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Performance Analysis of Intelligent Bio Inspired Computing For Efficient Estimation of Channel Coefficients in MIMO System

Wasiq Ali*, Yaan Li*, Jiao Zhang, Yuxing Li
SchoolofMarineScienceandTechnology,NorthwesternPolytechnicalUniversity,P.OBox24,127West Youyi Road, Xi'an, 710072, shaanxi, China.
*Corresponding Author: Wasiq Ali**

Abstract: *In this paper an intelligent bio inspired computation mechanism is explored for efficient estimation of channel coefficients in MIMO system. In this intelligent bio inspired scheme, Genetic Algorithm (GA) is applied as a global optimizer to estimate the channel coefficients in MIMO network. Intelligent bio inspired computing is done for equal number of antennas at transmitter and receiver end making a square channel matrix. Rayleigh fading channel is used in this research work for checking the trend of received signal for channel matrix of 3×3 and 4×4 order. Two scenarios of measured noise are taken for better projection of results. Mean Square Error (MSE) based fitness function is designed for evaluating the true response with the estimated one. This function is intelligent enough to find the best solution with only one sample. Reliability, performance and effectiveness of the genetic algorithm is tested on the bases of accuracy, convergence and computational complexity analysis using statistical operators. Enough number of independent Monte-Carlo runs are applied for comprehensive statistical analysis of the proposed technique.*

Keywords: *Intelligent bio inspired computing, channel estimation, genetic algorithm, Rayleigh fading channel, computational complexity*

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I. Introduction

In the past few years a lot of efforts have been done on Multiple Input Multiple Output (MIMO) technology to boost the channel capacity, which directly effect the service quality of the overall communication network [1]. By means of multiple antennas at transmitter as well as receiver end a MIMO scheme acheives higher data rate, larger coverage, better link robustness and spatial diversity without increasing total bandwidth or transmission energy [2]. However, for decoding and data detection at receiver end, the MIMO system heavily depends upon the factor of Channel State Information (CSI) [3][4]. It has been verified that MIMO system shows better performance by increasing number of array elements at transmitter or receiver end, when the channel is flat fading and exactly known to the receiver [5]. Channel estimation is one of the most noticeable factor in any type of communication system [6]. Numerous channel estimation methods have already been established for MIMO systems. These methods are generally classified into three major classes: (1) training-based method, (2) blind method, and (3) semiblind method, which is a combination of the first two methods [7,8]. Estimation of channels coefficient is hard optimization problems, therefore, one has to exploit the strength of intelligent bio-inspired computing platform in this domain. Genetic Algorithm (GA) is one of the prominent technique for solving hard practical optimization problems in the domain of bioinspired computing [9]. First particle implementation studies of GA belongs to professor John Holland of University of Michigan USA during early 70's of last century [10]. Due to its effectiveness GA is considered to be one of the best algorithm in the class of bio inspired algorithms[11]. GA is developed on mathematical modelling of natural biological evolution processes [12]. Research community inspired by GA due to its resemblance with usual behaviors predicted in life at the level of complexity, which assumed that life could have evolved in shorter span of time against the records of the fossil fuels [13]. Due to these fact, optimization techniques based on GA are used to solve complex and practical problems viably, accurately and robustly[14]. GA is a computational search algorithm to determine optimal solutions in a massive solution space, inspired by biological evolution of species [15]. In channel estimation the basic aim is to decrease the Euclidean margin between the estimated and the desired channel coefficients, so it can be considered as a problem of optimization. A perfect channel estimation algorithm should miminize the Euclidean distance in MIMO channel [16]. The straight forward answer of this complex issue is inversion of channel matrix and this involves the famous Minimum Mean square Error (MMSE) and Least Squares (LS) estimation methods [17]. Intelligent computing algorithms like Genetic Algorithm (GA) [18][19] and Particle Swarm Optimization (PSO) [20] [21], are of low-complexity and provide better solution for channel estimation in MIMO. Genetic algorithm has the advantages of significantly less computational complexity, greater robustness and is closer to the optimal solution. GA is not new to the application of channel estimation in MIMO. In literature it is used for channel estimation with different approaches [22][23]. In [24] GA is combined with PSO for channel estimation in MIMO-OFDM system. It is also explored for MIMO channel estimation by using the technique of blind channel estimation based upon spectral factorization [25]. In [26], GA is used just for refinement of resulting channel model; however, it shows inaccurate channel model because blind channel estimation model is applied. Despite that GA finds applications in channel estimation, the prime issue is initialization of algorithm which has not been focused largly. Our work gets motivated by the results obtained from these discussed works and we put effort to improve the estimation of channel matrix by using conventional MSE channel estimation method.

