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Optimum Channel Estimation using BFO and GA in MIMO-OFDM System

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Abstract— The amalgamation of Multiple Input Multiple Output (MIMO) Orthogonal Frequency Division Multiplexing (OFDM) systems in wireless communication has always remained as one of the promising solution for improving data rate and spectral efficiency from past 10-20 years. It provides high diversity, and spatial multiplexing gain considered as their key features. The terminology used, to reduce the multipath propagation problems introduced over the channel. The effect of these problems can be evaluated from the channel for proper detection of symbols at the receiver side by performing Channel Estimation. In this analysis, the basic aim is to reduce the length of guard band until the signals get collide with each other. Then basic channel estimation techniques have been adopted such as Least Square (LS), Discrete Fourier Transform (DFT) and Minimum Mean Square Error (MSE). The results of these techniques have been further applied to two evolutionary algorithms named as Bacterial Foraging Optimization (BFO) and Genetic Algorithm (GA) that will optimize the estimation results. The performance of such algorithms has shown extreme trade-off between the performance of Bit Error Rate (BER), Mean Square Error (MSE) and Signal to Noise ratio (SNR). The entire recreation is taken place in MATLAB environment.

Index Terms— BER, BFO, DFT, GA, LS, MIMO, MSE, OFDM.

1. INTRODUCTION

From past many years, Wireless Communication has played an important role in the areas of military, environment, health and home. Due to high power sources, low complexity and high energy efficiency, development of wireless networks becomes easier [1]. The aspiring human needs to realize their dreams for achieving fast and reliable communication that could be available "anytime anywhere" have fulfilled partially with the expansion in the techniques of this field. Recently MIMO-OFDM gaining the attention of researchers in the problems of channel measurements and modeling, channel estimation, synchronization, IQ (in phase-quadrature) imbalance and PAPR (peak-to- average power ratio).To have high performance and extensive network coverage it depends on accurate channel state information. The collaboration of MIMO-OFDM systems leads to high data rate over radio links, increased throughput, extended range, better coverage and higher network capacity. Thereby reducing the probability of error results in high Signal to Noise ratio (SNR) [2]. Channel estimation plays a significant role for MIMO- OFDM systems. It is defined as the identification of channel between a pair of transmitters and receivers. Whenever the signal transmits through the channel it may suffer from several detrimental effects such as scattering, reflection and many more.

In such case, an utmost requirement is to estimate the channel impulse response as signal dispersed in time, frequency and spatial domain. For that, behavior of an unknown FIR filter whose coefficients are time-varying correlated to the channel for the estimation [2]. Iterative Least square Channel estimation algorithm has been proposed for MIMO-OFDM systems to achieve high estimation accuracy [3]. A robust and improved LS channel estimation algorithm has been suggested that employed on noise correlation to reduce the variation in estimation error. This improved version showed the noise reduction performance closely related to MMSE criteria [4].

For this reason, this proposed research work considers an innovative employment of the multi objective optimization problems. Our new algorithm allows intense trade-off between Bit Error Rate (BER), Mean Square Error (MSE) performance against Signal to Noise Ratio (SNR). Their values evaluated on the basis of GA (Genetic Algorithm) and BFO (Bacterial Foraging Optimization) Algorithm.

The paper summarized as follows: Section-II describes the problem statement on which the research work focuses upon and the respective methodology to complete the work. Section-III defines the BFO optimization algorithm for channel estimation. Section-IV and V discuss the steps to execute the BFO and GA algorithm for optimization. The experimental study and results are described in Section-VI. Finally, the paper concludes in Section-VII.

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2 Problem Formulation and Research Methodology

Channel estimation refers to checking the transmission channel for the data transfer that how much data it can send through it. As the bandwidth of the system is fixed, we need to check that if there is any way out through which the channel performance can be increased. Guard band plays a vital role in improvising the rate of transmission in the network. A guard band is the difference between two signals. It is kept to avoid collision between two signals. The problem of this paper is based on the same. There are several channel estimation techniques like LS (Least Square), MMSE (Minimum Mean Square Error) and DFT (Discrete Fourier Transform). The work explained in this paper has also put some emphasis in changing the guard band and checking its impact over the transmission rate.

