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The Presentation of Adaptive Beam-Forming Algorithms GSC-LMS in Indoor and Outdoor Scenarios

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***Abstract*- In this paper, we investigate the multiple-input multiple-output systems (MIMO) and the co-channel interference cancelation in these systems. In recent years, the usages of array antennas in the receiver/ transmitter or both have greatly increased in telecommunication systems. Due to the increasing transmission data rate and the decreasing error rate, the MIMO systems in wireless communication systems are very important. In the third, fourth, and fifth generations of wireless communications in order to increase the network capacity and spectrum efficiency, the same frequency channel is allocated to different users. This leads to co-channel interference for the users with the same frequency channel. Thus, it is essential to eliminate inter-channel interference in telecommunication networks. In this paper, an adaptive algorithm is evaluated to eliminate the co-channel interference in MIMO systems. We also investigate the algorithm in indoor and outdoor environments using the Wiener model, with direct and indirect channels using the Rayleigh and Rice fading models and calculate the error probability in different conditions. In order to improve the performance of the system in uplink transmission, auxiliary antennas and linear arrays of antennas at the receiver are used. The results of the proposed algorithm are simulated and compared with the previous conventional methods.**

***Index Terms*-** MIMO system, Auxiliary antennas, Least Mean Square (LMS) algorithm.

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I. INTRODUCTION

With the increasing demand for data transmission in the next decade, fifth-generation systems are evolving rapidly [1]. Fifth-generation networks combine with intelligent systems such as advanced signal processing [2], device-to-device technology [3], the Internet of Things, edge computing [1], and additional wireless technologies [4], all of which have received a lot of attention in recent years [5]. The 5G Cellular Network is expected to support a large number of mobile devices with global access services. According to forecasts, mobile data traffic volume should increase at least 1000 times in the 2020s than in 2010 [6]. Some advantages of 5G technology are achieving higher capacity, better spectral and energy efficiency, i.e., 1000 times of current 4G technology, 10 times more in data rate, and 25 times more in the average cell efficiency [7]. To achieve these ambitious goals, advanced fifth-generation wireless technologies are being developed. The high density of wireless devices is one of the major challenges for the development of current and future wireless networks. Since the radio spectrum resources are limited, multiple wireless users share the same time and/or frequency resources, there is interference between the users, which leads to a reduction in the capacity of cellular networks. Many efforts have been made to study interference management techniques. Due to the use of multiple antennas in MIMO systems, beamforming is introduced as an effective method to manage the interference. In beamforming, the transmitted signals are directed in a direction to minimize their negative effect on the receivers [8].

For uplink communications in MIMO systems, the non-linear detectors like Successive Interference Cancellation and Sphere Decoder provide acceptable performance. However, the computational complexity increases with the number of antennas, which makes them infeasible to use in Massive MIMO systems [9], [10]. In [11] a multiuser MIMO receiver proposed which learns to jointly detect in a data-driven fashion, without assuming the type of channel model or requiring channel state information (CSI). In case, [11] propose a data-driven implementation of the iterative soft interference cancellation algorithm which referred as DeepSIC. Linear precoding techniques for massive MIMO systems under a single-cell (SC) scenario are provided in [12]. In [13], a comprehensive review of the various embodiments of digital and analog beamforming designs by employing average CSI has been presented.

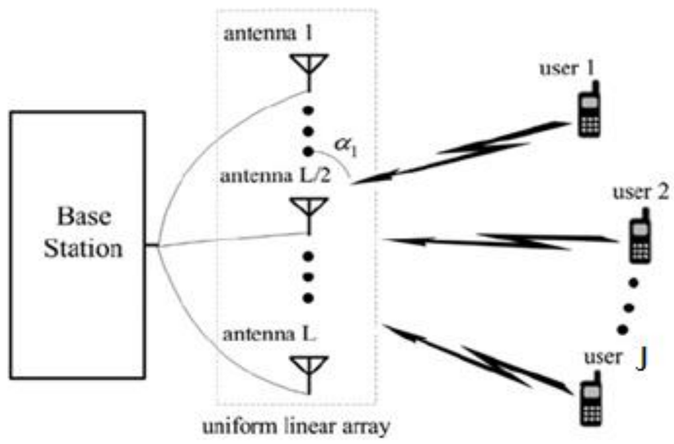
Array antennas are used in the transmitters and the receivers of the telecommunication systems because they improve the performance of these systems. In order to exploit the maximum capacity created by these antennas in the transmitter and the receiver components, appropriate processes must be used. The first practical use of array antennas is beamforming in fuzzy array systems, which were initially performed in the analog form. An undesirable signal that has the same frequency as the target signal is called co-channel interference. In the cellular communication systems, the co-channel interfering and the desired transmitter are located in the same cell or the different cell. In the first and second generations of cellular communications, identical frequencies were not assigned to two transmitters in the same cell; therefore, the undesired signal with the same frequency was placed in adjacent cells. However, in the third, fourth, and fifth generation of cellular telecommunications, the same frequency is assigned to the different transmitters in the same cell which increases the spectrum efficiency and network capacity. Therefore, the bit rate in the cell increases, but interference management in these networks will be critical to improving the system performance. In [14], an improved adaptive algorithm is proposed to suppress the narrowband interference in a straight wide spectrum sequence. The first Least Mean Square (LMS) algorithm was proposed by Vidro and Huff [15], this method is popular because of its simplicity and global reputation, but its degree of convergence and state error is not very satisfactory. Derivatives of LMS have partially solved the problems. Adjusting the LMS is directly proportional to the input vector, so the input is very large, the algorithm suffers from the noise amplification problem.

Normalized LMS algorithm [16] employs the square of the Euclidean norm in the input vector and solves the problem well. Also, the variable step of the LMS algorithm [17] has greatly improved the degree of convergence. These derivatives minimize the mean square error (MSE) between the desired signal and the estimation. In [18], an adaptive interference cancellation scheme is presented to suppress the interference signal for MIMO relays on both sides. This scheme uses the adaptive filter to monitor the time variation of the interference channel. In addition, the proposed scheme is independent of the relay, thus, there is no need to modify the relay architecture in Long Term Evaluation (LTE) or fifth generation networks. As a result, it can be applied directly to the relay without additional complexity. In this work, to eliminate the co-channel interference in MIMO systems, we introduce an adaptive algorithm which first estimate the angel of income signal turn the beam of array to the desire direction by determining the array weights. Also, we investigate the performance of the proposed method in different channel models including indoor and outdoor environments using Wiener model with Rayleigh and Rice fading channels. Furthermore, we use auxiliary antennas with the aim of improving the uplink transmission.