Now the research question is to find out optimized channel coefficients for the MIMO system. The primary goal of this research work is to evaluate the mean squared error (MSE) based applicability of intelligent bio inspired computing for efficient estimation of channel co-efficients in MIMO system. In bio inspired computing GA algorithm is exploited as optimization mechanism in Rayleigh fading channel. Two scenarios are created like channel estimation in Rayleigh fading channel without measurment noise and with 20 db noise.In each scenario two cases for channel estimation are developed by taking channel matrix of order 3×3 and 4×4. In every scenario accuracy, convergence and computational complexity of the algorithim is analyzed by using statistical operators. This paper is arranged as follows. In section 2 governing equations for MIMO signal model are developed. Section 3 explores the idea of genetic algorithm methodology. Discussion and results are explained in section 4. The final section reveals the main contribution of this study.

II. Mimo Signal Model

Let us consider a MIMO system comprising $N_T$transmitting and $N_R$receiving antennas. The signal $X_i(k)$ is transmitted at time instant k by i^{th}antenna can be written as:

$$\mathbf{X}_i(k) = [\mathrm{x}_1(k),\ \mathrm{x}_2(k), ...,\ \mathrm{x}_{N_T}(k)]^T \tag{1}$$

All the transmitted signals are given in vector form with length equal to N_T, while $(.)^T$ is representing transpose operation. Impulse response of channel $\varphi_{ji}(k)$ having length L+1 between single transmitting antenna i and single receiving antenna j which can communicate with each other. For a conventional complex Single Input Single Output (SISO) network, its shown in vector form as follows:

$$\varphi_{ji}(k) = [\varphi_{ji}(0), \varphi_{ji}(1), ... ,\ \varphi_{ji}(L)]^T \tag{2}$$

Similarly, the MIMO system is shown in complex channel matrix of length L+1 having dimension $N_R \times N_T$ is given below:

$$\boldsymbol{\varphi}(k) = \begin{bmatrix} \varphi_{11}(k) & \cdots & \varphi_{1N_T}(k) \\ \vdots & \ddots & \vdots \\ \varphi_{N_R 1}(k) & \cdots & \varphi_{N_R N_T}(k) \end{bmatrix} \tag{3}$$

Where k=0,…,L. Meanwhile the received signal at time instant k by j^{th}antenna is represented by $z_j(k)$. All the received signals at receiving antenna N_R are given in vector of length N_R as:

$$\mathbf{Z}_j(k) = [\mathrm{z}_1(k), \mathrm{z}_2(k), ..., \mathrm{z}_{N_R}(k)]^T \tag{4}$$

If noise is added which is normally supposed to be additive white Gaussian noise (AWGN) with zero mean and unit variance, then updated form of received signal at antenna j is given as:

$$\mathbf{Z}_j = [\mathrm{x}_1\ , ...,\ \mathrm{x}_{N_T}] \begin{bmatrix} \varphi_{j1} \\ \vdots \\ \varphi_{jN_T} \end{bmatrix} + \upsilon \tag{5}$$

Addition of AWGN noise is represented by υ. Moreover, for noise the spatial correlation matrix is defined by the following relation:

$$\mathrm{Q}_{jj} = E\left[\upsilon(k)\upsilon^H(k)\right] = \sigma_j^2 I_{N_R} \tag{6}$$

In above relationship I represent the identity matrix and a symbol $(.)^H$ is the representation of complex conjugate (Hermitian) transpose. The overall row matrix of input signals is given as:

$$\mathbf{X} = [\mathrm{x}_1, \mathrm{x}_2, ..., \mathrm{x}_{N_T}] \tag{7}$$

While the impulse response of channel is given as:

$$\boldsymbol{\varphi}_{ji} = [\varphi_{j1}^T, \varphi_{j2}^T, ..., \varphi_{jN_T}^T]^T \tag{8}$$

Above channel matrix is of the length N_T (L+1) encloses the elements of the channel impulse reactions $\varphi_{ji}(k)$ where k=0,….,L among all transmit antennas and the j^{th}receive antenna. All elements of the channel impulse responses called channel coefficients $\varphi_{ji}(k)$ where k=0,….,L that have to be estimated. The overall receive vector $\mathbf{Z}_j$ at the MIMO receiver follows the computation of transmitted signal, channel matrix and addition of noise, given as:

$$\mathbf{Z}_j = \mathbf{X}\boldsymbol{\varphi}_j + \upsilon \tag{9}$$

Governing mathematical relations in case of estimation of channels coefficient in MIMO network, the model (3) based on transmitting antennas N_T and receiving antennas N_R, for received signal$z_j(k)$ is given as follows:

$$\mathrm{z}_j(k) = \sum_{i=1}^{N_T} \varphi_{ji}(k)\mathrm{x}_{i(k)} + \upsilon_j(k),\ \ j = 1,\ 2,...,N_r \tag{10}$$