The basic intention of this research work is to optimize the above-mentioned techniques using two algorithms namely BFO (Bacterial Forging Optimization) and Genetic Algorithm (GA). Then compare the algorithm results on the basis of the parameters named as Bit Error Rate and Mean Square Error against Signal to Noise ratio that computes the percentage of improvement. The research methodology is clearly explained in Figure 1 that shows the steps required to execute the proposed work.

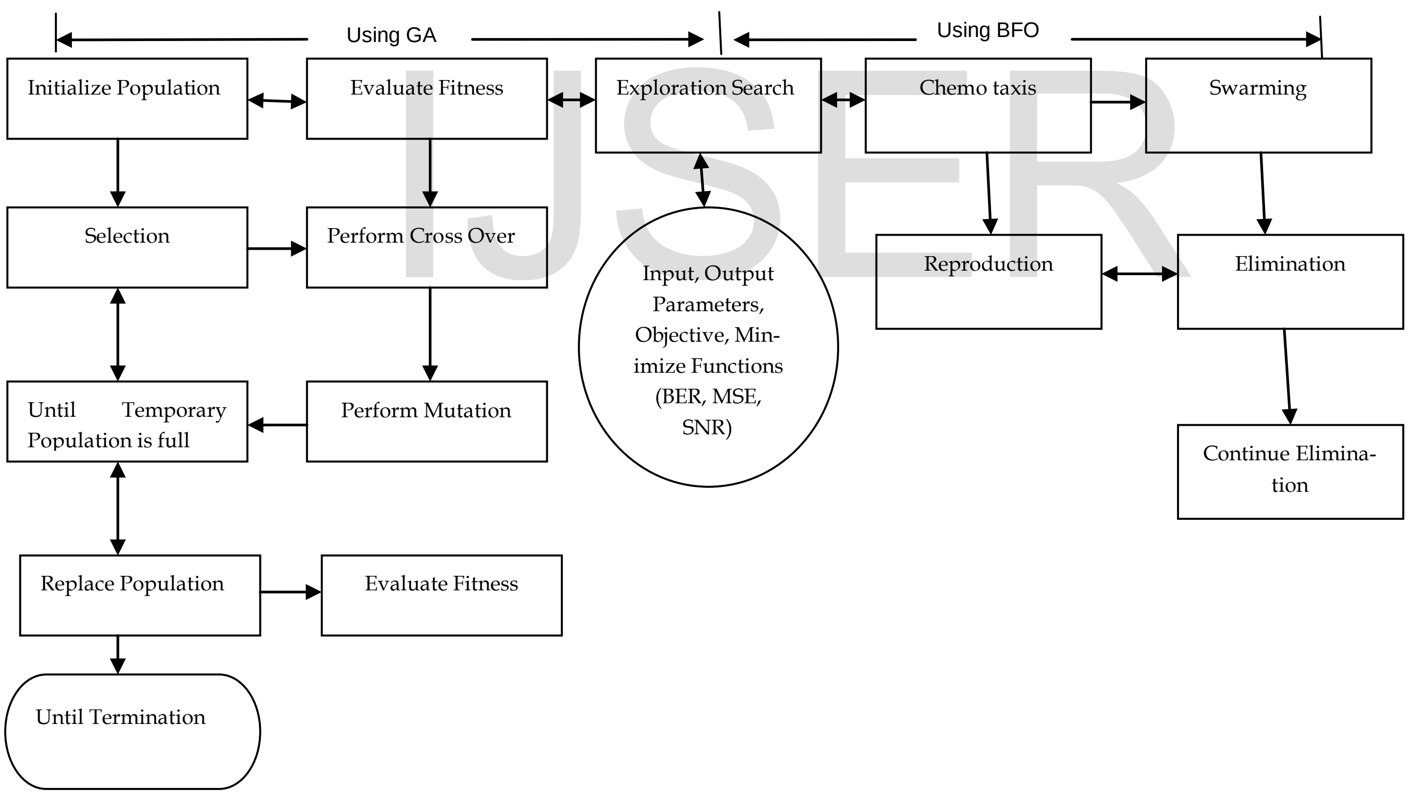

Fig. 1 Proposed Flowchart

3. BFO Algorithm Configuration

In the history of optimization algorithms, various algorithms have been developed such as Genetic Algorithm, Ant Colony Optimization, Particle Swarm Optimization, and Evolutionary Programming (EP). A new optimization algorithm called as BFOA (Bacterial Foraging Optimization) introduced in 2002 by

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Passion for distributed optimization and control [5]. The foraging behavior of Escherichia Coli (E.coli) bacteria leads to the evolution of BFOA. Bacteria search for nutrients in a way that increase the energy acquired per unit time.

E.coli bacteria consist of a set of flagella, i.e., a slender thread like structure. It is having a thickness of 1 μm that extend up to 2μm, and it get divided into two parts under suitable conditions in 20 min. These flagella driven by a biological motor, enable it to rotate (or spin) clockwise or anticlockwise at a rate of 100-200 rps (rotations per second). During its rotation in clockwise or anticlockwise, they work as propellers and after which an E.coli may run or tumble [6].

BFOA explained in four prime steps:

A) Chemotaxis: By the existence of some chemical attractants and repellants, few motion patterns, i.e., taxes will be generated by the bacteria are called Chemo taxes. Two discrete methods that E-coli bacteria follow to move are: Swimming where it can swim for a fixed period in the same direction. Another one is tumbling where it can move in an anticlockwise direction. The bacteria can move alternatively between these two operations for a complete lifetime. The bacteria tumble with lesser number of tumbling unlike in unfavorable conditions