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Performance of Conjugate Gradient Signal Detection in Large Scale AdGeSM-MIMO

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ABSTRACT: Large scale MIMO (LS-MIMO) **system is an emerging technology for upcoming wireless communication. It serves large number of users simultaneously by increasing quantity of antennae at the BS (base station) which boost the capacity gain, link reliability and spectral efficiency of wireless communication. The energy consumption is high due to huge quantity of transmitting antennae. The signal detection is also performed with complicated matrix inversion. Hence, one of the significant challenge is to design low complex signal detection with low power consumption. In this paper, Conjugate Gradient (CG) technique with Adaptive Generalized Spatial modulation (AdGeSM) is proposed for reducing the computational complexity as well as energy consumption. The suggested procedure for detecting the signal reduces the computational complexity by avoiding complicated matrix inversion. AdGeSM approach reduces energy consumption and hardware complexity by decreasing number of radio frequency chain. The analysis of proposed algorithm of signal detector indicates that the complexity can be diminished from O($\mathrm{N_u^3}$) to O($\mathrm{N_u^2}$), where $\mathrm{N_u}$ is the number of users. Simulation outputs specify that the proposed procedure outperforms the existing algorithms additionally achieves the near-optimal overall performance of the basic linear minimum mean square error (L-MMSE) algorithm.**

Keywords: Large Scale MIMO, Generalized Spatial Modulation, complexity, Signal Detection.

I. INTRODUCTION

Recently, large-scale MIMO (multiple-input multiple-output) have gained popularity due to its expanded spectral efficiency and link reliability. LS- MIMO system is an advanced technology which utilizes a huge variety of antennae to serve multiple user terminals simultaneously without using extra transmission bandwidth [1]. Although the large scale MIMO has many advantages but also has some challenges like hardware implementation, estimation of channel, antenna configurations and signal detection at base station. Specifically a significant challenge is to design signal detection with less computational complexity and power consumption [2]. The maximum likelihood (ML) optimal detector uses an exhaustive search technique. It's complexity increases exponentially with the number of transmit antennae, which makes it unfeasible for LS-MIMO systems [3]. Some non-linear detectors, for example, Sphere Decoder, Ordered Successive Interference Cancellation (OSIC) are proposed to accomplish close-optimal performance. But still their complexity is unaffordable for LS-MIMO systems. Some current detection algorithms, along with Linear ZeroForcing detector (L-ZF) and MMSE (Minimum Mean Square Error), with near-optimal performance were examined, however, those detectors need to utilize high dimensional matrix inversion. This further increases computational complexity[4]. In recent years, the approximate matrix inversion algorithms based on Iterative methods are used to deal with the matrix inversion operation, required by the MMSE signal detection [5].

A low-complexity MIMO technique that provides single active transmit antenna in each time slot is termed as Spatial Modulation. Spatial Modulation (SM) reduces number of RF-chains in LS-MIMO system. The information used is conveyed to several mediums such as modulation symbol and active antenna index.This transmission scheme provides higher energy efficiency and higher throughput. In the Space Shift Keying (SSK) scheme, information is transmitted through an antenna index. There were no transmitted symbols. Hence system complexity gets reduced. But it also reduces spectral efficiency [6].

In Generalized Spatial Modulation (GeSM), transmission rate is higher which activates more number of transmit antennae in each time slot. The GeSM can be considered as special case of Spatial Modulation where an antenna index considered as an additional resource to convey more information bits. Modulated symbols are sent through the active antenna and it gives better performance with similar spectral efficiency [7].

In this work, Adaptive Generalized Spatial Modulation (AdGeSM) based signal detection method named Conjugate Gradient (CG) is used to detect the information signal without performing matrix inversion. Proposed AdGeSM allows the choice of several antennae for transmitting symbol at the equivalent signaling interval. Antennae are selected according to the incoming information bits. It reduces the quantity of power amplifiers without losing a spectral efficiency. The Energy efficiency is improved due to decrease in the number of Radio frequency chains. Conjugate Gradient (CG) is an iterative method which estimates transmitted signal without performing matrix inversion. The proposed approach can reduce the computational complexity from $\mathrm{O}(\boldsymbol{N_u^3})$ to $\mathrm{O}(\boldsymbol{N_u^2})$ by setting the number of expansion terms or iterations, where N_u is the number of users. Hence, Conjugate Gradient (CG) method based signal detection technique with Adaptive Generalized Spatial Modulation (AdGeSM) is proposed to reduce the computational complexity. Due to ADGeSM, energy efficiency is improved as compared to conventional LS-MIMO. Conjugate Gradient (CG) iterative method achieves the near-optimal performance.