In case of each symbol time slot (STS), above equation is given as:

$$\mathrm{z}_j = \sum_{i=1}^{N_T} \varphi_{ji}\mathrm{x}_i + \upsilon_j,\ \ \ j = 1,\ 2,...,N_r \tag{11}$$

The generic equation of channel estimation model (9) without noise, i.e., υ = 0 is given below:

$$\mathrm{z}_j = \sum_{i=1}^{j} \varphi_{ji}\mathrm{x}_i \tag{12}$$

Similarly estimated channel model by taking the adaptive channel coefficient matrix $\hat{\varphi}_{ji}$ of the MIMO system based on N_T and N_R transmitting and receiving antennas can be written as:

$$\hat{\mathrm{z}}_j = \sum_{i=1}^{j} \hat{\varphi}_{ji}\mathrm{x}_i \tag{13}$$

Where $\hat{z}_j$ is the estimated received signal obtained. In order to estimate the coefficients of channel by intelligent hybrid computing technique a fitness error function based upon mean square sense is given as:

$$\xi = \left|\mathrm{z}_j - \hat{\mathrm{z}}_j\right|^2 \tag{14}$$

By using equation (12) and (13), the fitness function (14) for each STS in updated form is given below:

$$\xi = \frac{1}{N_T N_R}\sum_{i=1}^{N_T}\left|\sum_{j=1}^{N_R}\varphi_{ji}\mathrm{x}_i - \sum_{j=1}^{N_R}\hat{\varphi}_{ji}\mathrm{x}_i\right|^2 \tag{15}$$

Similarly, the fitness function of MIMO system by consideration of the noise υ for each STS is given below:

$$\xi = \frac{1}{N_T N_R}\sum_{i=1}^{N_T}\left|\left(\sum_{j=1}^{N_R}\varphi_{ji}\mathrm{x}_i + \upsilon_j\right) - \left(\sum_{j=1}^{N_R}\hat{\varphi}_{ji}\mathrm{x}_i + \upsilon_j\right)\right|^2 \tag{16}$$

With the availability of appropriate adaptive weights of $\hat{\varphi}_{ji}$ such that $\zeta \rightarrow 0$ then the approximate received signal approaches the desire signal, i.e., $\hat{z}_j \rightarrow z_j$and consequently channel coefficients are estimated, i.e., $\hat{\varphi}_{ji} \rightarrow \varphi_{ji}$.

III. Methodology of Genetic Algorithm

In this section, simulation studies are conducted for intelligent bio inspired computing algorithm using well known software package of optimization techniques. This package is based on GA in MATLAB environment by invoking its built-in functions. MATLAB optimization toolbox is used for GA with settings of program 'GA' and tool 'gaoptimset' is used with setting of parameters as listed in Table 1.

Table 1: Setting of parameters for GA

Parameters	Setting	Parameters	Setting
Generations	1000	Creation Function	@gacreationuniform
Tolerance Function	10^{-15}	Mutation Function	@mutationadaptfeasible
Stall Generation	100	Crossover Function	@crossoverheuristic
Tolerance Constraints	10^{-15}	Selection Function	@selectionstochunif
Fitness Limit	10^{-15}	Population Size	40
Population Range	[0;1]	Elite Count	4
Variables	16	Others	Defaults

The standard working of GA is given in Fig. 1, while one set of working of its operators, i.e., selection, mutation,
crossover, elitism etc., is shown in Fig. 2.