where it tumbles fastly to search a nutrient gradient. In the favorable conditions, the bacteria cover a longer distance. Suppose $\omega^i(j, k, l)$ represents i-th bacterium at j-th chemotactic, k-th reproductive and l-th elimination-dispersal step. C defines how many steps taken in a random direction while tumbling. Therefore during chemotaxis the movement of the bacterium expressed as:

$$\omega^i(j+1, k, l) = \omega^i(j, k, l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \quad (1)$$

Where Δ represents a vector in a random direction.

C (i) defines how many steps taken in a random direction as nominated by the tumbling.

These are some actions that a bacterium will take during a chemotactic process [6]:

- Bacteria in an objective or ordinary medium, alternately tumble and runs that means it is searching.
- If a bacteria swims up to a nutrient gradient where it does not come across the harmful substances, it swims longer that means it is looking for increasingly favorable atmosphere.
- If a bacteria swims away from the nutrient gradient due to its interaction with the harmful substances, then seek that means it is evading unfavorable atmosphere.

B) Swarming: An intriguing gathering conduct has been watched for a few motile types of microbes including E.coli and S. Typhimurium, where tangled and steady spatial-worldly examples (swarms) are framed in semisolid nutrient medium. A collection of E.coli cells masterminds themselves in a voyaging ring by climbing the supplement inclination when put in the midst of a semisolid matrix with a solitary supplement chemo-effecter. The cells when fortified by an abnormal state of succinate, discharge an attractant aspertate, which helps them to total into gatherings. In this way, they move as concentric examples of swarms with high bacterial thickness [7]. The cell to cell signaling in E.coli swarm can be represented by the following function [7]:

$$J_{cc}(\omega, N_p(j,k,l)) = \sum_{i=1}^{D} J_{cc}(\omega, \omega^i(j,k,l)) = \sum_{i=1}^{D}\left[-g_{attractant}\exp\left(-s_{attractant}\sum_{m=1}^{N_p}(\omega_m-\omega_m^i)^2\right)\right] + \sum_{i=1}^{D}\left[t_{repellant}\exp\left(-s_{repellant}\sum_{m=1}^{N_p}(\omega_m-\omega_m^i)^2\right)\right] \quad (2)$$

