MULTI USER DETECTION FOR FD-MC-CDMA IN PRESENCE OF CFO USING ADAPTIVE AIDED GENETIC ALGORITHM

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Abstract: - Modern wireless communication systems require very huge data rates, anti-blocking capability in a multiuser environment. The parameters to meet these requirements are enhancing spectrum productivity and error execution in wireless communication models. This can be achieved by optimization of Receiver performance. In this paper a novel adaptive population sized aided Genetic Algorithm (GA) aided Multiuser detection (MUD) for Frequency Division Multi carrier CDMA (FD-MC-CDMA) technique is implemented. An adaptive Multi User Detection technique is presented to advance the efficiency of FD-MC-CDMA communication system in company of career frequency offset (CFO). Due to the existence of CFO, BER would be increased. From experimental results it is demonstrated that Adaptive Genetic Algorithm (AGA) aided MUD has minimized the complication of MUD for increased number of users deprived of ominously minimizing the attainable result. In this approach, Adaptive Genetic Algorithm (AGA) is used for population size enhancement to run an optimal solution among computational complexity and the accuracy of convergence.

Key words : Multiuser detection (MUD), MAI,Frequency Division Multi carrier CDMA (FD-MC-CDMA), career frequency offset (CFO), ML algorithm, Adaptive Genetic Algorithm (AGA),SIC,PIC.

1. Introduction

Modern wireless communication, merging of MUD and Soft Computing approaches have obtained better results. Data detection techniques in multi carrier modulation methodology are categorized as either single user detection (SUD) or MUD. The conventional SUD comprises of a group of filters corresponding to the scattering codes. The spreading code fit for other users is deliberated as MAI which is treated as a Noise. The single operator detector suffers from two issues. Initially, MAI generated by the additional co-channel operators is an important restraint to the capability of the specific user. Multiuser detection is a strategy for mitigating MAI effects at the receiver side. MUD is the intellectual approximation/demodulation of transferred bits in MAI and it has frequently no limitation. Multiuser receivers include the optimum ML receiver, linear de-correlating receiver, linear MMSE receiver, SIC receiver, PIC receiver, decision feedback receiver, multistage interference cancellation receiver, and so on [1,2,3]. The MUD [4] treats the MAI as a fragment of the data relatively than noise. Henceforth, by dispensing this added data, momentous performance improvements are achieved reaching to the ultimate border of the single-user detectors. Consequently, study in this domain is still enduring at all time, and the goal is to detect the optimal results which will trade-off the efficiency and difficulty of MUD approaches.

The optimum identifier functions joint detection with ML recognition. As the difficulty of ML recognition raises exponentially with the numerous users, its usage is restricted in real time appliances using a minimum number of individuals. Meeker joint detection approaches could be comprehended by means of block linear equalizers.

The optimal MUD [5] depending on the ML is computational complex which is exponentially accumulating through numerous individuals. Therefore, the optimal ML multiuser detector is unrealistic to execute. This density restriction tends to several suboptimum multiuser detection applications. In MUD, the MAI element can be eradicated or annulled by the usage of entire individuals scattering code in the system to be accessible to every individual. A diversity of MUD methods, like the least squares (LS) [6],and MMSE [6],[4],SIC [6],[5], PIC [14], [6-38], [5] and MLD [8] ,[6], [8] methods might be raised for the purpose of splitting diverse individuals at the Base Station on a per-subcarrier basis.

2. Genetic algorithm (GA) in wireless communication systems

GA is well known stochastic exploration technique widely accepted to resolve issues associated to Multi Carrier Models effectively. GA is stochastic-gradient dependent optimization technique whose elementary characteristics are [16]: Through simulations, it is shown that planned receiver could attain a nearby optimal BER efficiency on supposing faultless channel evaluation at a meaningfully minimum computational complexity compared to the essentials needed by the ML optimal MUD.

The GA task is to progress this populace in the direction of improved results in a repetitive way. Typically, the progression initiates from an entirely arbitrary population and occurs on a sequence of consecutive generations as shown in Figure 1.