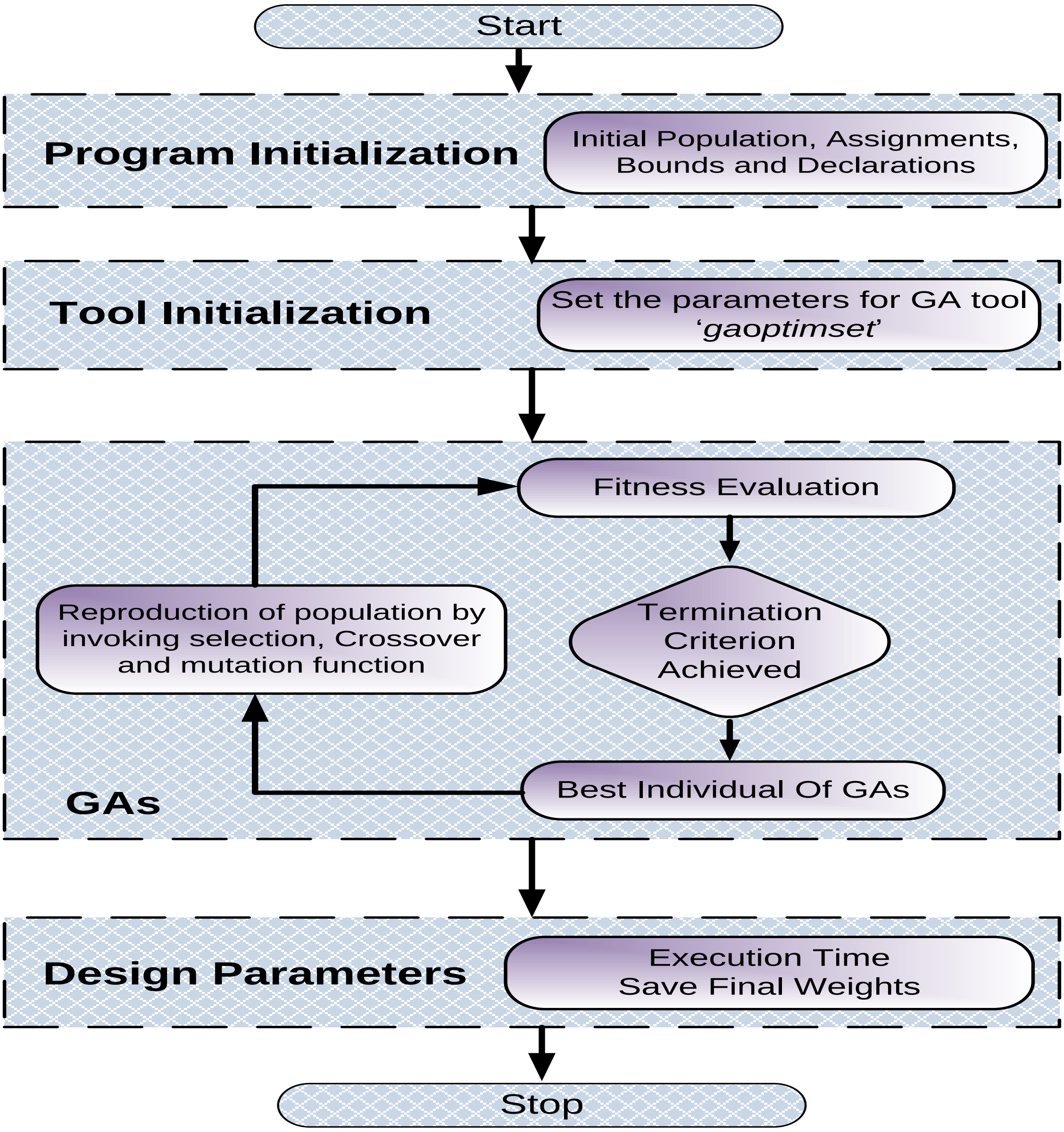


Figure 1: GA standard working flow

Steps for intelligent bio inspired methodology based upon GA are given below:

Step 1: GA parameters initialization:

The initial population of GA is created with a set of chromosomes which are randomly generated with real values having genes equal to number of channels coefficient in MIMO system. Initialize the parameter of GA program using function 'gaoptimset' with setting as given in Table1.

Step 2: Fitness Evaluation:

Calculates fitness value for each chromosome of population using equation (14) and its constitution parts as given in equations (15) and (16).

Step 3: Termination Criteria:

Predefined values of GA program are set for termination of algorithm as:

- The fitness limits are achieved, e.g., fitness limit is less than or equal to 10^{-15}
- Total number of generations are executed, i.e., generation/iteration value is equal to 1000

If termination criterion attained then advance to step 5, else continues.

Step 4: Reproduction:

Updated population creates next generation by using reproduction operators that are crossover, mutation and selection mentioned in table 1.

Step 5: Storage: For GA save all the values of fitness, execution time, maximum generation, and best individualfor evaluating the performance of the algorithm.
Step 6: Statistical Analysis: Repeat all of the procedure from step 1 to step 6 for large number of independent runs of GA to get data for realistic statistical analysis.