Where $J_{cc}(\omega, N_p(j, k, l))$ is fitness function value that need to be added for the minimization of actual fitness function. It represents a time-varying fitness function. D is the total number of bacteria; N_p is the number of variables to be optimized and $\omega = [\omega_1, \omega_2, \ldots, \omega_{N_p}]$ is a point or a position of bacterium in N_p dimensional search domain. $t_{repellant}$, $s_{repellant}$ are the discrete coefficients that should be selected properly.

C) Reproduction: In this scenario, the population of bacteria is arranged in ascending order in terms of accumulated cost. The bacteria that did not get any nutrient during its lifetime of foraging are not “healthy” and they cannot reproduce. While the healthiest bacteria divided into two bacteria that positioned at same location. In this way, population size remains constant [7].

D) Elimination and dispersal: Steady or sudden changes, usually, occurs in the community environment. Where a bacterium populace lives may happen because of different reasons e.g. a critical neighborhood ascent of temperature may destroy a gathering of microorganisms that are presently in a district with a high centralization of nutrient gradients. Events can occur in such a manner, to the point that all the microscopic organisms in a district are destroyed, on the other hand; a group is dispersed into another area. To mimic this wonder in BFOA, few microbes are exchanged at irregular with a little likelihood while the new substitutions are haphazardly instated over the search space [7].

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4. GA ALGORITHM CONFIGURATION

Genetic algorithm resembles the process of natural selection in such a way that produces solutions to confined and unconfined optimization and search problems. The general principle of Genetic algorithm is the sustainability of the population of encrypted solutions to various optimization problems that evolve in time. It belongs to a class of the evolutionary algorithm that are used to provide optimum solutions using methods that enthralled from the natural evolution such as inheritance, mutation and crossover [8].The genetic algorithm uses three main principles followed to create the next generation from the present population as shown in Figure 2.

Fig 2: Three principles used in Genetic Algorithm

The last step, that is, Selection of best genotypes plays a very crucial role that select the group of individuals, called genesis, which contribute to the population at the next generation. They contribute their genes- the entries of their vectors- to their progeny. These individuals selected according to the fitness based method where fitter or best solution is, usually, selected [9].

4.1 Steps to execute Genetic Algorithm[9]

- Originates the process of the algorithm by initializing a random initial population which is a set of potential solutions or points in the search space.
- Computes the fitness value of each member or individual of the present population in order to create new community or generation.
- On the basis of fitness value, selection of members called genesis or parents takes place.
- Some of the individuals having lower fitness values considered as Elite that are passed directly to the next generation.
- Genetic solution reproduction depends upon two operators that are Crossover and Mutation.
- Crossover guarantees the algorithm to evaluate the best genes from discrete individuals and then recombined them to have increased average fitness value. It creates a potentially imperious progenies for the next generation.
- Mutation applies random changes to an individual in the present generation that will provide genetic diversity. It also enables algorithm to search over a broader space for reducing the untimely convergence that causes trapping of algorithm in global minima.
- Replaces the present population with the progenies to create the next generation.

5. IMPLEMENTATION

The beginning of the implementation will be the initialization of channel with specified number of symbols and its guard band. A reduction in the value of guard band will takes place until the signals does not start colliding. Then the next step will be the application of LS, DFT and MMSE channel estimation techniques. It includes the configuration of transmitter and receiver, generalization of FFT process that will calculate the total number of transmitted and received symbols. The estimated values will be passed onto the customised neural network acting as a classifier used to validate these values. Then these values will act as input to the optimization algorithms i.e. GA and BFO. The algorithms will be executed as explained in earlier sections. Both of these algorithms respond according to their fitness function.