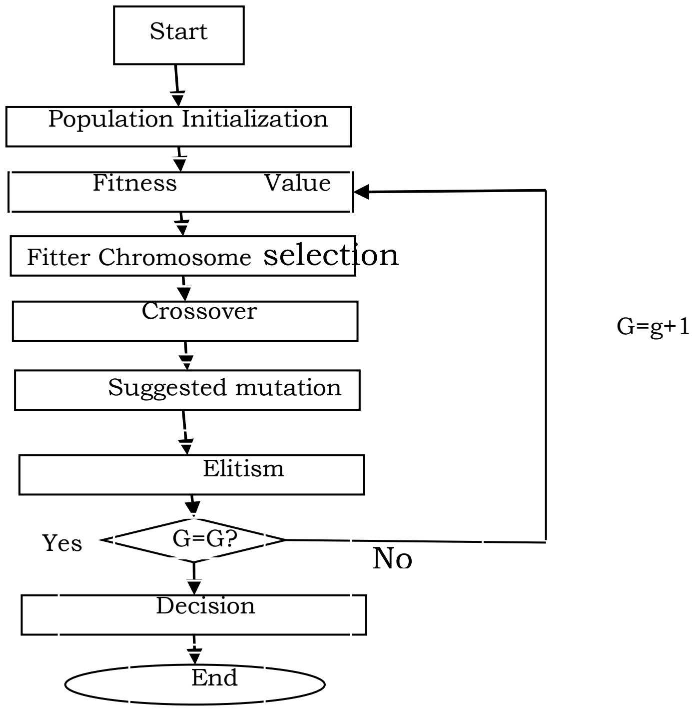

Fig.1: Flow chart for suggested Genetic Algorithm assisted Multiuser detection scheme

Fig.1 displays the flow chart of GA to define the functions of the suggested approach under this research.

The genetic operator's cycle stated priori forms the foundation for the GA assisted optimization[10], generating an offspring populace with an enhanced mean fitness. This evolution endures till the iteration indices acquire its maximum.

3. Multi user detection using Genetic algorithm:

Even though numerous optimal and sub-optimal MUD methodology exist in the literature, lot of effort has to be done on the further enhancement in efficiency of MUD techniques [11]. The computational complexity of the conventional MUD techniques might be abridged from exponential to polynomial, but it is always essential to furthermore minimize the complexity simultaneously with the increased number of Users. The suggested intelligent Genetic Algorithm assisting MUD technique is one of the approaches to minimize the complexity and obtain a system with more accuracy and better performance. The complete implementation of MUD using genetic algorithm is explained in following sections.

Initially, an experimental information vector is defined in the suggested GA aided MUD as $\hat{b} = [\hat{b}_{1,}\hat{b}_2, \ldots, \hat{b}_k]$ for k individuals then

$$\hat{r}(t) = \sum_{k=1}^{K} \sqrt{E_k}\hat{b}_k s_k(t) \otimes h_k(t) \quad (1)$$

where E_k is signal energy per bit of k_{th} individual, b_k is the k_{th} individuals' information controlled using BPSK, and $s_k(t)$ is the k_{th} individual scattering waveform and $h_k(t)$ is the frequency selective fading channels. The recommended GA aided MUD procedure will give optimal or near-optimal expected value $\hat{b}_k$ of b_k for the k_{th} individual.