The rest of this paper is organized as follows: Section II presents the considered system model. In Section III, we propose solutions to the problem of interference in our scheme. Also included in Section

II. SYSTEM MODELS

The schematic of the MIMO system consisting of transceiver pair is shown in Fig.1. The system model in Fig. 1 considered with J users (where J could be any number). The base station (BS) is considered as the receiver; both the transmitter and the receiver use the array antennas. Our problem is to control the interference in the MIMO system with a uniform linear array of antennas in the



odulation, coding, and signal processing. Then, the desired signal is received at the BS after passing

Fig. 1 System model.

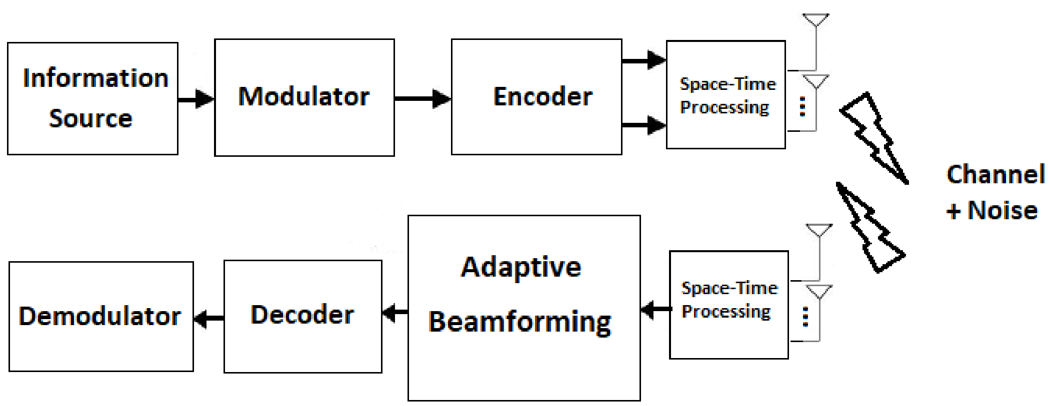


Fig. 2 block diagram of MIMO system.

receiver. In this paper, we consider a cellular network with a number of multi-antenna users. The BS receives an interfering signal including the desired signal and the unwanted signal from the other users. Fig. 2 depicts the entire MIMO system from the signal transmission by the transmitter to signal reception by the receiver. This block diagram at the transmitter contains the information source, m through the fading channel and adding the white Gaussian noise. There are blocks in the receiver that reverse the operation performed on the transmitter, and the adaptive algorithm block for interference management has been added.

III. BASIC DEFINITIONS

In this section, to model our problem, first, we start with reviewing the uniform linear array and how to model the incoming signal, then, we discuss the least mean square algorithm and explain how it works.

A. Uniform Linear Array (ULA)

In a uniform linear array (ULA), the antennas are arranged linearly with equal distance. The ULA

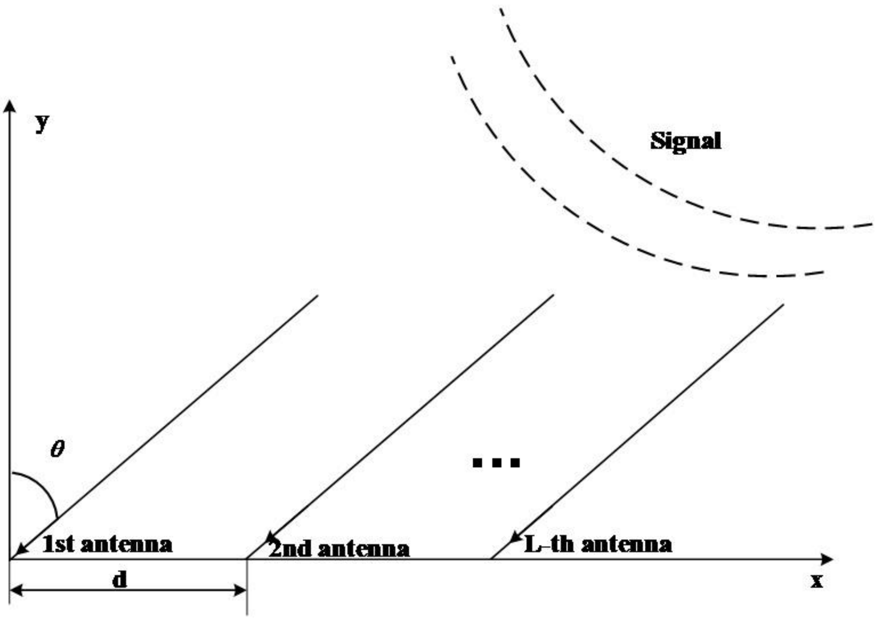


Fig. 3. Uniform linear array (ULA).

model is shown in Fig. 3. The variable θ is the angle of the direction of arrival (DOA) and axis y. An array consists of L antenna used to receive a signal at the receiver. It is assumed that the received signal is a combination of the signal of interest (SOI) and the m interference signal ($\leq m < L$).

The input angle of desired signal and the interfering signals are θ_0 and $\theta_i \ (i = 1, \dots, m)$, respectively. The distance between two adjacent antennas is $d = \frac{\lambda}{2}$ and therefore, the phase difference between them is $\pi \sin \theta$. When the input angel is $\theta_k \ (k = 0, \dots, m)$, the output response of the uniform linear array given by

$$a(\theta_k) = [1, e^{j\pi \sin \theta_k}, \dots, e^{j\pi\,(\mathrm{M}-1) \sin \theta_k}]^T. \tag{1}$$

As a result, the output vector is written as follows:

$$a = [a(\theta_0), a(\theta_1), \dots, a(\theta_m)], \tag{2}$$

And $x(n)$ is defined as the received signal with a length of N at any time as follows:

$$x(n) = [x(1), x(2), \dots, x(N)] = a \times S + v. \tag{3}$$

We define S as the signal matrix of size $(m + 1) \times N$ that contains the desired signal and m interference signal. Also, v is defined as additive white Gaussian noise (AWGN), which we assume AWGN noise and signal are independent [10].