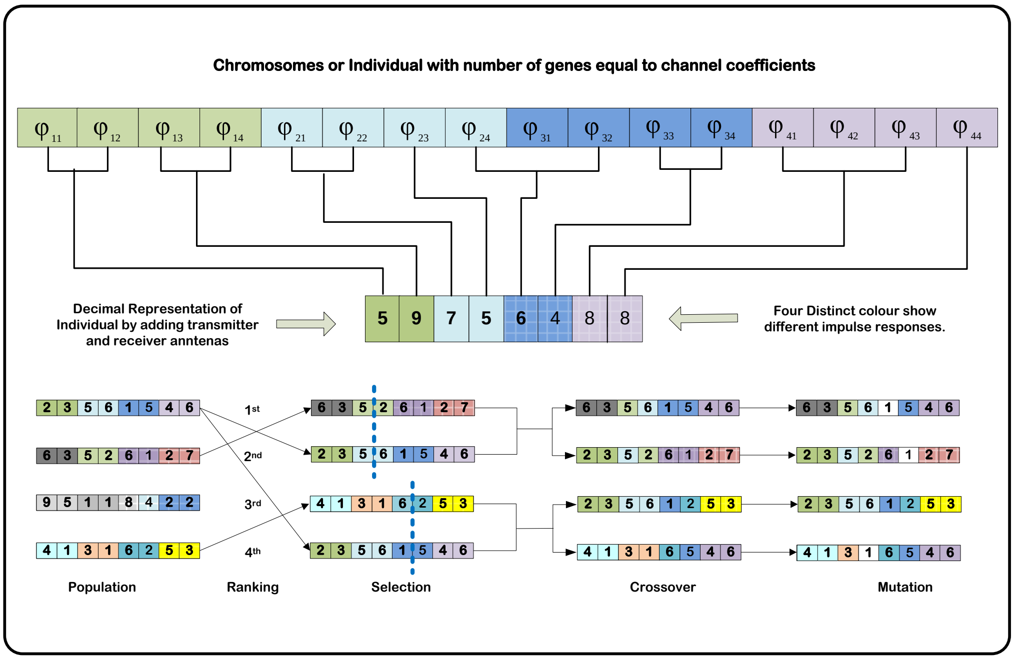


Figure 2: Working of GA operator

IV. Simulation Results And Discussion

Results of intelligent bio inspired computing approach for efficient estimation of channel co-efficients in MIMO network are discussed in this part of study. For better projection of results we make 2 scenarios and in every scenario there are two cases.

4.1 Scenario 1: Channel Estimation without Measurment Noise

In this scenario, relatively easy model of channel coefficient estimation for MIMO network as given in (9) is taken by ignoring the effect of measurment noise. For each STS the governing expression for this case is written as:

$$\mathbf{Z}_j = \mathbf{X}\boldsymbol{\varphi}_j \tag{17}$$

The two cases of the problem are taken for the studies as:

4.1.1 Case 1: Transmitting antennas $N_T = 3$ and receiving antennas $N_T = 3$

For case 1 the signal matrix **X**is of order 3×1 and channel matrix **φ** is of order 3×3 and receiving signal is passing through Rayleigh fading channel without considering measurment noise. For this cases, the channel estimation parameters are taken as follows:

$$\mathbf{X} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}^T \quad \boldsymbol{\varphi} = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} \\ \varphi_{31} & \varphi_{32} & \varphi_{33} \end{bmatrix} \tag{18}$$

The general equation of channel estimation presented in model (11) for only taking the single snap shot k=1 given below with its fitness evaluation function:

$$z_1 = \sum_{i=1}^{3} \varphi_{1i} x_i \ , \ z_2 = \sum_{i=1}^{3} \varphi_{2i} x_i , \ z_3 = \sum_{i=1}^{3} \varphi_{3i} x_i$$
$$\xi = \frac{1}{18} \sum_{i=1}^{3} \left| \sum_{j=1}^{3} \varphi_{ji} x_i - \sum_{j=1}^{3} \hat{\varphi}_{ji} x_i \right|^2 \tag{19}$$

4.1.2 Case 2: Transmitting antennas $N_T = 4$ and receiving antennas $N_T = 4$

For case 2 the signal matrix **X**is of order 4×1 and channel matrix **φ** is of order 4×4 and receiving signal is passing through Rayleigh fading channel. For this cases, the channel estimation parameters are taken as follows:

$$\mathbf{X}=\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}^T \quad \boldsymbol{\varphi}=\begin{bmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} & \varphi_{14} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} & \varphi_{24} \\ \varphi_{31} & \varphi_{32} & \varphi_{33} & \varphi_{34} \\ \varphi_{41} & \varphi_{42} & \varphi_{43} & \varphi_{44} \end{bmatrix} \qquad (20)$$

