The Perfect Match: RIS-enabled MIMO Channel Estimation Using Tensor Decomposition

Bilal Ahmad, Kevin Weinberger, Aydin Sezgin, Bilal Zafar, and Martin Haardt

Email: {bilal.ahmad, kevin.weinberger, aydin.sezgin}@rub.de, {bilal.zafar, martin.haardt}@tu-ilmenau.de

Abstract — The deployment of reconfigurable intelligent surfaces (RISs) in a communication system provides control over the propagation environment, which facilitates the augmentation of a multitude of communication objectives. As these performance gains are highly dependent on the applied phase shifts at the RIS, accurate channel state information at the transceivers is imperative. However, not only do RISs traditionally lack signal processing capabilities, but their end-to-end channels also consist of multiple components. Hence, conventional channel estimation (CE) algorithms become incompatible with RIS-aided communication systems as they fail to provide the necessary information about the channel components, which are essential for a beneficial RIS configuration. To enable the full potential of RISs, we propose to use tensor-decomposition-based CE, which facilitates smart configuration of the RIS by providing the required channel components. We use canonical polyadic (CP) decomposition, that exploits a structured time domain pilot sequence. Compared to other state-of-the-art decomposition methods, the proposed Semi-Algebraic CP decomposition via Simultaneous Matrix Diagonalization (SECSI) algorithm is more time efficient as it does not require an iterative process. The benefits of SECSI for RIS-aided networks are validated with numerical results, which show the improved individual and end-to-end CE accuracy of SECSI.

I. INTRODUCTION

A reconfigurable intelligent surface (RIS) consists of 2D arrays of low-cost metamaterials that can change their reflection pattern over time. Different elements can be configured independently and affect the wireless environment by reflecting the incoming electromagnetic waves in the desired direction. In this way, a distant receiver can be served by a base station (BS) that was out of reach before, either because of the absence of the line-of-sight path or because the typical multipaths were not strong enough. At the same time, the RIS can reduce the signal strength towards an undesired user by adding the reflected electromagnetic waves destructively at the user equipment (UE) [1]. All the array elements are configured by an external controller, whose purpose is to configure the elements’ reflecting behavior in an adaptive manner without the requirement of new radio-frequency chains [2]. Thus, the RIS does not generate new interference, which allows it to not only support the network in a variety of ways [3], [4] but also to enable new applications that were not possible before [5]. However, all of these benefits are only achieved if the channel state information (CSI) at the transceivers can be obtained, such that the RIS can be configured accordingly. Due to the RIS’s passive nature, obtaining the channel estimates becomes a challenging task as conventional channel estimation (CE) techniques cannot be applied directly. This is because the estimated BS-RIS-UE channel of these approaches is the sum of all individual reflected channel paths, each of which are a combination of the BS-RIS and RIS-UE channels [2]. However, to configure the RIS beneficially, the channel’s components, i.e., each individual BS-RIS and RIS-UE channel, are required.

To this end, the development of new CE methods becomes imperative in order to tackle these new challenges efficiently and obtain the necessary information. In [6], the authors propose an RIS-assisted MISO (multiple-input and single-output) CE technique, using a minimum variance unbiased estimator. This CE technique is adapted to a communication scenario in [7] and combined with an opportunistic transmission scheme to reduce the estimation time as it became a limiting factor. To counteract the estimation time when large surfaces are deployed, a two-stage algorithm has been introduced [8] where a sparse matrix factorization step is followed by a matrix completion stage. In [9], the relationship among Terahertz multiple-input and multiple-output (MIMO) communication, RIS CE, and beam training was established. Recently, tensor-based CE techniques have received increased attention where the received pilot data follows a specific structure, e.g., PARAFAC [10], [11], PARATUCK [12], and Tucker2 [13]. In [10], tensor-based bilinear alternating least squares (BALS) and a least squares Khatri-Rao factorization (LSKRF) have been introduced where knowledge of the RIS phase shifters during the training phase is assumed at the receiver. The same method was extended to incorporate long-term and short-term electronic impairments in [11], where a four dimensional tensor is decomposed through trilinear alternating least squares (TALS) and higher order singular value decomposition (HOSVD). The work in [12] assumes the...
a pilotless transmission and a semi-blind receiver capable of joint channel and symbol estimation.