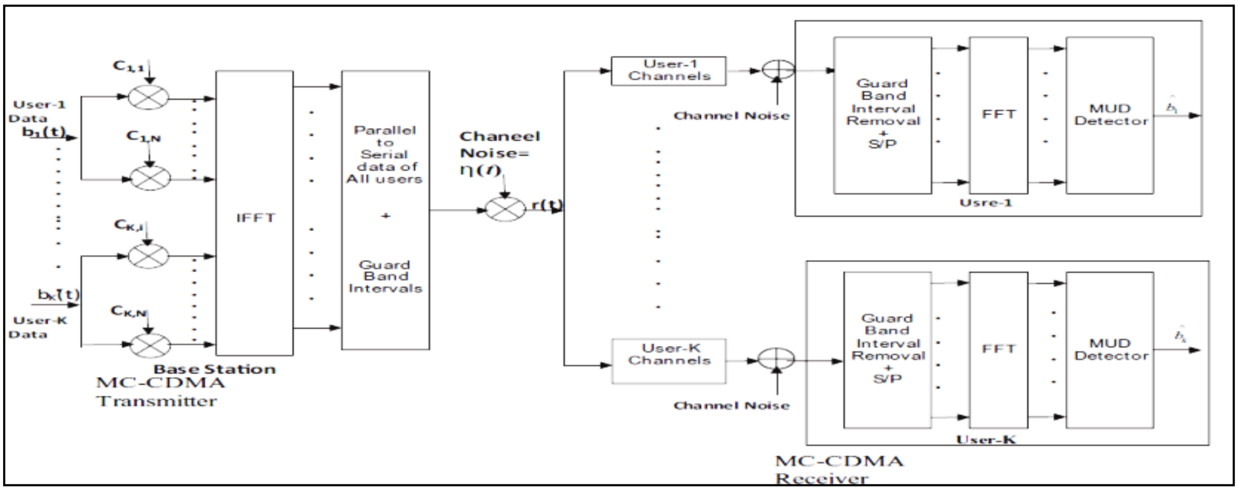

Fig. 2: suggested FD-MC-CDMA system with MUD

4. Suggested adaptive population sizing genetic algorithm

In this paper, a novel adaptively methodology is suggested into the existing GA sided MUD approach in FD-MC-CDMA [13] shown in Fig. 2, over numerous frequency Selective Communication Channels like Rayleigh Channel, Rician Channel along with occurrence of CFO. Here, the CFO is used along with suggested approach so to obtain a robust MUD technique to be employed into the model. In specific, an appropriate selection of population size and iteration number is obligatory so as to evade very huge computational weight and to retain performances worthy.

Initially, GA are not definite to attain the optimum results since its effectiveness is described fundamentally with the population size P, i.e. by the quantity of individuals in a populace, and the sum of iterations employed. Therefore, the dimension of the population size in a GA is a foremost aspect in defining the correctness of convergence [12]. As the populace size upsurges, the GA has a healthier choice of detecting the worldwide optimal results; though the computational cost likewise rises as a function of the population dimension. The GA-aided MUD has to compute the objective functions of equation on number of times. Thus, the adaptive genetic algorithm is suggested to enhance the population size such that the computational complexity and also the accuracy of convergence should be optimal.

5. Adaptive Genetic Algorithm (AGA)

The AGA dependent MUD techniques used adaptive techniques for population size enhancement. GA is convergent, however amount of convergence hinges on quantity of iterations G and/or the populace size P [17]. As specified above, if P and/or G are adequately big, for our suggested GA aided MUD methodologies the optimal recognition results. Nevertheless, rising P raises the computational intricacy of the MUD system. It is unreasonable to pursue somewhat greater amount of convergence or somewhat less BER performance at the cost of additional computational complexity. Thus, an adaptive population sizing GA is employed to resolve the complicated issue. Moreover, the decline of computational complexity, suggested adaptive population sizing GA could enhance BER [15]. The suggested procedure is identical to a Conventional GA however at the termination of distinctive selection, reproduction, and mutation stages, the populace dimension could increase or decrease depending on an enhancement of the finest fitness enclosed in population. The dimension of populace alters whenever

- An upgrading in finest fitness, or
- No enhancement in finest fitness for a "long time".

If none of the above happens, populace dimension diminishes with the minor proportion (1-5%). The inspiration after procedure is to employ huge populace dimensions for investigation and less populace dimension for misuse. In their study, rate of growth X for population is specified as,

$$X = increaseFactor \times (maximumEvalNum - currentEvalNum) \times \frac{maximumfitness_{new} - maximumfitness_{old}}{initial\ Max\ Fltness}$$

Where $increase\ Factor$ is a restriction in the range (0,1), $maximumEvalNum$is the extreme quantity of fitness estimations permitted for the complete run $currentEvalNum$ is the present assessment number, and $maximum\ itness_{new}$, $maximum\ Fitness_{old}$, and $initial\ Max\ Fitness$, are finest fitness values in the present, earlier, and initial iterations. The initial populace, in addition to minimal and maximal population sizes where the procedure need to function shall be defined. In our suggested GA dependent MUD experimentations,

initial Pop Size=20, *increase Factor*=0.1, *V*=500, *decrease Factor*=0.4, *min Pop Size*=5, *max Pop Size*=100 is employed

6. Experimental results and its analysis of Adaptive Genetic Algorithm aided MUD

In this section the efficiency evaluation of suggested AGA dependent MUD for a FD-MC-CDMA grounded communication system is presented. The BER of suggested approach was compared with earlier Multi User Detection approaches like SIC, PIC and GA dependent MUD to show the enhancement of suggested adaptive population sized aided genetic algorithm. The simulations used for experiment are mentioned in table 1.