The general equation of channel estimationpresented in model (11) for only taking the single snap shot k=1 given below with its fitness evaluation function:

$$z_1=\sum_{i=1}^{4}\varphi_{1i}x_i\ ,\ z_2=\sum_{i=1}^{4}\varphi_{2i}x_i\ ,\ z_3=\sum_{i=1}^{4}\varphi_{3i}x_i\ ,\ z_4=\sum_{i=1}^{4}\varphi_{4i}x_i$$

$$\xi=\frac{1}{32}\sum_{i=1}^{4}\left|\sum_{j=1}^{4}\varphi_{ji}x_i-\sum_{j=1}^{4}\varphi_{ji}x_i\right|^2 \qquad (21)$$

4.1.3 Accuracy and convergence analysis for scenario 1

The proposed mechanismof GA algorithm is applied for attaining the efficient channel coefficients as per procedure for hundred independent runs. The values of MSE are plotted against number of independent Monte Carlo runs for case 1 and case 2 in Fig. 3 on semi-logarithmic scale. The results for the best run of the algorithm, a run with minimum MSE value, mean and standard deviation values of MSE are presented in Table 2 for both cases. It is seen from Table 2 that best, mean and standard deviation values of GA for case 1 are around 10^{-09} to 10^{-10}, whereas for case 2 accuracy of the results is around 10^{-07} to 10^{-08} respectively which is clearly evident for effectiveness of proposed scheme. The MSE for case 2 is little lower because of more channel matrix coefficients.

Table 2: Fitness values achieved by the algorithm for both cases in scenario 1without noise

Mode	Case 1 Mean Square Error	Case 2 Mean Square Error
Best	0.578E-10	1.279E-08
Mean	6.255E-09	5.793E-07
Standard Deviation	1.240E-09	2.369E-07

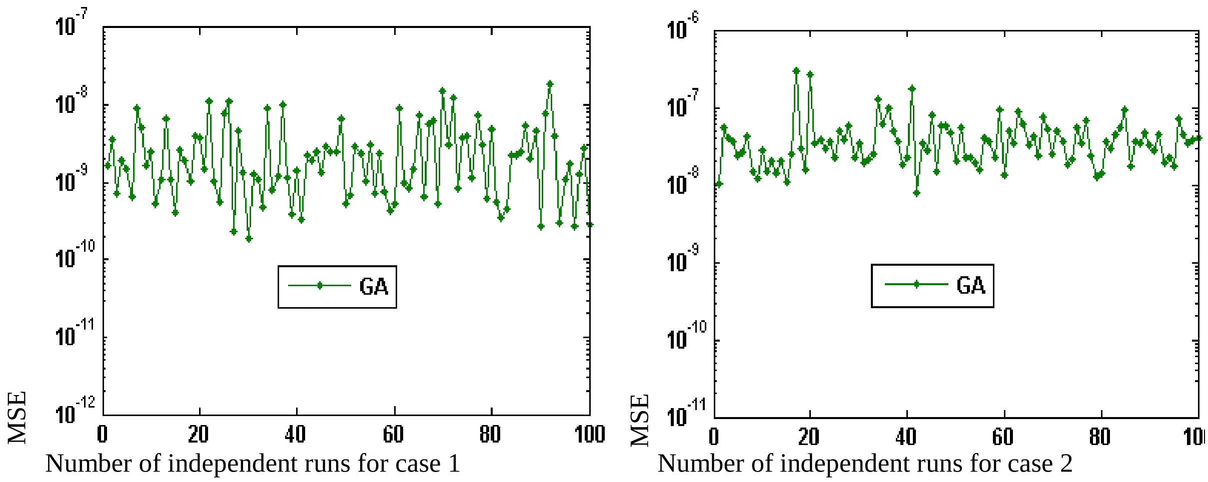


Figure 3: GA accuracy result for 3×3 and 4×4 channel matrix estimation in scenario 1 without noise

From above results it is quite clear that for both cases GA is performing very well for effiecient estimation of channel co-efficients in MIMO. In comparison case 1 have much better results from case 2 because of less computational complexity.

4.1.4 Computational Complexity Analysis for scenario 1

Computational complexity analysis is an important feature of any algorithm to show its effectiveness with respect to time. Here computational complexity analysis of GA optimization algorithm is carried out using different complexity operators based on mean execution time (MET), mean generations (MGs), and mean function evaluations (MFEs). Values of MET, MGs and MFEs calculated for 100 independent runs of the algorithms are given in Table 3 for both cases. It is found that the respective values of METs, MGs and MFEs are around 40±20 second(s),650±300 second(s),2500±1500second(s). Case 2 takes little longer to optimized the parameter from case 1 due to the fact that it has more coefficients to estimate. Simulation studies performed in this study on Haier Laptop with Intel (R) Core (TM) i3-4010U CPU@ 1.70GHz Processor, 4.00 GB RAM running MATLAB 2017a in Windows 8.1 Professional environment.