In this paper, we propose to employ tensor decomposition for RIS-aided MIMO CE with the Semi-Algebraic canonical polyadic decomposition via Simultaneous Matrix Diagonalizations (SECSI) algorithm [14]. The proposed algorithm has been applied previously for canonical polyadic (CP) decomposition of biomedical data in [15] and [16], where its lower memory requirements and smaller computation time over ALS has been demonstrated. To our knowledge, this is the first work that is using SECSI for the RIS-aided wireless MIMO CE problem. Moreover, the SECSI algorithm can be used for the uplink and the downlink MIMO as well as for the multiuser MISO uplink CE. The SECSI algorithm is not only non-iterative in nature but also outperforms ALS when the factor matrices have a high correlation among their columns. This aspect of high correlation can be observed in the BS-RIS and RIS-UE channels as well as in the low-rank nature of mm-Wave MIMO channels [13]. The improved performance of SECSI over ALS and LSKRF in terms of separate (BS-RIS, RIS-UE) and cascaded (BS-RIS-UE) CE under the assumption of highly correlated channels, makes it a perfect match for performing CE in RIS-assisted MIMO.

II. NOTATIONS

In this paper, scalars are represented as \((a, b, c)\), vectors as \((\mathbf{a}, \mathbf{b}, \mathbf{c})\), and matrices as \((\mathbf{A}, \mathbf{B}, \mathbf{C})\). We use \(\mathbf{A}^T\) for the transpose of \(\mathbf{A}\), \(\mathbf{A}^H\) for the Hermitian transpose of \(\mathbf{A}\), \(\mathbf{A} \otimes \mathbf{B}\) for the product of \(\mathbf{A}\) and \(\mathbf{B}\), \(\odot\) and \(\otimes\) for the Khatri-Rao and Kronecker product of \(\mathbf{A}\) and \(\mathbf{B}\) respectively, and \(\mathbf{a} \circ \mathbf{b}\) for the outer product of \(\mathbf{a}\) and \(\mathbf{b}\). An \(N\)-way tensor with the size \(I_0\) along the mode \(n = 1, 2, ..., N\) is represented as \(\mathbf{A} \in \mathbb{C}^{I_1 \times I_2 \times \ldots \times I_N}\), and \(\|\mathbf{A}\|_2\) denotes the higher order norm of the tensor \(\mathbf{A}\). Moreover, an \(n\)-mode product between a tensor \(\mathbf{A} \in \mathbb{C}^{I_1 \times I_2 \times \ldots \times I_N}\) and a matrix \(\mathbf{B} \in \mathbb{C}^{J \times I_n}\) is defined as \(\mathbf{A} \times_n \mathbf{B}\), for \(n = 1, 2, ..., N\) [19]. The CP decomposition of the three-dimensional tensor \(\mathbf{X} \in \mathbb{C}^{I_1 \times I_2 \times I_3}\) with rank \(R\) is defined as \(\mathbf{X} = \sum_{r=1}^{R} \mathbf{X}_{r} \otimes \mathbf{B}_{r} \otimes \mathbf{C}_{r}\), where matrices \(\mathbf{A} \in \mathbb{C}^{I_1 \times R}, \mathbf{B} \in \mathbb{C}^{I_2 \times R}, \mathbf{C} \in \mathbb{C}^{I_3 \times R}\) are called factor matrices containing the vectors along the columns, whose outer product forms a rank-1 tensor.

III. SYSTEM MODEL

An RIS-assisted MIMO communication system is considered where a BS and a UE are both equipped with multiple antennas. The RIS has \(N_t\) passive elements while the BS and the UE have \(N_t\) and \(N_r\) antennas, respectively. We consider only the RIS-assisted, i.e., the BS-RIS and RIS-UE paths, while the direct line-of-sight path, i.e., BS-UE, is either blocked or too weak to be taken into consideration, as shown in Fig. 1. We can use the same CE method for the uplink channel by reversing the roles for the BS and UE. We assume that the channel remains the same during the channel coherence time and divide this time into \(b = 1, \ldots, B\) frames where each frame is further divided into \(t = 1, \ldots, T\) time slots. The downlink channel between the BS and the RIS is denoted as \(\mathbf{y} = [y_1^T, \ldots, y_N^T]^T \in \mathbb{C}^{N_r \times 1}\) and \(\mathbf{H} \in \mathbb{C}^{N_t \times N_r}\) while the RIS-UE channel is represented by \(\mathbf{G} \in \mathbb{C}^{N_r \times N_r}\).