The main contribution of our work is given as follows:

–To improve the BER performance more than the existing approaches without matrix inversion.

– To select the transmission antenna using AdGeSM in order to reduce the hardware complexity and power consumption.

– To enhance the transmission reliability and to eliminate the inter-user-interference due to extreme narrow beam.

II.RELATED WORK

Kuai *et al.*, (2019) introduced Sparsity Learning based blind signal detection algorithm for Generalized Spatial Modulation (GeSM) large scale MIMO. In this work channel estimation and multiuser detection is done using joint antenna activity detection for GeSM massive MIMO. Considering the signal sparsity of GeSM and channel sparsity of massive MIMO, a double-sparsity model was established. In order to use the signal and channel sparsity efficiently, the message-passing based blind algorithm was developed [8].

Shafivulla *et al.,*(2018) introduced low complexity signal detection in MIMO systems by enhancing the sub-optimal Zero Forcing Detector (ZFD) estimate using minimum eigenvector of matrix. Optimal bit-error-ratio was offered by Maximum Likelihood Detector (MLD) for an un-coded MIMO communication. Also, when the higher order modulated signal streams are detected with multiple transmit antennae, the computational complexity increases. This work proposed a new approach which has low complexity similar to Zero forcing Detector (ZFD) and also BER performance close to maximum likelihood Detector (MLD) [9].

Feng *et al.*, (2019) presented a new algorithm named Modified Iterative Discrete Estimation (MIDE) for low complexity signal detection. MIDE was designed with a damping factor based on Euclidean distance between the iterative-solutions to accelerate the convergence of algorithm. MIDE avoided the calculations such as matrix inversion. Simulation results showed that MIDE outperforms the existing signal detection algorithms. BER and computational complexity of proposed system is better than existing algorithms [10].

Liu *et al.*, (2019) introduced a Weighted Neumann Series (WNS) approach based on matrix inversion approximation for low complexity signal detection. WNS based least MMSE was proposed to reduce error among WNS-based and exact matrix inversion. The weights were optimized using on or else off-line learning. Simulation outcomes has shown that the proposed WSN based LMMSE detection using off-line computation outperforms the existing Neumann Series (NS) signal detection with faster convergence speed [11]. Anis *et al.*, (2019) presented an approach named Alternating Minimization (AltMin) for the detection of low complexity signal. This method was a good solution for MMSE approach in the applications of massive MIMO where the number of user equipment (UE) antennae are very high compared to the base station (BS) antennae. The proposed AltMin method avoids the complicated matrix inversion and therefore, achieved low computational complexity. Bit error rate (BER) performance of this algorithm is similar to MMSE technique, with less order complexity [12].

Gao *et al.*, (2014) proposed low complexity signal detection algorithm based totally on Richardson method. In this method, a zone-based initial solution is utilized by simply checking the values of the received signals. Signal detection is completed without complex matrix inversion. It reduces the required number of iterations because of fast convergence rate [13].

Gao *et al.*, (2014) proposed Successive over Relaxation (SOR) Approximation detection algorithm for LS-MIMO. SOR method can avoid matrix inversion needed by MMSE signal detection algorithm. This method exploits the symmetric positive definite property of channel matrix of large scale MIMO [14].

III. SYSTEM MODEL OF ADGESM-MIMO

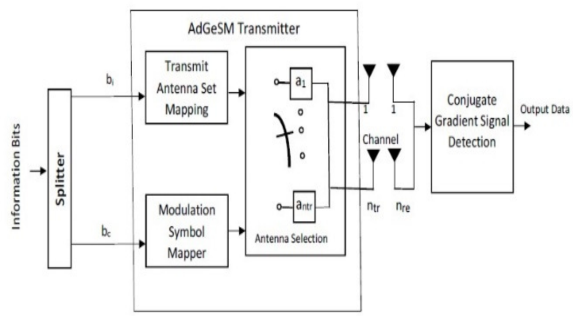

Fig. 1. Architecture of AdGeSM-MIMO.