Table 3: Computational complexity of GA for both cases in scenario 1without noise

Complexity Measures		**Scenario 1**	
		Case-1	**Case-2**
MET	**Values**	35.56	55.61
	STD	20.70	33.09
MG	**Values**	574.54	976.53
	STD	423.58	720.59
MFEs	**Values**	2502.0	3910.0
	STD	1603.72	2103.15

4.2 Scenario 2: Channel Estimation with 20db Measurment Noise

In this scenario, a complex model of channel coefficient estimation for MIMO network as given in (9) is taken by addingmeasurment noise of 20 db. For each STS the governing expression is written as:

$$\mathbf{Z}_j = \mathbf{X}\boldsymbol{\varphi}_j + \upsilon \tag{22}$$

The two cases of the problem are taken for the studies as:

4.2.1 Case 1: Transmitting antennas $N_T = 3$ and receiving antennas $N_T = 3$

In this case the signal matrix **X**is of order 3×1 and channel matrix **φ** is of order 3×3 and receiving signal is passing through Rayleigh fading channel with 20db measurment noise. For this cases, the channel estimation parameters are taken as follows:

$$\mathbf{X} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}^T \quad \boldsymbol{\varphi} = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} \\ \varphi_{31} & \varphi_{32} & \varphi_{33} \end{bmatrix} \tag{23}$$

The general equation of channel estimation presented in model (11) for only taking the single snap shot k=1 given below with its fitness evaluation function:

$$z_1 = \sum_{i=1}^{3} \varphi_{1i} x_i + \upsilon, \quad z_2 = \sum_{i=1}^{3} \varphi_{2i} x_i + \upsilon, \quad z_3 = \sum_{i=1}^{3} \varphi_{3i} x_i + \upsilon$$

$$\xi = \frac{1}{18} \sum_{i=1}^{3} \left| \left(\sum_{j=1}^{3} \varphi_{ji} x_i + \upsilon_j \right) - \left(\sum_{j=1}^{3} \hat{\varphi}_{ji} x_i + \upsilon_j \right) \right|^2 \tag{24}$$

4.2.2 Case 2: Transmitting antennas $N_T = 4$ and receiving antennas $N_T = 4$

For case 2 the signal matrix **X**is of order 4×1 and channel matrix **φ** is of order 4×4 and receiving signal is passing through Rayleigh fading channel with 20db of measurment noise. For this cases, the channel estimation parameters are taken as follows:

$$\mathbf{X} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}^T \quad \boldsymbol{\varphi} = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} & \varphi_{14} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} & \varphi_{24} \\ \varphi_{31} & \varphi_{32} & \varphi_{33} & \varphi_{34} \\ \varphi_{41} & \varphi_{42} & \varphi_{43} & \varphi_{44} \end{bmatrix} \tag{25}$$

The general equation of channel estimation presented in model (11) for only taking the single snap shot k=1 given below with its fitness evaluation function:

$$z_1 = \sum_{i=1}^{4} \varphi_{1i} x_i + \upsilon \text{ , } z_2 = \sum_{i=1}^{4} \varphi_{2i} x_i + \upsilon \text{ , } z_3 = \sum_{i=1}^{4} \varphi_{3i} x_i + \upsilon \text{ , } z_4 = \sum_{i=1}^{4} \varphi_{4i} x_i + \upsilon$$

$$\xi = \frac{1}{32} \sum_{i=1}^{4} \left| \left(\sum_{j=1}^{4} \varphi_{ji} x_i + \upsilon_j \right) - \left(\sum_{j=1}^{4} \hat{\varphi}_{ji} x_i + \upsilon_j \right) \right|^2 \qquad (26)$$