The \(N\) RIS elements are capable of changing their phase shifts individually and their reflection pattern at time \(t\) is denoted by a vector \(s[t] = [s_1 e^{j\phi_1}, \ldots, s_N e^{j\phi_N}]\), where \(\phi_n \in (0, 2\pi)\) and \(s_n \in \{0, 1\}\) represent \(n\)-th element’s phase shift and activation (on/off) pattern, respectively. We assume that \(\mathbf{H}\) and \(\mathbf{G}\) are constant during \(B\) frames and the received signal is given as

\[
\mathbf{w}[t] = \mathbf{G} \cdot \text{diag}(s[t]) \cdot \mathbf{H} \cdot \mathbf{x}[t] + \mathbf{n}[t], \quad 1 \leq t \leq T,
\]

where \(\mathbf{x}[t] \in \mathbb{C}^{N_t \times 1}\) is the transmitted symbol vector during time slot \(t\) and \(\mathbf{n}[t] \in \mathbb{C}^{N_r \times 1}\) is an additive white Gaussian noise (AWGN) vector. We propose that the RIS phase shift vector \(s \in \mathbb{C}^{N_t \times 1}\) remains the same during \(T\) time slots and that the pilot signals \(\mathbf{x}[t]\) for \(1 \leq t \leq T\) are repeated over the \(B\) frames.

If we receive the pilot symbols during time slots in each \(b\)-th frame, then the received signal matrix \(\mathbf{W}[b] = [\mathbf{w}[b, 1], \ldots, \mathbf{w}[b, T]] \in \mathbb{C}^{N_r \times T}\) takes the form

\[
\mathbf{W}[b] = \mathbf{G} \cdot \text{diag}(s[b]) \cdot \mathbf{H} \cdot \mathbf{X}^T + \mathbf{N},
\]

where \(\mathbf{X} = [\mathbf{x}[1], \ldots, \mathbf{x}[T]^T \in \mathbb{C}^{T \times N_t}\) and \(\mathbf{N} = [\mathbf{n}[1], \ldots, \mathbf{n}[T]^T] \in \mathbb{C}^{N_t \times T}\).

A. Tensor structure of the received data

To simplify the signal model, we ignore the noise term in the following description but it will be considered while performing simulations. We define a phase shift matrix \(\mathbf{S} = [s[1], \ldots, s[B]]^T \in \mathbb{C}^{B \times N_t}\) while \(\text{diag}(s[b]) \in \mathbb{C}^{N_t \times N_t}\) represents a diagonal matrix that has the \(b\)-th row of the phase shift matrix \(\mathbf{S}\) on its main diagonal. We can rewrite the received signal part of (2) as

\[
\mathbf{W}[b] = \mathbf{G} \cdot \text{diag}(s[b]) \cdot \mathbf{H} \cdot \mathbf{X}^T,
\]

By multiplying with \(\mathbf{X}\) on both sides of (3) we get

\[
\mathbf{Y}[b] = \mathbf{G} \cdot \text{diag}(s[b]) \cdot \mathbf{H} \cdot \mathbf{X},
\]

where \(\mathbf{Y}[b] = \mathbf{W}[b] \cdot \mathbf{X}\). The matrix \(\mathbf{Y}[b]\) can be seen as the \(b\)-th frontal slice of a 3D tensor \(\mathbf{Y} \in \mathbb{C}^{N_t \times N_r \times B}\) as shown in Fig. 2. The matrices \(\mathbf{G}, \mathbf{H}\), and \(\mathbf{S}\) fulfill the requirement for a PARAFAC structure as they can be treated as factor matrices of

![Diagram](image310x685 to 548x788)
nels (BS-RIS, RIS-BS) are arranged as factor matrices of a factor matrix $G \in \mathbb{C}^{N \times N}$ and $H \in \mathbb{C}^{N \times N_1}$, remain unchanged during all the frames.