Let us consider uplink large scale AdGeSM-MIMO system which uses multiple receive antennae at BS and multiple user terminals with single antenna. Number of transmit antennae (n_{tr}) are very less compared to number of receive antennae(n_{re}). The channel information is assumed to be perfectly known at the receiver. One or else more than one number of transmit antennae gets activated simultaneously at any time interval and transmit the same constellation symbol. Number of active antennae (n_{ac}) are not fixed but always less than the number of transmit antennae. It will vary according to the input information bits.

Initially input data is split into two parts. The first part is used for antenna selection and the subsequent section is modulated using signal constellation. Then, the modulated signal is transmitted through the flat fading channel. At the receiver, signal is detected with Conjugate Gradient Approximation (CGA) method.

The number of possible combination of active antennae for input data transmission is given by

$$C = \binom{n_{tr}}{n_{ac}} \tag{1}$$

Where C is calculated by the binomial function. To convey additional information, these antenna combinations are useful.

The input information bits are divided into number of blocks. The length of each block is '*b*'. Then each block is split into two parts.

$$b = b_i + b_c \quad (2)$$

The first b_i bits are used to choose active antennae and last b_c bits are used to choose modulation symbol.

$$bi = \left\lfloor \log_2 \left(\sum_{n=1}^{n_{ac}} \binom{n_{Tr}}{n} \right) \right\rfloor \quad (3)$$

$$b_c = \log_2(M) \quad (4)$$

Where *M* represents the size of constellation. Hence at a time *b* number of bits can be transmitted using AdGeSM MIMO system.

The mapping process at the transmitter for number of transmitting antennae(n_{tr}= 4) and Binary Phase Shift Keying (BPSK) is shown in Table 1. The number of active antennae are one or two depending upon input bits. The incoming data is split by the transmitter into blocks of *b* bits which includes b_i and b_c.

The first three bits (b_i) are utilized to select active antennae. The last one bit (b_c) is used to map modulation symbol. For BPSK modulation, symbol $v_m \in \{v_1, v_2\}$ is used in the constellation. The set of active transmitting antennae carry the same complex symbol v_m, but the other antennae transmit zero.

For example, considering Table 1, if input bits are [0 0 1 0] then first three bits 001 activate the second antenna while the last bit 0 is mapped to a v_1 of BPSK constellation. This means the second antenna is activated to transmit the symbol v_1 while the other antennae transmit zeros which are represented as $[0 \ \ v_1 \ \ 0 \ \ 0]^T$. If the bits 1011 is chosen, antenna 1 and antenna 3 will be activated, transmitted vector is $[v_2 \ 0 \ \ v_2 \ \ 0]^T$ which means the first and third antenna gets activated. Both the antennae transmit the symbol v_2.

A. Conjugate Gradient signal detection

Consider a LS-MIMO, with one base station equipped with n_{re} antennae, which can serve n_{tr} single-antenna user terminals. The value of $n_{re} \gg n_{tr}$ for LS-MIMO. The signal from the base station antenna is received and it is mentioned as

$$y = H_m v_m + n_m \quad (5)$$

Where, $v_m \epsilon C^{n_{tr}}$ signifies the transmitted vector, n_m represents the zero-mean Gaussian noise with variance $\sigma_m^2 = \frac{N_0}{2}$ and $H_m \epsilon C^{n_{tr} * n_{re}}$ indicates the flat Rayleigh fading channel matrix whose entries are considered to be independently and identically distributed (i.i.d.) with zero mean and unit variance [15].

Table 1: Transmitted vector V_m for different input bits (BPSK modulation).