Parameters	Value
Number of Users	4
Modulation Scheme	BPSK
Spreading Code	WALSH
Number of subcarriers	16
Fading Effects	Rayleigh and Rician
Noise	AWGN
Processing gain	32
GA selection	Fitness aided
GA crossover	Uniform Crossover
Initial population size	20
Minimum population size	5
Maximum population size	100
GA Mutation Probability	0.1
GA Crossover Probability	1
Elitism	yes
Increase factor	0.1
Decrease factor	0.4
No of Iterations	Fitness is aided on Adaptive Genetic Algorithm

Table 1: Simulation parameters of suggested AGA assisted MUD

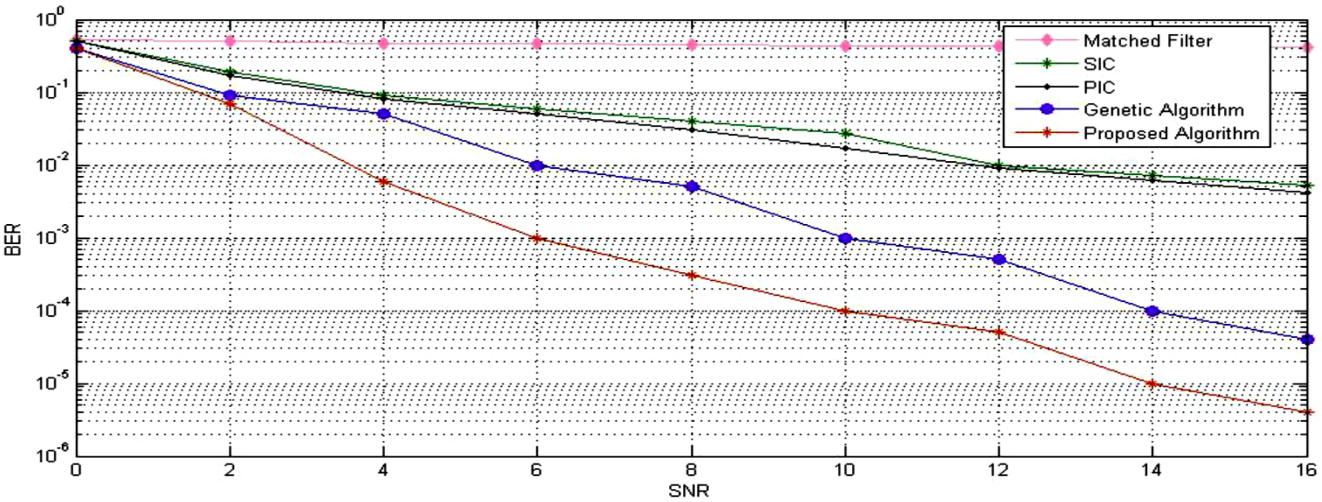

Fig. 3: Bit error rate performance comparison of suggested scheme with existing matched filter, SIC method, PIC method and conventional genetic algorithm

Fig.3 represents the BER performance evaluation of suggested approach with prevailing corresponding filter, SIC, PIC method and Traditional GA. From the fig.2, it is observed that, as the SNR is increasing, the BER is decreasing. It is shown that the suggested BER efficiency of suggested method is higher matched to prevailing matching filter, SIC, PIC methodology and MUD by means of traditional GA. The comparative analysis of suggested approach with earlier approaches through BER values is shown in table 2.

SNR (dB)	BER				
	Matched Filter	SIC	PIC	GA	Adaptive GA
0	0.7	0.7	0.7	0.6	0.5
2	0.65	0.1	0.1	0.1	0.08
4	0.62	0.08	0.06	0.05	0.008
6	0.6	0.04	0.03	0.01	0.001
8	0.55	00.02	0.02	0.004	0.0004
10	0.51	0.01	0.01	0.001	0.0001
12	0.48	0.008	0.007	0.0006	0.00006
14	0.4	0.006	0.005	0.0001	0.00001

Table.2: Bit error rate performance comparison of suggested scheme with existing matched filter, SIC method, PIC method and conventional genetic algorithm