B. Multiple Signal Classification (MUSIC) Algorithm

The MUSIC is an algorithm used to estimate the angle of the incoming signal. In order to estimate the angle, MUSIC calculates the autocorrelation of input signal x including multiple snapshots as follow:

$$R_{L\times L}(n) = E[X(n)X^H(n)] \tag{4}$$

$$R(n) = \frac{1}{N}\sum_{m=0}^{N-1} X_m(n)X_m^H(n) \tag{5}$$

In fact, the matrix R(n) can be decomposed as:

$$R(n) = U\Lambda U^H \tag{6}$$

Consisting of a unitary eigenvector matrix $U = [U_0 \;\; U_1 \;\; \dots \;\; U_{L-1}]]$ and Λ is a diagonal matrix of real eigenvalues. Using eigenvalues, the matrix R(n) is separated into two subspaces as:

$$R(n) = S\Lambda_s S^H + N\Lambda_n N^H \tag{7}$$

Where with assuming the number of receive array antennas L is greater than the number of source signals J and the number of snapshots N is greater than the number of receive array antennas L. Therefore, $S = \left[u_0, \dots, u_{J-1}\right]_{L\times(J-1)}$ is a signal subspace with

$\Lambda_s = diag[\lambda_1, \dots, \lambda_{J-1}]_{(J-1)\times(J-1)}$ and $N = [u_J, \dots, u_{L-1}]_{L\times(L-J)}$ is a noise subspace with

$\Lambda_N = diag[\lambda_J, \dots, \lambda_{L-1}]_{(L-J)\times(L-J)}$.

Since autocorrelation matrix $R(n)$ is Hermitian, its eigenvectors are orthogonal to each other and by sorting in decreasing order, the first J vectors corresponding to J largest eigenvalues span the signal subspace S. Then remaining $L-J$ eigenvectors correspond to noise subspace N, which is orthogonal to signal subspace ($N \perp S$). Finally, the power spectrum of MUSIC for each angle can be estimated as follow:

$$P_{music}(\theta) = |a^H(\theta)N|^{-2} \tag{8}$$

After calculating P_{music} for all angles, the peaks determine the angle of incoming signals [19].

C. Adaptive least mean squares (LMS) algorithm

An adaptive least mean squares algorithm is proposed to adjust the array coefficients in real time [1]. First, we introduce this algorithm briefly in order to solve the considered interference problem in the previous section. The output of the array antennas are as follows:

$$y(n) = w^H(n)x(n), \tag{9}$$

Where $w^H(n)$ is defined as the estimation vector coefficients of filter for all receiving antenna:

$$w(n) = [w_1(n), \dots, w_L(n)]^H, \tag{10}$$

and the input vector $x(n)$ is defined as follows:

$$x(n) = [x_1(n), \dots, x_L(n)]^H. \tag{11}$$

The desired output of this adaptive algorithm is:

$$d(n) = w_o^H(n)x(n) + N(n), \tag{12}$$

where w_0 denotes the optimal coefficient of adaptive algorithm, and N is as AWGN noise. The calculated optimal coefficients by LMS algorithm are given by as follows:

$$\min P_{out} = \min E[|y(n)|^2]. \tag{13}$$

By solving this optimization problem, the weights are calculated as follows:

$$w(n+1) = w(n) + \mu u(n)e^*(n), \tag{14}$$

where μ is defines as step coefficient for algorithm. To minimize the error using the LMS algorithm, the weights are updated according to above equation (14). Also, the error in each step is defined as the difference between the desired signal and the observed signal in the previous step:

$$e^*(n) = d^*(n) - u^H(n)w^*(n), \tag{15}$$

where u is defined as the eigenvector for the signal and the step coefficient is calculated as follows:

$$0 < \mu < \frac{2}{|\lambda_{max}|}, \tag{16}$$

which depends on the largest eigen value of the correlation matrix, i.e., $R = E[x(n)x^H(n)]$ or λ_{max}, hence,

$$w_0 = R^{-1} \times E[d(n)x(n)], \tag{17}$$

where $E[d(n)x(n)]$ indicates the correlation or similarity between two vectors $x(n)$ and $d(n)$. Based on the presented method in this section, we use generalized sidelobe cancellation (GSC) beam formation and combine it with the LMS adaptive algorithm. In the next section, the block algorithm is introduced.

IV. PROPOSED ALGORITHM

The purpose of this algorithm is to control the interference using the adaptive algorithm. Fig. 4 shows the blocks of the algorithm to minimize the errors and update weights.

- Using the Multiple Signal Classification (MUSIC) angle estimation method to calculate the desire antenna angle ($\hat{\theta}_d$) of the transmitter. $\hat{\theta}_d$ is the output of this step.

- GSC beamforming algorithm for eliminating interference signals by canceling sub-lobes. At the output of this step, the interference signal eliminated.

- LSM adaptive algorithm is used to optimize the received signal by minimizing error and updating weights. This algorithm is very important due to its applicability. The output is desire signal.

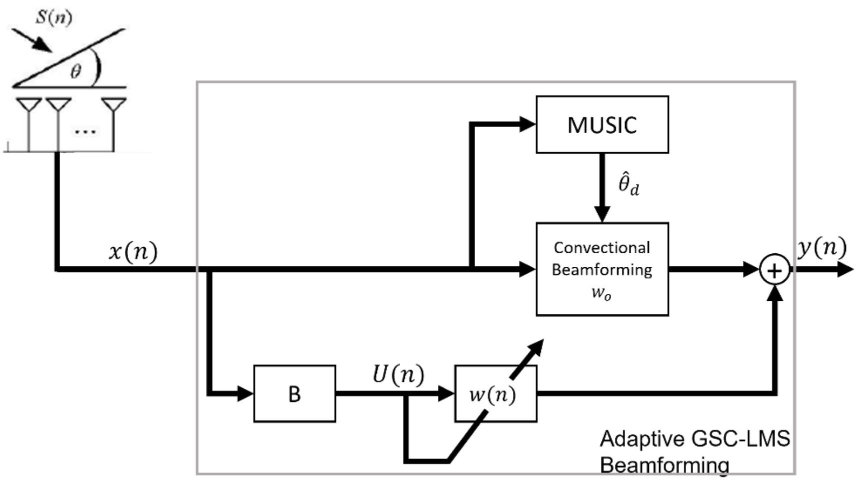


Fig. 4 The block diagram for the proposed algorithm

In the proposed method, the weights are updated in the adaptive algorithm so that the interference caused by undesirable angles in the pattern antenna is minimized. Also, we show that the proposed algorithm performs better than the LMS algorithm in terms of error performance.

A. *Performance of the proposed algorithm*

The GSC beamforming algorithm is a beamforming technique that consists of two stages. The first stage uses the weight vector W_0 to form the main beam in direction θ_d that is calculated by the MUSIC algorithm. The second stage, matrix B is the first block of the desired signal.

$$W_0 = a[(\theta = \theta_d)]_{(L\times 1)}, \tag{18}$$

$$B = I_{(L\times L)} - W_0 {W_0}^H. \tag{19}$$

The output signal from the first block is as follows:

$$U_{(L\times N)} = B^H_{(L\times L)} X_{(M\times N)}. \tag{20}$$

It is used for adaptive weight vectors to cancel the interference paths. In the proposed method, the LMS algorithm is used for the lowest output power of the beamforming. The beamforming output is written as:

$$y_{(1\times N)}(n) = W^H_{(1\times L)}(n) U_{(L\times N)}(n) \tag{21}$$

Where the weight vector is expressed as
$W(n) = [W_1(n) \;\; W_2(n) \;\; \dots \;\; W_L(n)\;]^T_{L\times 1}$ and the matrix U(n) can be viewed as the Undesired signals and it is expressed a $U(n) = [U_0(n) \;\; U_1(n) \;\; \dots \;\; U_{N-1}(n)]$.