B. Tensor decomposition

The CP decomposition is named differently by different authors e.g., PARAFAC (PARAllel FACTor) analysis, CANDECOMP (CANonical DECOMPosition), or CAND (CANonical Decomposition) [20]. The CP decomposition of the 3D tensor $\mathbf{X} \in \mathbb{C}_I \times \mathbb{C}_J \times \mathbb{C}_K$ with rank $R$ is defined as

\[
\mathbf{X} = \sum_{r=1}^{R} f_1^{(r)} \circ f_2^{(r)} \circ f_3^{(r)} = \mathcal{I}_{3,R} \times 1 \mathbf{F}_1 \times 2 \mathbf{F}_2 \times 3 \mathbf{F}_3,
\]

where $\mathbf{F}_1 \in \mathbb{C}_I \times R$, $\mathbf{F}_2 \in \mathbb{C}_J \times R$, and $\mathbf{F}_3 \in \mathbb{C}_K \times R$ are called factor matrices containing the loading vectors $\mathbf{f}_r$ (in Fig. 2) along their columns, whose outer product forms a rank-1 tensor. The super-diagonal tensor $\mathcal{I}_{3,R} \times 1$ has 1’s on its super-diagonal and all the other elements are zero. The tensor rank $R$ is a number that corresponds to the minimum number of rank-1 tensors that add up to produce $\mathbf{X}$. Fig. 3 shows the representation of the CP decomposition in (5) of a 3D tensor $\mathbf{X}$ with rank $R = 3$.

IV. SEMI-ALGEBRAIC CP DECOMPOSITION VIA SIMULTANEOUS MATRIX DIAGONALIZATION (SECSI)

The original semi-algebraic algorithm for CP decomposition has been presented in [14] and we have modified the existing SECSI algorithm for our particular MIMO CE problem. Since we know one of the factor matrices, we can skip some intermediate steps. This not only reduces the computational time but also improves the accuracy of the rest of the factor matrices. The SECSI algorithm proves to be more accurate than ALS for CP decompositions when the columns of the factor matrices are highly correlated [14]. Since MIMO channels (BS-RIS, RIS-BS) are arranged as factor matrices of a tensor, the SECSI algorithm seems to be a more accurate option for CP decomposition. Furthermore, the SECSI (non-iterative) algorithm decomposes a tensor faster than the ALS (iterative) method, [14] which is helpful particularly when the CE has to be performed with a shorter channel coherence time.

The rest of this section derives the modified SECSI algorithm for CP decomposition of a 3D tensor $\mathbf{X}$. The relation between the CP decomposition and the HOSVD [19] is described as

\[
\mathbf{X} \equiv \mathcal{I}_{3,R} \times 1 \mathbf{F}_1 \times 2 \mathbf{F}_2 \times 3 \mathbf{F}_3 \equiv \mathbf{S} \times 1 \mathbf{U}_1 \times 2 \mathbf{U}_2 \times 3 \mathbf{U}_3,
\]

where $\mathbf{X} \in \mathbb{C}_{I_1} \times \mathbb{C}_{I_2} \times \mathbb{C}_{I_3}$, $\mathbf{S} \in \mathbb{C}_{I_1} \times \mathbb{C}_{I_2} \times \mathbb{C}_{I_3}$, $\mathbf{F}_1 \in \mathbb{C}_{I_1} \times R$, $\mathbf{F}_2 \in \mathbb{C}_{I_2} \times R$, $\mathbf{F}_3 \in \mathbb{C}_{I_3} \times R$ and $\mathbf{U}_1 \in \mathbb{C}_{I_1} \times R$, $\mathbf{U}_2 \in \mathbb{C}_{I_2} \times R$, $\mathbf{U}_3 \in \mathbb{C}_{I_3} \times R$.

The 1-mode unfolding of $\mathbf{X}$ is given by

\[
\mathbf{U}_1 \cdot ([\mathbf{S}]_{(1)} \cdot [\mathbf{U}_3 \odot \mathbf{U}_2]^T) = \mathbf{F}_1 \cdot ([\mathcal{I}_{3,R}]_{(1)} \cdot [\mathbf{F}_3 \odot \mathbf{F}_2]^T).
\]