Input Bits	Active antenna indices	Transmitted signal vector
0000	(1)	$[v_1 \ \ 0 \ \ 0 \ \ 0]^T$
0001	(1)	$[v_2 \ \ 0 \ \ 0 \ \ 0]^T$
0010	(2)	$[0 \ \ v_1 \ \ 0 \ \ 0]^T$
0011	(2)	$[0 \ \ v_2 \ \ 0 \ \ 0]^T$
0100	(3)	$[0 \ \ 0 \ \ v_1 \ \ 0]^T$
0101	(3)	$[0 \ \ 0 \ \ v_2 \ \ 0]^T$
0110	(4)	$[0 \ \ 0 \ \ 0 \ \ v_1]^T$
0111	(4)	$[0 \ \ 0 \ \ 0 \ \ v_2]^T$
1000	(1,2)	$[v_1 \ \ v_1 \ \ 0 \ \ 0]^T$
1010	(1,3)	$[v_1 \ \ 0 \ \ v_1 \ \ 0]^T$
1011	(1,3)	$[v_2 \ \ 0 \ \ v_2 \ \ 0]^T$
1100	(1,4)	$[v_1 \ \ 0 \ \ 0 \ \ v_1]^T$
1101	(1,4)	$[v_2 \ \ 0 \ \ 0 \ \ v_2]^T$
1110	(2,3)	$[0 \ \ v_1 \ \ v_1 \ \ 0]^T$
1111	(2,3)	$[0 \ \ v_2 \ \ v_2 \ \ 0]^T$

The main function of signal detection is to estimate transmitted signal vector $\widehat{v_m}$ using channel matrix coefficients H_m and received signal vector y. MMSE equalizer is used at the Base station (BS) side to minimize the MSE from transmitted symbol lv_m, MMSE detector computes $\widehat{v_m}$ transmitted symbol vector which is expressed as

$$\widehat{v_m} = (H_m^H H_m + \sigma_m^2 I_m)^{-1} H_m^H y \quad (6)$$

Where, I_m denotes the identity matrix with dimension n_{tr} and A_m denotes the MMSE detection matrix i.e

$$A_m = (H_m^H H_m + \sigma_m^2 I_m) \quad (7)$$

Also matched filter output can be represented as

$$y_m = H_m^H y \quad (8)$$

By using Eqns. 7 and 8 transmitted vector $\widehat{v_m}$ is expressed as

$$\widehat{v_m} = A_m^{-1} y_m \quad (9)$$

The computational complexity required to calculate Matrix Inversion in MMSE method is O (N_u^3) Where N_u isthe number of users. This complexity increases with an increase in the number of users. To avoid matrix inversion, a low complexity signal detection algorithm named Conjugate Gradient method is proposed. The proposed method attains iteratively MMSE estimation without performing Matrix inversion. Also, analysis of computational complexity is done to indicate the superiority of proposed method over the existing method.

CG is an iterative method. In each iteration the updated transmitted signal vector is given by

$$\widehat{v_m}^{(j+1)} = \widehat{v_m}^{(j)} + \mu_m^{(j)} d_m^{(j)} \quad (10)$$

where 'j' denotes no. of iterations and $d_m^{(j)}$ denotes the direction of conjugate with step size $\mu_m^{(j)} with$respect to A_m that is

$$(d_m^{(i)})^H A_m (d_m^{(j)}) = 0 \quad \text{for } i = \text{j} \quad (11)$$

Consider the initial value of error residual is

$$e_r^{(0)} = y_m \quad (12)$$

Also, initial value of conjugate direction is given by

$$d_m^{(0)} = e_r^{(0)} \quad (13)$$

Updated error residual is calculated by Eqn. (14)

$$e_r^{(j+1)} = e_r^{(j)} - \mu_m^{(j)} A_m d_m^{(j)} \quad (14)$$

The step size $\mu_m^{(j)}$ is error residual at j[th] iteration which is given by

$$\mu_m^{(j)} = \frac{{e_r^{(j)}}^H e_r^{(j)}}{{e_r^{(j)}}^H A_m d_m^{(j)}} \quad (15)$$

Scalar parameter β_m is;

$$\beta_m^{(j)} = \frac{{e_r^{(j+1)}}^H e_r^{(j+1)}}{{e_r^{(j)}}^H e_r^{(j)}} \quad (16)$$

Then, calculate updated Conjugate direction as:

$$d_m^{(j+1)} = e_r^{(j+1)} + \beta_m^{(j)} d_m^{(j)} \quad (17)$$

Updated error residual is minimized using updated conjugate direction. The final transmitted vector is obtained when error residual value becomes zero.

B. Computational complexity analysis

Complexity of an algorithm is determined by the number of multiplications required for j[th] iteration. In each iteration, to compute the updated transmitted signal vector $\widehat{v_m}^{(j+1)}$, N_u times multiplication is needed. To calculate updated Conjugate direction $d_m^{(j+1)}, N_u$ times multiplication is required.