The output power of the beamforming is:

$$P(W(n)) = E[y(n)y^H(n)], \quad (22)$$

where $E[\cdot]$ is the expected value. By substituting (21) in (22) and using

$R_u(n) = E[U(n)U^H(n)]$ yields:

$$P(W(n)) = W^H(n)R_u(n)W(n) \quad (23)$$

The gradient of $P(W(n))$ with respect to $W(n)$
is given by:

$$\nabla_W W^H RW|_{W=W(n)} = 2R_u(n)W(n) \quad (24)$$

The update equation for the array weight vector of the proposed GSC beamforming based on the method of steepest descent is given by the equation (14).

B. Algorithm analysis

The proposed algorithm is investigated and compared for the Rayleigh and Rice channel models. Probability density function (PDF) of the Rayleigh channel for the variable x and $b > 0$ is given by:

$$f(x|b) = \frac{x}{b^2}\exp\left\{-\frac{x^2}{2b^2}\right\}; x \geq 0. \quad (25)$$

The probability density function (PDF) of the Rice channel for the variable x and $s > 0$ is given by:

$$f(x|b) = I_0(\frac{xs}{\sigma^2})\exp\left\{-\frac{x^2}{2b^2}\right\}; x \geq 0, \quad (26)$$

where I_0 is the modified Bessel function with zero order and the first type.

The received signal is investigated based on the BPSK and QPSK modulations. The transmitted signal based on BPSK modulation is as follows:

$$s_n(t) = \sqrt{\frac{2E_b}{T_b}\cos\left(2\pi ft + \pi(1-n)\right)}, n = 0,1, \quad (27)$$

and the transmitted signal based on BPSK modulation is as follows:

$$s_n(t) = \sqrt{\frac{2E_s}{T_s}\cos\left(2\pi ft + \frac{\pi}{4}(2n-1)\right)}, n = 1,2,3,4, \quad (28)$$

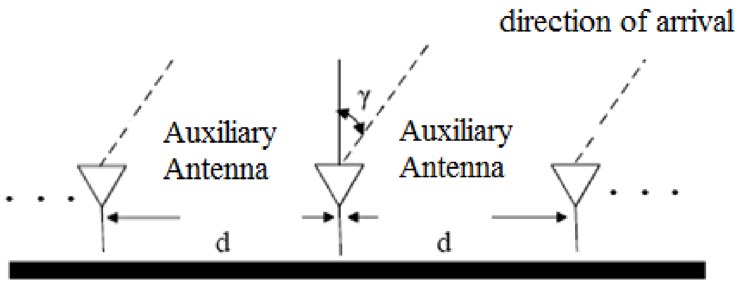


Fig. 5. Arrangement of auxiliary antenna between the main antennas.

where E_b and E_s represent the energy of the transmitted bit and symbol. T_b And T_s are defined as the time duration of the transmission bits and symbols. The parameters and indicate the frequency and time, respectively.

The transmission scenarios in the indoor and outdoor channels are investigated based on the Wiener model. Path loss due to the environmental condition is defined as follow:

$$PL = A\log_{10}(d[m]) + B + C\log_{10}(\frac{f_{c[GHz]}}{0.5}), \quad (29)$$

where A, B, and C are defined at [20]. The distance between the receiver and transmitters (meter) and the carrier frequency of the transmitted signal (f_c) is measured in gigahertz (GHz). If there is a sufficient distance between the receiving antennas at the base station, the arrangement of the main and auxiliary antennas to use the auxiliary antenna technique is shown in Fig. 5.

By defining S_p as the received signal in the main channel, the received signal at the auxiliary channels is given by:

$$S_r = S_p\theta(\gamma), \quad (30)$$

Where $\theta(\gamma)$ is defined as $\theta(\gamma) = \left[e^{j\theta_1}e^{j\theta_2}e^{j\theta_n}\right]$ and depends on the arrangement of the antennas and the angle of entry of the signal. Also, n is the number of auxiliary antennas in the linear array.

$$\theta(\gamma) = e^{-j\psi}\left[1\ e^{-j\phi}\ \dots\ \ e^{-j(n-1)\phi}\right]^T, \quad (31)$$

where $\phi = \frac{2\pi d}{\lambda}\sin(\gamma)$ and $\psi = \frac{2\pi d}{\lambda}\cos(\gamma)$. The variable d is the distance between two array antennas, λ is the wavelength of the received signal and γ is the radiation angle of the signal. Using the adaptive algorithm, the output SNR is calculated based on the optimal weights. Using the update weights (W) by the adaptive algorithm, the signal to noise ratio plus interference at the output is calculated as follows:

$$SINR_{out} = 20\log(\frac{W^H(n)R_sW(n)}{W^H(n)R_NW(n)}), \tag{32}$$

where the correlation matrices are defined as follows:

$$R_s = \sqrt{\epsilon_1}a(\theta_d)a^H(\theta_d), \tag{33}$$

$$R_N = \sum_{j=2}^{J}\sqrt{\epsilon_j}\ a(\theta_d)a^H(\theta_d) + \sigma_n^2 I_{M\times M}, \tag{34}$$

where θ_d is estimated in the previous section, ϵ_1 is the energy of the desired transmitted signal and ϵ_j is the energy of the interference signals. L is the number of the receiver antenna.

B1. Calculation of the error probability

The error probability for the BPSK modulation at the fading channel with gain $|h|^2$and rate $\frac{E_b}{N_0}$ is calculated as:

$$P_b = \frac{1}{2}\mathrm{erf}\left(\sqrt{\frac{|h|^2E_b}{N_0}}\right) = \frac{1}{2}erf\left(\sqrt{SINR}\right). \tag{35}$$

The effective signal to noise ratio in this channel is $SINR = \frac{|h|^2E_b}{N_0}$. Using the adaptive algorithm with optimized weights W, the output SINR is calculated as follows:

$$SINR_{out} = \left(\frac{W^H(n)R_sW(n)}{W^H(n)R_NW(n)}\right). \tag{36}$$

By substituting (36) in (35), we have:

$$P_b = \frac{1}{2}\mathrm{erf}\left(\sqrt{\frac{W^H(n)R_sW(n)}{W^H(n)R_NW(n)}}\right). \tag{37}$$

By considering the Rician channel model, given the coefficient |h|, the effective SINR is changed. The path loss coefficient (PL) in the indoor and outdoor scenarios introduced in the previous section affects the effective SINR and produces new weights. Also, by adding the auxiliary antennas in the receiver, L increases, which improves the error probability and increases the effective SINR.