Fitness Function used for Bacterial Foraging Optimization Algorithm

Rosenbrock fitness function used may represent as

$$F_1(x) = \sum_{i=1}^{n-1}[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2] \qquad (3)$$

Where, x_{i+1} is the next bit pattern, and x_i is the current bit pattern. If the next bit pattern has a higher value than the threshold value, then x_{i+1} will become the most optimized bit set.

Fitness Function used for Genetic Algorithm

Function = fitness (e, F_s, F_t)

$$d = (1-e) * ((1-F_s) / F_t) \qquad (4)$$

where F_s is current bit value which has to be estimated, F_t is the total summation of all the bits to be transferred and e is the error rate for the current slot of the bit.

6. RESULTS

In this section, the results of optimization algorithms on channel estimation techniques are discussed. These results evaluated on the basis of Mean Square Error (MSE), Bit Error Rate (BER) and Signal to Noise Ratio (SNR). MSE evaluates the average of the square of the “errors”. It defined as the difference between the actual input to the estimator and what value finally estimated. Whereas, BER defined as how many bits are in error from the total number of transmitted bits for a fixed time interval. It is a unitless performance measure. SNR quan-

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tifies the desired signal power from the background noise power. It is, usually, measured in decibels (dB).

Figure 3 shows the graph between MSE and SNR for LS, DFT and MMSE channel estimator. It is showing that MMSE estimator is producing a significant reduction in error with the increase in the value of SNR up to 30 dB after optimizing with BFO.

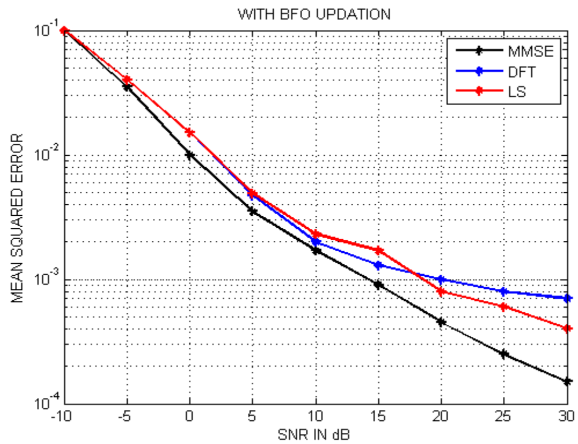

Fig.3 Graph between MSE vs. SNR for LS, DFT and MMSE channel estimators after optimizing withBFO.

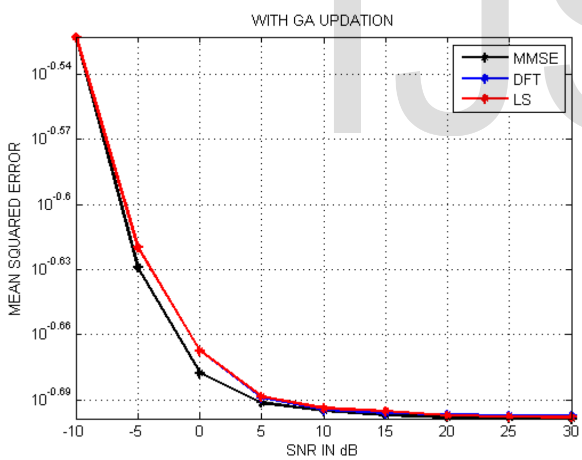

Fig.4 Graph between MSE vs. SNR for LS, DFT and MMSE channel estimators after optimizing with GA

Whereas, Figure 4 shows the graph between MSE and SNR for LS, DFT and MMSE channel estimator. The simulation is representing MMSE to be a good channel estimator with the reduction of error at very low value of SNR. This value keeps on decreasing with high SNR after optimizing with GA.