The column space of $[\mathbf{X}]_{(1)}$ is spanned by $\mathbf{U}_1$ as well as by $\mathbf{F}_1$. Therefore, there exists an invertible transform matrix $\mathbf{T}_1 \in \mathbb{C}_{R \times R}$ such that $\mathbf{F}_1 = \mathbf{U}_1 \cdot \mathbf{T}_1$. Similarly for the second and third mode, we have $\mathbf{T}_2$ and $\mathbf{T}_3$ respectively. We can substitute these matrices in (6) such that,

\[
\mathcal{I}_{3,R} \times 1 \mathbf{U}_1 \cdot \mathbf{T}_1 \times 2 \mathbf{U}_2 \cdot \mathbf{T}_2 \times 3 \mathbf{U}_3 \cdot \mathbf{T}_3 = \mathbf{S} \times 1 \mathbf{U}_1 \times 2 \mathbf{U}_2 \times 3 \mathbf{U}_3.
\]

Eq. (8) shows the comparison between CPD and HOSVD and the core tensor $\mathbf{S}$ can be written as

\[
\mathbf{S} = \mathcal{I}_{3,R} \times 1 \mathbf{T}_1 \times 2 \mathbf{T}_2 \times 3 \mathbf{T}_3.
\]

We can also write it as

\[
\mathcal{I}_{3,R} = \mathbf{S} \times 1 \mathbf{T}_1^{-1} \times 2 \mathbf{T}_2^{-1} \times 3 \mathbf{T}_3^{-1}.
\]

The invertible matrices, $\mathbf{T}_1^{-1}$, $\mathbf{T}_2^{-1}$ and $\mathbf{T}_3^{-1}$ diagonalize the core tensor $\mathbf{S}$. After 3-mode multiplication of the core tensor by $\mathbf{U}_3$, i.e., $\mathbf{S}_3 = \mathbf{S} \times \mathbf{U}_3$, we get

\[
\mathbf{S}_3 \times 1 \mathbf{T}_1^{-1} \times 2 \mathbf{T}_2^{-1} = \mathcal{I}_{3,R} \times 3 \mathbf{U}_3 \cdot \mathbf{T}_3.
\]

The invertible matrices $\mathbf{T}_1$ and $\mathbf{T}_2$ diagonalize the matrices $\mathbf{S}_{3(m_3)} \forall m_3 \in \{1, \ldots, I_3\}$ i.e., the 3-mode slices of $\mathbf{S}_3$. By removing one of the transform matrices from the right hand side of (12), we have

\[
\mathbf{S}_{3(m_3)}^{\text{rhs}} = \mathbf{T}_1 \cdot \text{diag}(\mathbf{F}_{3(m_3)} \odot \mathbf{F}_{3(p_3)}) \cdot \mathbf{T}_1^{-1},
\]

and from the left hand side we get

\[
\mathbf{S}_{3(m_3)}^{\text{lhs}} = \mathbf{T}_2 \cdot \text{diag}(\mathbf{F}_{3(m_3)} \odot \mathbf{F}_{3(p_3)}) \cdot \mathbf{T}_2^{-1}.
\]

The symbol $\odot$ denotes the inverse Hadamard product (element wise division). The pivoting slice from (13) is selected such that its condition number is the minimum among all the 3-mode slices of $\mathbf{S}_3$. The diagonal elements that we get as a result of (13) are the scaled version of the $m$-th row of the factor matrix $\mathbf{F}_3$. Therefore, this multiplication of diagonal
elements with a scalar from $F_{3(\ldots)}$ is associated to the typical scaling ambiguity of the CP decomposition. We obtain the transform matrices $T_1$ and $T_2$ and two estimates of the matrix $F_3$ after the diagonalization of the tensors $S_{\text{rhs}}^3$ and $S_{\text{rhs}}^3$ along the 3-mode. The joint diagonalization of (13) and (14) can be calculated by the algorithm proposed in [22]. Therefore, from (5) and the relation $F_1 = U_1 \cdot T_1$, the transform matrix $T_1$ is obtained, and $F_3$ is obtained from the diagonal elements of the diagonalized tensor. The rest of the factor matrix is then calculated by the relation of the least square (LS) fit, i.e., $F_2 = [X^{(2)}] \cdot [F_3 \circ F_1]^{-T}$, where the superscript $(-)^T$ denotes the transposition and matrix inversion together. Similarly, we can find the link between the truncated HOSVD and the CP decomposition from the diagonalization of the tensor $S_{\text{rhs}}^3$, and we can calculate $F_2 = U_2 \cdot T_2$, $F_3$ can be calculated from the diagonal elements, and $F_1$ can be obtained via an LS fit. Finally, after diagonalization of all three modes, we obtain 6 estimates of each factor matrix and only those estimates are selected that result in the minimum reconstruction error between the estimated and the original tensor. In our modified version of SECSI, we already know one of the factor matrices in $n$-mode, i.e., $F_n$. Therefore we can find the transform matrix $T_n$ from the relation $F_n = U_n \cdot T_n$ by avoiding the diagonalization step. The matrix $F_n$ also improves the accuracy of other factor matrices with LS fit relation.