B2. Degree of Complexity

To evaluate and compare the algorithms, we must determine the computational complexity or power required. Most measurements are given by the criterion of a flop (floating point operation), that definitions differ between the different authors. In this section, the computational complexity of uplink transmission is evaluated using an adaptive algorithm and compared with conventional methods. Based on signal modulation and detection in each branch of the system, the diversity of MIMO, a number of flaps is calculated based on the toolbox LIGHTSPEED in MATLAB software [21]. As a result, the degree of complexity increases with the number of antennas and users. Providing an algorithm to increase system performance is usually associated with a s by increased cost, the most common of which increase the system complexity. But it must be evaluated to what extent the increase in complexity is acceptable in return for performance improvement. The error probability of the system in different conditions for this algorithm is investigated. Based on the number of the FLOPS in the MATLAB software, the degree of complexity of the algorithm is calculated. The simulation results related to the performance of the proposed algorithm are given in the next section.

V. SIMULATION RESULTS

In this section, the proposed algorithm, which includes a combination of the LMS method and GSC beamforming, is compared with the LMS method without beamforming. We simulate the different indoor and outdoor scenarios, the fading channels, and considered modulation. The effect of the convergence parameter on the adaptive algorithm, the transmitted power, and the effect of the interference power in the simulation has been investigated. The proposed adaptive algorithm is simulated with methods such as zero forcing beamforming (ZFBF) and minimum mean square error (MMSE), for reducing the effect of the interference through the beamforming. In this way, the pre-encoders W_{ZF} and W_{MMSE} are multiplied as a matrix in the received signal from all antennas and each user's signal is received separately from other users. Auxiliary antennas have been used in the proposed method and the results have been simulated. The bit error rate (BER) for different users (interference) and the receiving antennas are simulated.

For the presented system model in the previous section, we simulate a MIMO system with N_t transmit antenna and N_r receiver antenna. The fading channel matrix between the transmitter and the receiver antenna is $H^{(M_r \times M_t)}$, which is generated as Rayleigh random variable. We generate a signal with desired modulation (BPSK) and transmit it through each transmitted antenna. Each of the transmitter antennas, which are arranged side by side in a linear array, has a specific input angel, which is introduced for antennas 1 to M as θ_0 to θ_{0M_t}. The transmitted signal passed through the Rayleigh channel with unknown interference signal and AWGN noise and was received at each receiver antenna. According to different transmission scenarios in indoor and outdoor environments, the amount of path loss in direct and indirect transmitting is different. The methods of interference cancelation for these scenarios are described in [17].

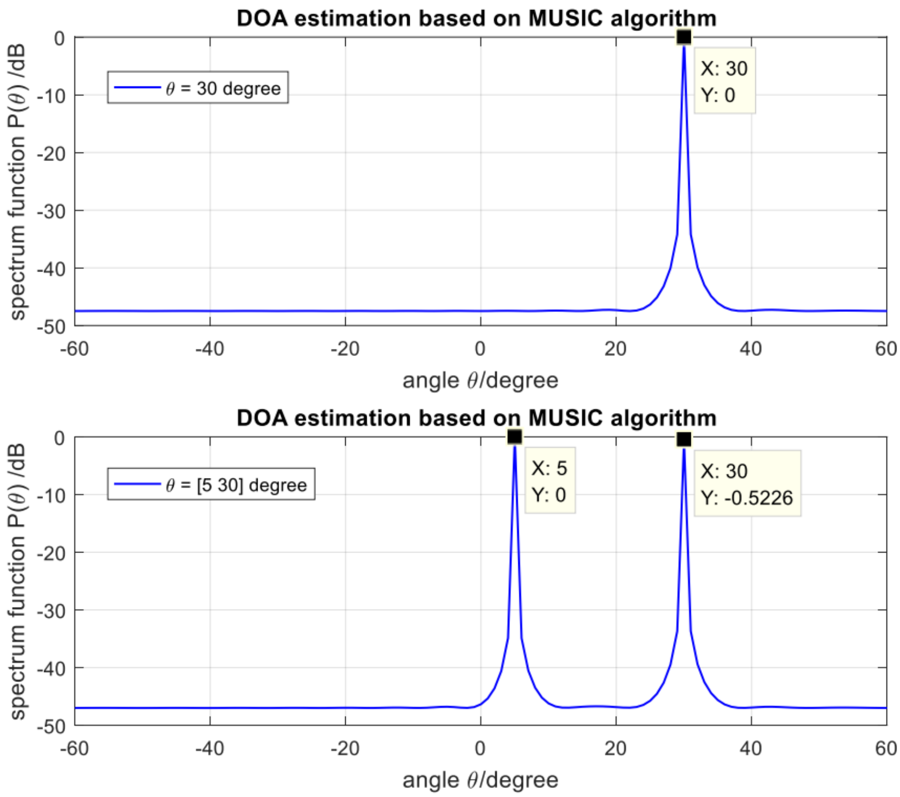


Fig. 6. Spectrum diagram in terms of angle for an input angle,30 degree and two input angles of 5 and 30 degrees.

Since the input angles of the desired signal are known from the transmitting antennas, then, using the beamforming determine the directions of the desired signal and cancel the interference signals. For this purpose, we determine the optimal coefficient resulting from an adaptive algorithm such as the LC-LMS method described in the previous section. The received signal is multiplied by the optimal coefficients and the input symbols are detected.

The simulations of the proposed algorithm (adaptive algorithm in beamforming) are performed for N=64 symbols with 500 repetitions. The transmitted power of the interfering transmitters is half the desired transmitter power, and the input angle of the desired signal is assumed to be $\theta_0 = 30$ degrees. The convergence parameter of the adaptive algorithm is considered to be $\mu = 0.0001$.

Fig. 6 shows the spectrum diagram in terms of angle from -60 to 60 degrees. The diagram is drawn for two cases. In the upper figure, the beam has an input angle of 30 degrees, and in the lower figure, there are two maximum angles of 5 degrees and 30 degrees, both of which are estimated using the MUSIC algorithm. The maximum value of $P(\theta)$ determines the DOA angle. The frequencies are different for multiple input angles.

