}(\boldsymbol{N^2})$	7×10^{-2}
Gauss-Seidel	$\frac{\boldsymbol{L(L+1)}}{\boldsymbol{2}}\boldsymbol{mO}(\boldsymbol{N^2})$	12×10^{-2}

5- Conclusions

NOMA technology uses the SIC receiver to detect user's signals which imposes an additional complexity on the system. In this paper, we proposed two methods to reduce the system complexity. The goal was complexity reduction in massive-MIMO-NOMA SIC receiver in presence of imperfect channel state information. we considered a general Massive-MIMO-NOMA system. The interference between clusters removed by a precoder and the interference between the users in a cluster removed by the SIC receiver. we used the Neumann series approximation method and the Gauss-Seidel decomposition method to compute matrices inverse in SIC receiver and a comparison between traditional LU decomposition method and Neumann series approximation and Gauss-Seidel decomposition methods investigated. Due to the SIC receiver method where users with the worth channel only detect their signal and users with the best channel, first have to detect the signal with more allocated power and then detect their signal, the BER for the user with more power is better than the user with less power. Also, with using matrix inverse calculation methods to reduce system complexity, there is a slight reduction in system performance. So, we can say that the Neumann series method and the gauss-seidel decomposition method for calculating matrices inverse, are two methods that we can use them in communication systems with less complexity. Also, we examined the effect of increase the δ^2 for channel state information in the SIC receiver and it was observed that increasing the amount of δ^2 for channel state information in the receiver, reduce the system performance slightly.

In general, since the goal of the paper was to reduce the receiver complexity, this was achieved, but the following suggestions can be used to make a tradeoff between the complexity and the performance of the system and improve the performance of the system

- Designing an optimal algorithm for clustering users with the least interference.
- Design and optimization a precoder to eliminate interference between clusters in order to provide the best performance for the system.
- Optimization of power allocation coefficients to reduce error probability.

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