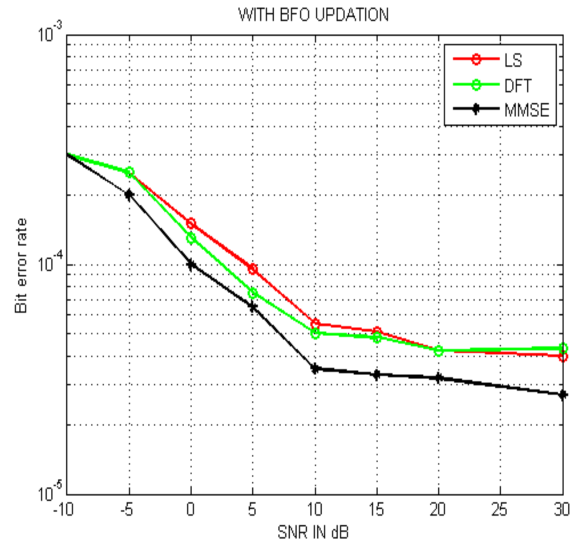

Fig.5 Graph between BER vs. SNR for LS, DFT and MMSE channel estimators after optimizing with BFO.

Figure 5 represents the graph between BER and SNR for LS, DFT and MMSE channel estimator where the curves on the graph have completely showed that MMSE to be the best one. It reduces the error at a very fast rate with BFO updation, unlike DFT and LS. This error rate reduction take place at very low value of SNR; that is at 10db.

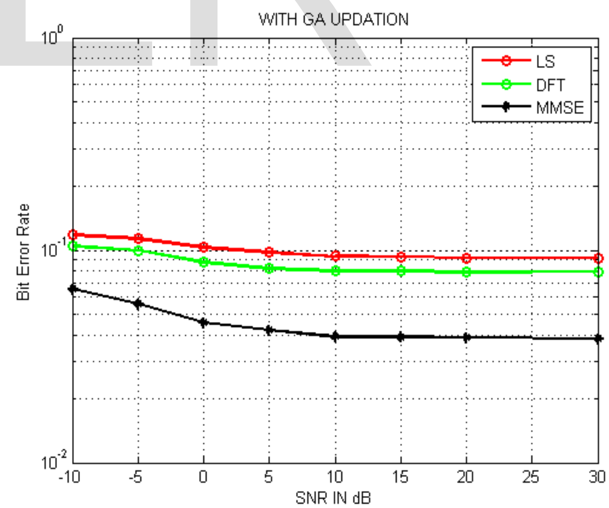

Fig.6 Graph between BER vs. SNR for LS, DFT and MMSE channel estimators after optimizing with GA

Similarly, Figure 6 displays the graph between BER and SNR for LS, DFT and MMSE channel estimator where it is also evaluated that MMSE responds better than other two techniques with GA updation. It also leads to a significant decrease in the Bit error rate with an increase in the Signal to noise ratio.

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7. Conclusion

In this paper, Optimization algorithms have been adopted named as Genetic Algorithm and Bacterial Foraging Algorithm for having optimum channel estimation in MIMO-OFDM systems. A Comparison has been made in terms of three parameters BER, MSE and SNR where MMSE channel estimation algorithm is considered to be the best one amongst all other such as DFT and LS. It shows the maximum error reduction at a very low SNR.

This paper also reviewed that more optimum results have been achieved through BFO rather than GA. After applying BFO and using MMSE as channel estimation technique MSE and BER reduces significantly at a very low value of SNR, that is, up to 5db. This paper also focussed on the reduction of guard band to that extent where the signals do not start colliding.

The current aspect of the work opens a lot of gates for the future research workers that estimation technique can be applied up to 100000 bits. The same procedure can also be tried with other optimization strategies such as Ant Colony optimization and Bee colony optimization. These optimization techniques have their limitation over the range of data. So future aspects may include the splitting up the range of the data into different regions so that optimization technique may get a chance to optimize them on time.

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