Fig. 7 shows the mean squares of the error in terms of the number of iterations of the algorithm. We assume that the number of transmitting users is 5, which includes 1 main user and 4 interfering users. The number of array antennas in the receiver is 10 and the optimal transmitter power to noise ratio is

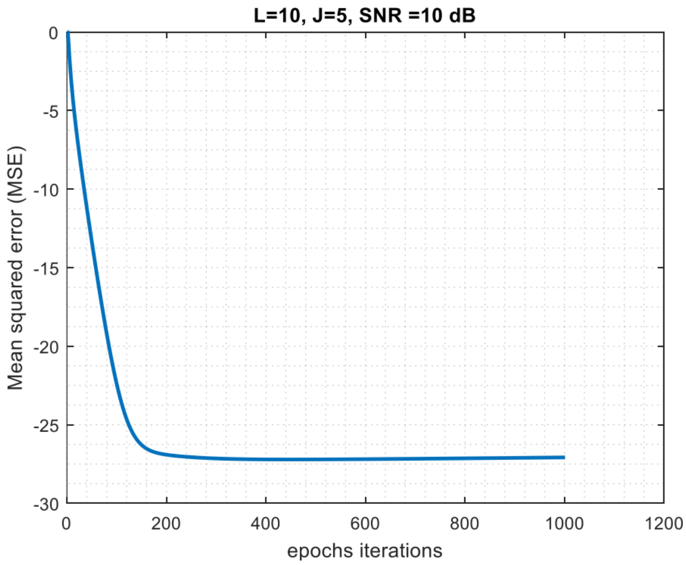


Fig. 7. Error diagram of MSE in terms of the number of iterations in the proposed algorithm.

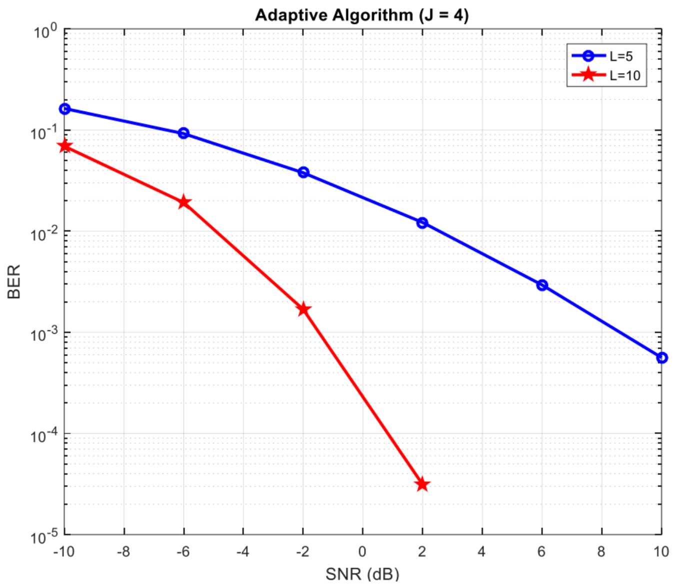


Fig. 8. The error probability in terms of SNR, for the number of $L = 5{,}10$ from the linear array of receiver antennas.

considered 10 dB. The channel model is considered Rayleigh fading and we also assume that the transmitted signal has BPSK modulation. Therefore, after sending the signal and estimating the input angle and beamforming, the vector of the receiving symbols is entered in LMS adaptive algorithm, and the weights are updated at each step. The average squares error (SME) is calculated per iteration of the algorithm. The number of this iteration is 1000 and the step factor of the algorithm is considered μ=0.0001. As can be seen, by increasing the number of iterations, the algorithm convergences and obtains the minimum error MSE error.

Fig. 8 shows the error probability vs. SNRs for different values of receiver antennas in the linear arrays. Assuming the number of users is 4, the figure is drawn for two cases of $L = 5, 10$. As can be seen, as the number of receiver antennas increases, the error probability decreases.

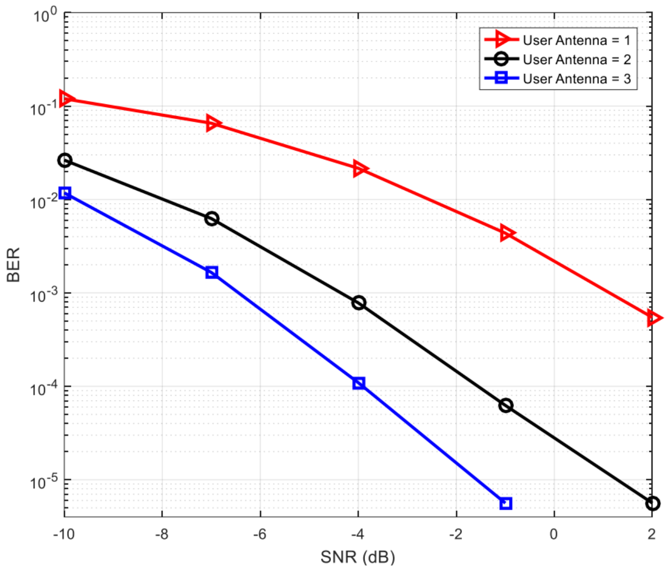


Fig. 9. BER in terms of SNR dB, for the number of antennas of the desired Transmitter user 1, 2 and 3.

Fig. 9 compares the error probability for the main user with the number of antennas 1, 2, and 3. The total number of users and received antenna is $J = 2$ and $L = 4$. In this simulation, BPSK modulation and the Rice channel model are considered. The proposed method is used to control the interference and the combine the received signals at the receiver using maximum ratio combining. The transmitter antennas send the same signal, therefore, as expected, increasing the number of transmitter antennas decreases the error probability.

In the adaptive algorithm, according to the block diagram of Fig. 4, the received signal is divided into two stages of estimating the beam angle using the MUSIC algorithm and updating the weights of the adaptive LMS algorithm. Finally, the desired signal is obtained by multiplying the weights optimized by the algorithm with a number of 1000 repetitions and a step factor of $\mu = 0.01$. The output signal with optimal weights is given by:

$$Y_{J\times 1} = W_{opt}X_{L\times N}. \tag{38}$$

To calculate the error probability per 500 repetitions, these procedures are repeated for all three methods. In each iteration, for a specific SNR, the detected signal at the receiver compares with the transmitted signal at the source, then, the error probability is obtained. Fig. 10 compares the error probability of the proposed algorithm, which includes a combination of GSC beamforming and LMS algorithm with the conventional LMS method. The simulation was performed under the same conditions with 4 receiving antennas and 2 receiving antennas, Rice channel model, and BPSK modulation. The results show the performance of the proposed algorithm is improved by adding the received beamforming to eliminate interference with the LMS algorithm.