Computing an error residual at j[th] iteration $\mu_m^{(j)}$ and updated residual $e_r^{(j+1)}$ includes $N_u^2 + 2N_u$ and $N_u^2 + N_u$ multiplications respectively. In addition, scalar parameter $\beta_m^{(j)}$ required 2N_u times multiplication. Hence overall complexity for each iteration is given by ($2N_u^2 + 7N_u$), where N_u is number of users.

IV. SIMULATION RESULTS

The proposed work is implemented on the MATLAB platform. Different combinations of receive and transmit antennae are considered. According to the number of transmit antennae, active antenna indices and modulation schemes are selected. Number of iterations is considered as 25. Initially, the signal detection is implemented with the initialization parameters. The performance of our proposed work is observed based on these parameters and compared with existing methods.

Table 2: Simulation parameters.

Description	Value
Number of transmit antennae ($\boldsymbol{n_{tr}}$)	4
Number of active antennae($\boldsymbol{n_{ac}}$)	1 or 2
Number of receive antennae($\boldsymbol{n_{re}}$)	64
Modulation scheme	BPSK
Variance of Gaussian noise	0.5 W

The Bit error rate performance of proposed work for n_{re}= 64 and n_{tr}= 4 number of antennae is shown in Fig. 2. Parameters for Simulation are mentioned in Table 2. One or two antennae are activated according to information bits to carry modulation symbol. Here BPSK modulation is used. Performance of proposed work is compared with MMSE [15], Symmetric Successive over Relaxation (SSOR) [16], Richardson [17] and Neumann Series Approximation [18] versus Signal to Noise Ratio (SNR).

The BER rate is more at zero SNR. BER rate decreases with an increase in Signal to noise ratio. Our proposed Conjugate Gradient (CG) method attained better performance as compared to other works.

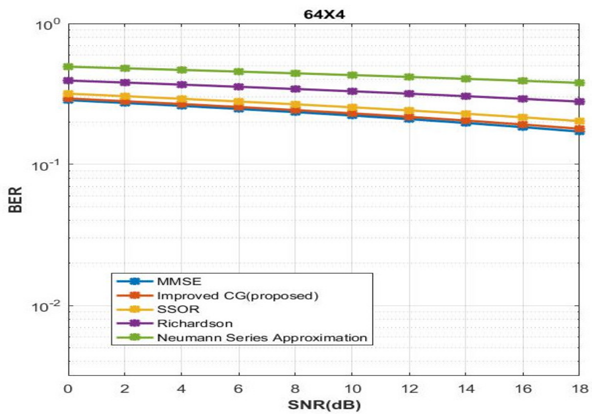

Fig. 2. BER performance for n_{re} x n_{tr} = 64 × 4 versus SNR (dB).

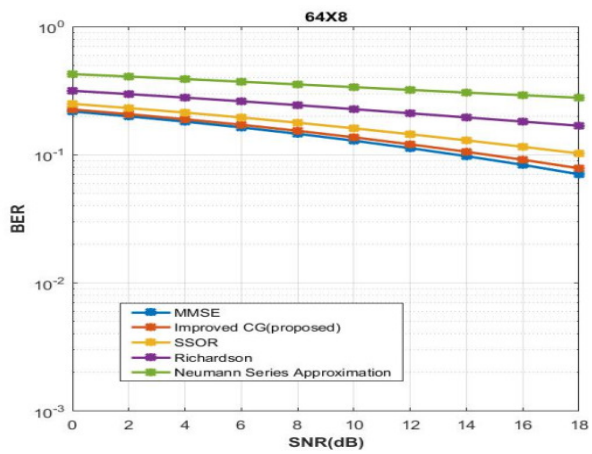

Fig. 3. BER performance for n_{re} x n_{tr} = 64 × 8 versus SNR (dB).

Fig. 3 shows the BER performance of proposed work for $n_{re} = 64$ and $n_{tr} = 8$ number of antennae. Our proposed work is compared with other existing works such as MMSE, SSOR, Richardson method and Neumann Series Approximation versus SNR. BER rate gets reduced at high SNR ratio. This graph shows that performance of Conjugate Gradient method is better than existing methods.