V. Numerical Results

In this section, we provide simulation results to evaluate the estimation accuracy of the SECSI algorithm and compare it with the BALS and the LSKRF [10] by varying multiple parameters like $N_1$, $N_2$, and $N$. MIMO channels have been generated with the open source SimRIS channel simulator [23] at 28 GHz frequency with (built-in) recommended Tx, Rx, and RIS coordinates of indoor and outdoor scenarios using a uniform linear array. In the simulations, we only consider the BS-RIS and RIS-UE channels and neglect the direct BS-UE channel and for the RIS phase shifters, a DFT matrix has been used. To reduce the computational burden in case of a very large number of RIS elements, we have introduced “tiling” on the RIS (used for the outdoor scenario). In tiling, some elements are coupled and their reflecting pattern is combined in such a way that the channel dimensions are reduced and consequently, the computation time is reduced significantly. For example if a 36 element RIS is divided into $3 \times 3$ tile size, the resulting RIS will behave like a $4 \times 4$ element surface as shown in Fig. 4. Different tiles can have different individual sizes and their elements are not necessarily adjacent to each other. The estimation accuracy of the algorithms has been plotted in terms of Mean Square Error (MSE) as defined in

$$\text{MSE} = E\{\|\hat{H} - H\|^2\}. \quad (15)$$

We also provide the MSE of the RIS-UE channel $G$, and the end-to-end channel $H_c$. The BS-RIS-UE channel, i.e., $H_c$, can be defined by selecting any phase shift pattern of the RIS at any time. For simplicity, we have selected the 1st row of $S$ to define $H_c$, as in

$$H_c = G \cdot \text{diag}(S(1,:)) \cdot H. \quad (16)$$

Fig. 5 (indoor scenario) and Fig. 6 (outdoor scenario) show the impact of the SNR on the MSE of the estimated channels. The MSE curves of $G$ (dashed lines with markers) and $H_c$ (dotted lines) vs SNR have been plotted. As shown in Fig. 5, SECSI significantly outperforms the other algorithms. In the outdoor scenario, Fig. 6 we have selected a higher number of BS and UE antennas as well as a higher number of RIS elements. In order to reduce the complexity, we have applied tiling. Similar to the indoor scenario, SECSI again exploits knowledge of the RIS phase shifters at the receiver and is able to provide higher quality estimates of the channels.

VI. Conclusions

We have proposed a tensor CP decomposition technique, namely the Semi-Algebraic CP decomposition via Simultaneous Matrix Diagonalization (SECSI), for RIS-aided MIMO channel estimation. Using structured time domain pilots, we can model the received signals as a 3D tensor that can be decomposed to extract the BS-RIS and RIS-UE channels. We have modified the existing SECSI algorithm, considering that the receiver has the knowledge of RIS phase shifters during the channel estimation phase. We have compared the performance of the SECSI algorithm with BALS and LSKRF in terms of the MSE and with simulations in indoor and outdoor scenarios demonstrating that the SECSI algorithms significantly outperforms the state-of-the-art tensor-based channel estimation methods.

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Fig. 5. Indoor scenario: MSE of \( \hat{H}, \hat{G}, \text{ and } \hat{H}_c \) over the SNR. Simulation parameters: \( N_t = N_r = N = 4 \), tensor rank = 4, no. of frames \( B = 4 \), SNR range = 1 : 30 dB, no. of iterations at each SNR = 5000.

Fig. 6. Outdoor scenario: MSE of \( \hat{H}, \hat{G}, \text{ and } \hat{H}_c \) over the SNR. Simulation parameters: \( N_t = N_r = 16 \), \( N = 1024 \), tile size = 16 \( \times \) 16, tensor rank = 4, no. of frames \( B = 4 \), SNR range = 1 : 30 dB, no. of iterations at each SNR = 5000.

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