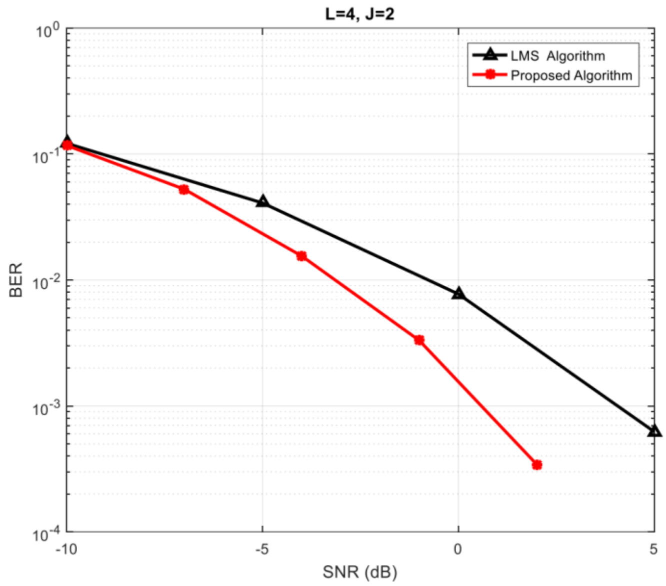


Fig. 10. Comparison of the error probability of LMS algorithm with the proposed Adaptation algorithm in terms of SNR.

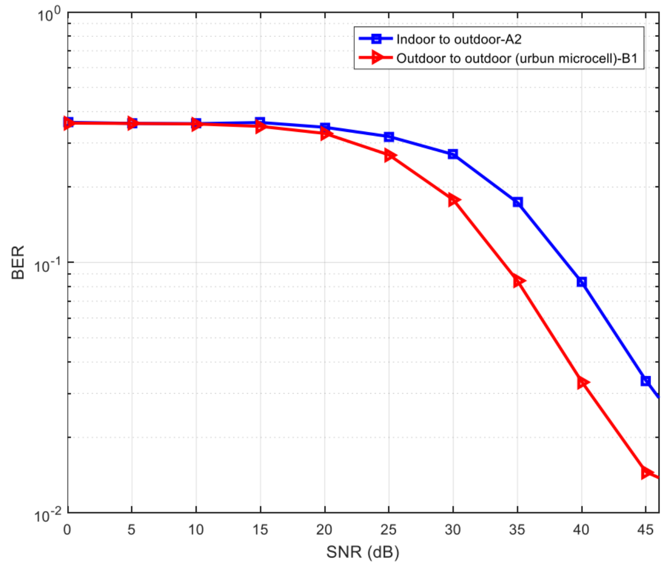


Fig. 11. Error probability based on SNR for two scenarios of the proposed algorithm by transmitting from indoor and outdoor environment.

Fig. 11 compares the error probability in the internal and external scenarios. This scenario is affected by the winner channel, which was introduced in the previous section. The parameters related to the transmission scenario from the indoor to the outdoor environment (A2 scenario at [20]) and transmission scenario from the outdoor to the outdoor environment in an urban region, for a distance of 500 meters between the transmitter and the receiver is considered. For a distance of 500 meters between the transmitter and the receiver in the indoor scenario, this distance is 100 meters indoors (from the transmitter to the wall of a building) and another 400 meters in the outdoor environment (from the wall to the receiver). In this simulation, the number of transmitter users is 2 and the number of the received linear array antennas is 4. The number of iterations to calculate the error probability is 700, also at the weight optimization algorithm, the number of repetitions of the 1000 and the step factor is 0.0001. The error probability results for both scenarios show that transmitting from the internal environment reduces the system performance. This is due to the user in the building environment, compared to the user in the outdoor environment, facing obstacles and losses caused by the walls and the building.

A. Comparison of the Proposed Adaptive Algorithm with the interference cancellation methods

1) Zero forcing (ZF) beamforming method

In ZF signal detection, the interference is canceled out by the weightW_{ZF} [22], [23], which is

$$W_{ZF} = (H^T H)^{-1} H^T. \quad (39)$$

In the next section, we use the ZF method to cancel the interference in the receiver.

1) Minimum mean square error (MMSE) beamforming method

In MMSE signal detection, the interference is reduced by improving the SINR, with W_{MMSE} weighting matrix that defined as follows:

$$W_{MMSE} = (H^H H + \frac{1}{SINR} I_k)^{-1} H^T. \quad (40)$$

In the received signal, multiplying the weight matrix MMSE and generates new noise [24], [25].

2) Comparison of MMSE, ZF methods and adaptive algorithm

Fig. 12 compares the proposed beamforming adaptive algorithm with the beamforming processing methods including ZF and MMSE matrix. Fig. 12 shows the error probability vs. SNRs. As mentioned in the previous section, in the ZF and MMSE methods the received signal is multiplied by the W_{ZF} and W_{MMSE} matrix. This eliminates the effect of the channel on the received signal as an equalizer.

By detecting the vector of the received signal from the resulting matrix, the desired signal is obtained and separated from the interference signals

$$Y_{ZF}(J \times N) = W_{ZF}(J \times L) X_{L \times N}, \quad (41)$$

$$Y_{MMSE}(J \times N) = W_{MMSE}(J \times L) X_{L \times N}. \quad (42)$$

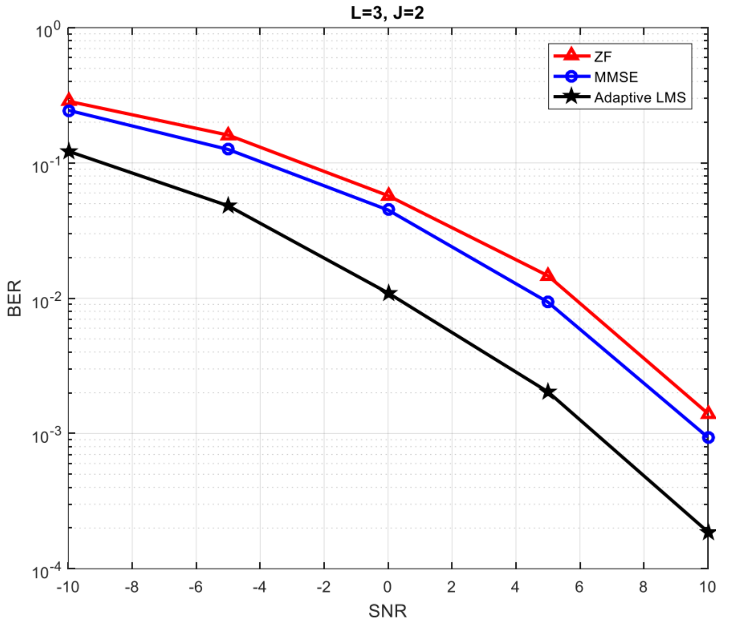


Fig. 12. Comparison the error probability based on SNR for the proposed LMS adaptive Algorithm with ZF and MMSE beamforming methods.

Therefore, the resulting matrices after passing the ZF and MMSE equalizers, include *J* vector of size *N* belonging to the *J* of transmit user. By separating the first line of theinterest user, the desired signal is detected.