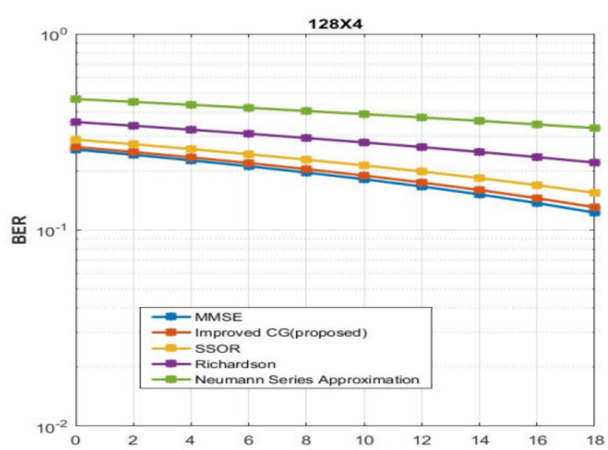

Fig.4. BER performance for n_{re} x n_{tr} = 128 × 4 versus SNR (dB).

Fig. 4 shows the BER performance versus SNR for LS-MIMO system which consists of $n_{re} = 128$ and $n_{tr} = 4$ antennae. Performance of this work is compared with other existing works such as MMSE, SSOR, Richardson and Neumann Series Approximation. The BER is low at high SNR value.

Graph shows that our proposed CG method achieved better performance when compared to other works.

Fig. 5 shows the BER performance against SNR for LS-MIMO which consists of $n_{re} = 128$ and $n_{tr} = 8$. In this case also when the SNR value is low then BER performance of the compared works is high. The value of the BER rate is decreasing with an increase in SNR value. This graph shows that our proposed CG method achieved better performance when compared to other works.

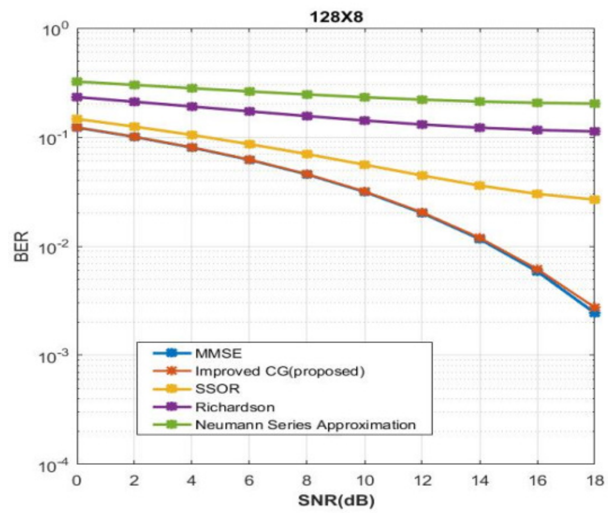

Fig. 5. BER performance for n_{re} x n_{tr} =128× 8 versus SNR (dB).

V. CONCLUSION

In this work, low complexity Conjugate Gradient Signal detection technique is proposed for Adaptive Generalised Large Scale MIMO. The main objective is to minimize the computational complexity by avoiding the complex matrix inversion and also to reduce the energy consumption. AdGeSM-MIMO is used for the antenna selection. AdGeSM scheme requires less number of Radio frequency chains which gives high energy efficiency and low hardware complexity. Conjugate Gradient method estimates the transmitted vector in iterative manner. For each iteration computational complexity is $2\ \mathrm{N_u^2} + 7\ \mathrm{N_u}$. Hence, complexity is reduced by one magnitude as compared to the direct method of matrix inversion.

Simulation results show that the proposed CG approach has achieved improved results. Also, the results revealed that the proposed approach can be efficiently used in LS-MIMO system to attain reduced computational complexity. The performance of proposed signal detection technique is compared with the traditional methods in terms of BER. The implementation result shows the improvement in performance of signal detection for the proposed approach.

VI. FUTURE SCOPE

Conjugate Gradient Signal detection method is done using linear MMSE filtering matrix and perfect Channel State Information (CSI).In future, this method can be implemented using nonlinear filtering matrix. It can also be implemented with imperfect CSI.

Conflict of Interest. The Authors declare that there is no conflict of interest.

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