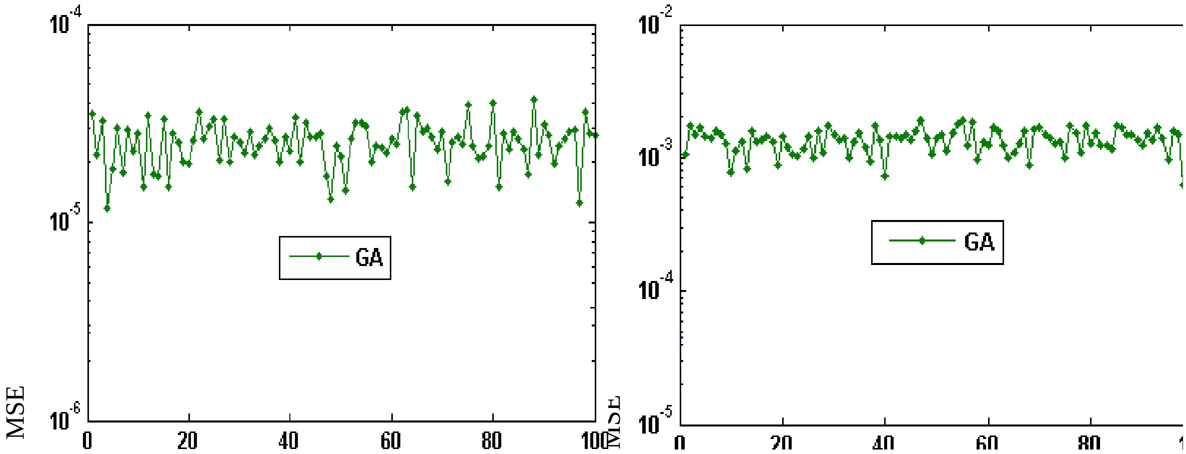
4.2.3 Accuracy and convergence analysis for scenario 2

The proposed mechanismof GA algorithm is applied for attaining the efficient channel coefficients in scenario 2 as per procedure for hundred independent runs. The values of MSE are plotted against number of independent Monte Carlo runs for case 1 and case 2 in Fig. 4 on semi-logarithmic scale. The results for the best run of the algorithm, a run with minimum MSE value, mean and standard deviation values of MSE are presented in Table 4 for both cases.

Table 4: Fitness values achieved by the algorithm for both cases in scenario 2 with 20 db noise

Mode	Case 1 Mean Square Error	Case 2 Mean Square Error
Best	1.255E-05	3.793E-03
Mean	8.736E-04	0.890E-03
Standard Deviation	5.890E-04	9.480E-02

It is seen from Table 4 that best, mean and standard deviation values of GA for case 1 are around 10^{-04} to 10^{-05} where as for case 2 accuracy of the results is around 10^{-02} to 10^{-03} respectively which is clearly evident for effectiveness of proposed scheme. The MSE for case 2 is little lower because of more channel matrix coefficients and inclusion of measurment noise.



Number of independent runs for case 1 Number of independent runs for case 2

Figure4: GA accuracy result for 3×3 and 4×4 channel matrix estimation in scenario 2 with 20db noise

From above results it is quite clear that for both cases GA is performing very well for effiecient estimation of channel co-efficients. In comparison case 1 have much better results from case 2 because of less computational complexity.

4.2.4: Computational Complexity Analysis for scenario 2

Here computational complexity analysis of GA optimization algorithm is carried out for scenario 2 using different complexity operators based on mean execution time (MET), mean generations (MGs), and mean function evaluations (MFEs). Value of MET, MGs and MFEs calculated for 100 independent runs of the algorithms is given in Table 5 for both cases. It is found that the respective values of METs, MGs and MFEs are around 200±50 second(s),850±200second(s), 3000±2000second(s). Case 2 takes little longer to optimized the parameter from case 1 due to the fact that it has more coefficients to estimate and also there is 20db measurment noise. Simulation studies performed in this study on Haier Laptop with Intel (R) Core (TM) i3-4010U CPU@ 1.70GHz Processor, 4.00 GB RAM running MATLAB 2017a in Windows 8.1 Professional environment.

Table 5: Computational complexity of GA for both cases in scenario 2 with 20db noise

Complexity Measures		**Scenario 2**	
		Case-1	**Case-2**
MET	**Values**	226.43	248.12
	STD	158.71	218.03
MG	**Values**	835.00	1030.90
	STD	650.70	935.85
MFEs	**Values**	4004.00	4900.00
	STD	2203.58	3069.20

V. Conclusion

A computational intelligent framework is developed effectively for MIMO network by exploiting the strength of optimization by intelligent bio inspired computing based on genetic algorithm. Estimation of 3×3 and 4×4 order channel coefficients matrix in MIMO system is made effectively by the proposed technique with consistent accuracy to prove the worth of the algorithm. The accuracy of GA is found superior for both scenarios as well as in both cases. It is observed that with the increase in order of channel matrix, the performance of GA for Rayleigh fading channel in terms of mean square error decrease and vice versa. In future one may explore and extend the designed scheme to solve higher order of channel matrix in linear and nonlinear MIMO networks representing complex and data intensive applications for which conventional methodologies fails. More variantions in design of GA can be made by changing initial population, generations and population range.

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