B. Algorithm Complexity

Fig. 13 shows the complexity of the algorithm. This complexity is calculated by simulating the desired system in MATLAB software and calculating the number of FLOPS when running the algorithm. As mentioned, the proposed algorithm has the complexity to improve performance and reduce the error probability compared to existing methods.

The following results are obtained by comparing the proposed GSC-LMS algorithm with the adaptive LMS algorithm method and the MMSE optimal beamforming method:

The complexity of the system here is greater than in the MMSE approach, and this price improves the quality of the system to reduce the error probability. This is due to the use of the iteration method in adaptive algorithms that both LMS and GSC-LMS algorithms need this iteration due to their compatibility. As can be seen from the curves, increasing the number of the receiver antennas reduces the error probability as well as increases complexity computational.

Fig. 13 shows that the proposed LMS and GSC-LMS algorithms do not differ much in system complexity, while the performance of the proposed algorithm is better than the conventional LMS method and achieves a lower error probability. Then, substituting the proposed method with the LMS method, which is very practical and implementable in practice, leads to better performance.

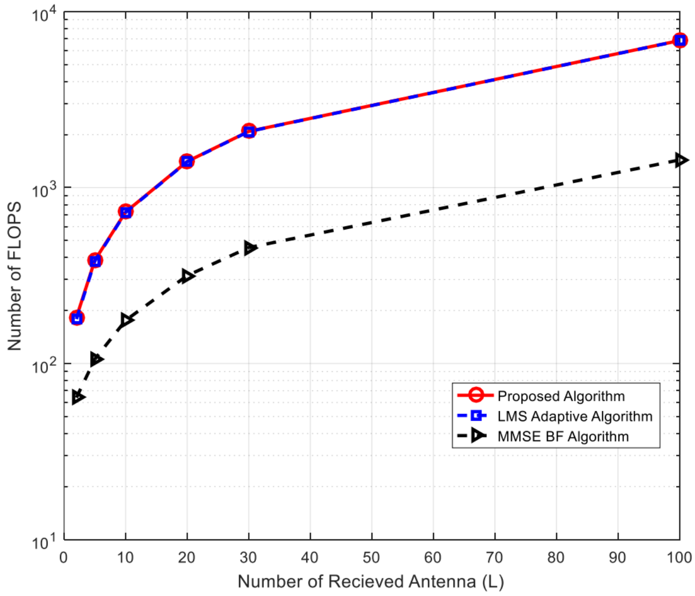


Fig. 13. Comparison of computational complexity of the algorithm (per number of FLLOP) Vs the number of receiving antennas for the proposed LMS and MMSE algorithm.

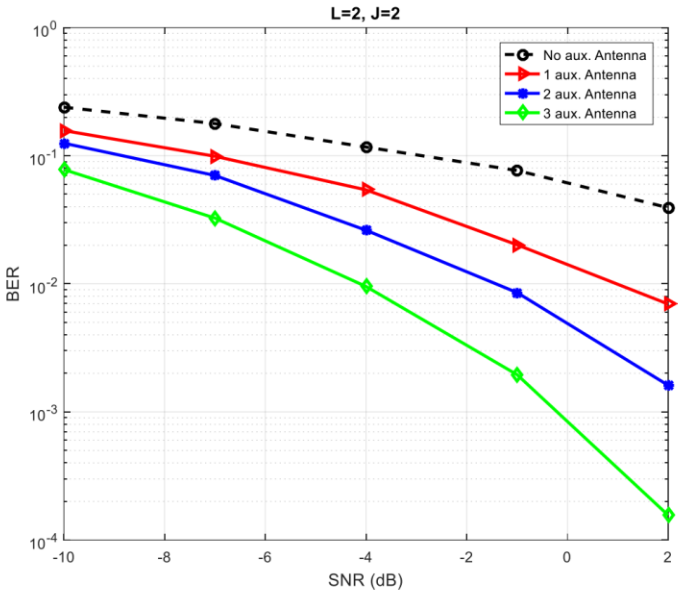


Fig. 14. Comparison of the error probability in terms of SNR and investigating the effect of the number of auxiliary antennas on receiver 1,2,3.

Without increasing complexity, eliminating interference in MIMO systems. Simulations are performed to compare the algorithms under the same conditions and similar system models. Also, the number of iterations and steps of adaptive algorithms are considered equal.

Fig. 14 shows the error probability of the proposed algorithm for two receiver antennas and two transmitter users compared to the use of auxiliary antennas. As you can see, with increasing the number of auxiliary antennas, the error probability improved. We assume that the channel model is Rayleigh fading and the interfering power is half the desired transmitter power, we also use the BPSK modulation. The linear array of auxiliary antennas is in the form of the arrangement discussed in the previous section, and the distance between two antennas is $d = 2\lambda$, which $\frac{\lambda}{2}$ is the minimum distance of auxiliary antennas.

We calculate the number of multiplications for the proposed algorithms as follow: The proposed method consists of three stages 1) applying MUSIC algorithm, 2) using GSC beamforming, and 3) using LMS algorithm. Hence, the total number of multiplications is summing of these three steps. To obtain the estimates of the signal and noise subspaces, the MUSIC algorithm requires an eigen decomposition of $\hat{R}$ and a spectral search. Therefore, Number of multiplications for MUSIC with L antennas and K space search points is [26]:

$$\frac{16}{3}L^3 + (K + \frac{L}{2})L(L+1). \tag{43}$$

The number multiplications for GSC beamforming are equal to L^2. The complexity of LMS algorithm for a vector of size L per iteration is equal to $2L$, and for P iteration is $2LP$ [27]. Therefore, the Total number of multiplications for the proposed algorithm are equal to

$$\frac{16}{3}L^3 + \left(K + \frac{L}{2}\right)L(L+1) + L^2 + 2\mathrm{L}P. \tag{44}$$

VI. CONCLUSION

In this paper, we proposed an adaptive algorithm to eliminate the interference using beamforming in a multi-user MIMO system. We also investigated the algorithm in indoor and outdoor environments using the Wiener model, with direct and indirect channels using the Rayleigh and Rice fading models and calculated the error probability in different conditions. We used the auxiliary antennas and linear array of the antennas in the receiver and confirmed the resulting performance improvement in the proposed algorithm. In the simulation results, the proposed algorithm was compared with the LMS adaptive algorithm method, and we showed its performance improvement in the figures. We also compared the adaptive beam-forming proposed method with the ZF and MMSE processing beamforming methods in terms of the error probability and complexity performance. We showed that our proposed algorithm achieves better performance with increasing complexity and achieves better performance compared to the LMS algorithm without increasing complexity.

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