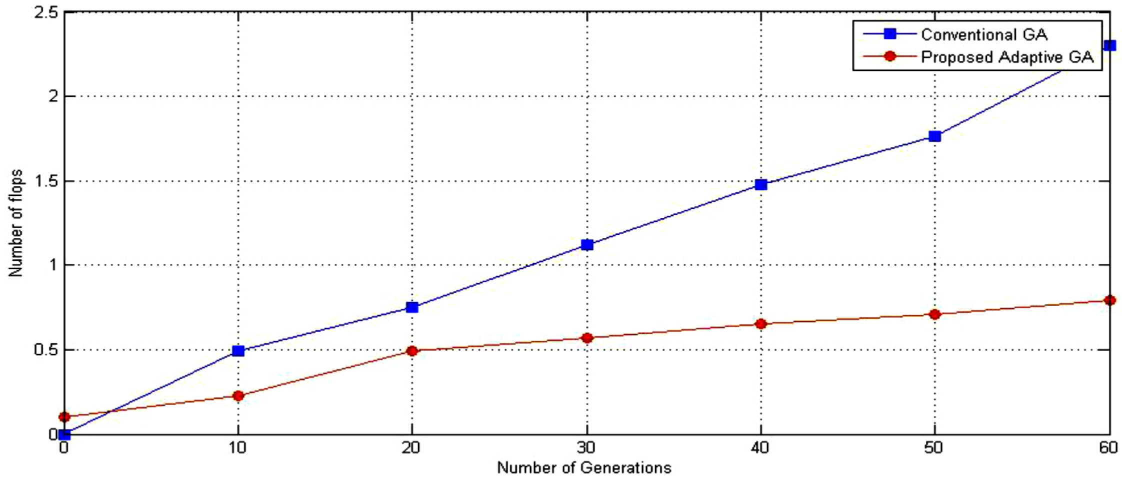

Fig.4: Comparison of computational complexity of suggested algorithm and conventional genetic algorithm

Fig.4 depicts the computational complexity comprised of MUD employing suggested method and Traditional GA. From the experiment outcomes it is obvious that complication of the suggested adaptive populace sizing GA dependent MUD is very lower compared to traditional GA dependent MUD. The complexity of the traditional GA dependent MUD augments through number of iterations, nevertheless the complexity of suggested AGA dependent MUD do not upsurges more with number of iterations. Table.3 provides relative investigation of the suggested method with former method using computational complexity.

Number of Generations	Complexity (Number of Flops)	
	Conventional GA	Suggested GA
0	0	0
10	0.5	0.2
20	0.7	0.5
30	1.2	0.6
40	1.5	0.7
50	1.75	0.75
60	2.25	0.8

Table.3: computational complexity comparison of suggested AGA with conventional GA

The complexity of suggested and earlier approaches was analyzed pertaining number of generations and number of individuals. Generally, the complexity increases with an increment in the generations and users. For the suggested approach, it will be same, but the suggested approach optimizes the generations such that the complexity will be optimal. In figure.6 and figure.7 computational complexity of suggested scheme is matched with GA aided MUD, SIC and PIC.

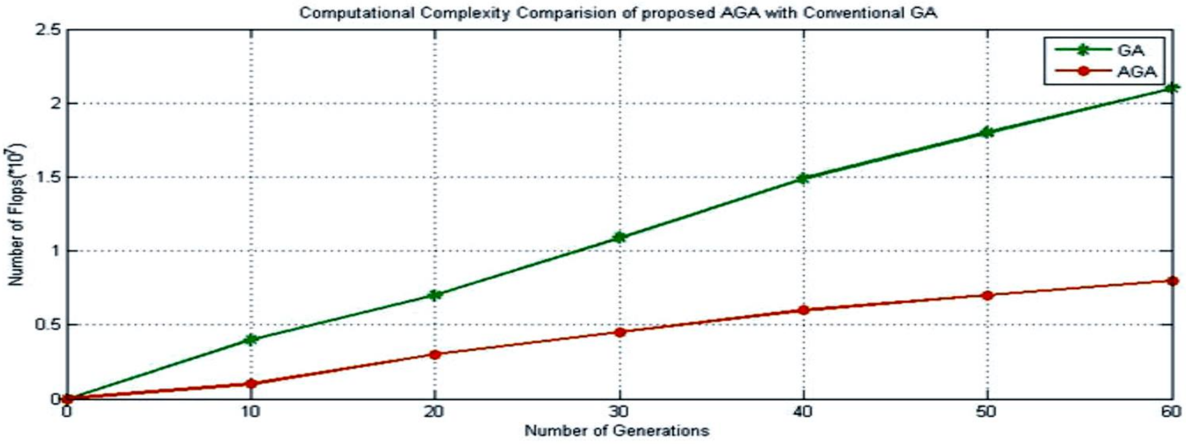

Fig.5: Comparison of Computational Complexity of Suggested AGA assisted MUD with Conventional GA Assisted MUD schemes

The computational complexity analysis of suggested AGA method with number of generations is shown in fig.5, which also shows that as the generations are increasing, the computational complexity is also growing, but compared to GA aided MUD, the computational complexity of suggested AGA aided MUD is less. Table.4 gives the computational complexity comparative analysis of AGA, GA methods.

Number of Generations	Complexity (Number of flops)	
	AGA	GA
0	0	0
10	0.14	0.42
20	0.32	0.73
30	0.45	1.12
40	0.69	1.52
50	0.72	1.65
60	0.78	2.12

Table.4 the computational complexity comparative analysis of GA and AGA.

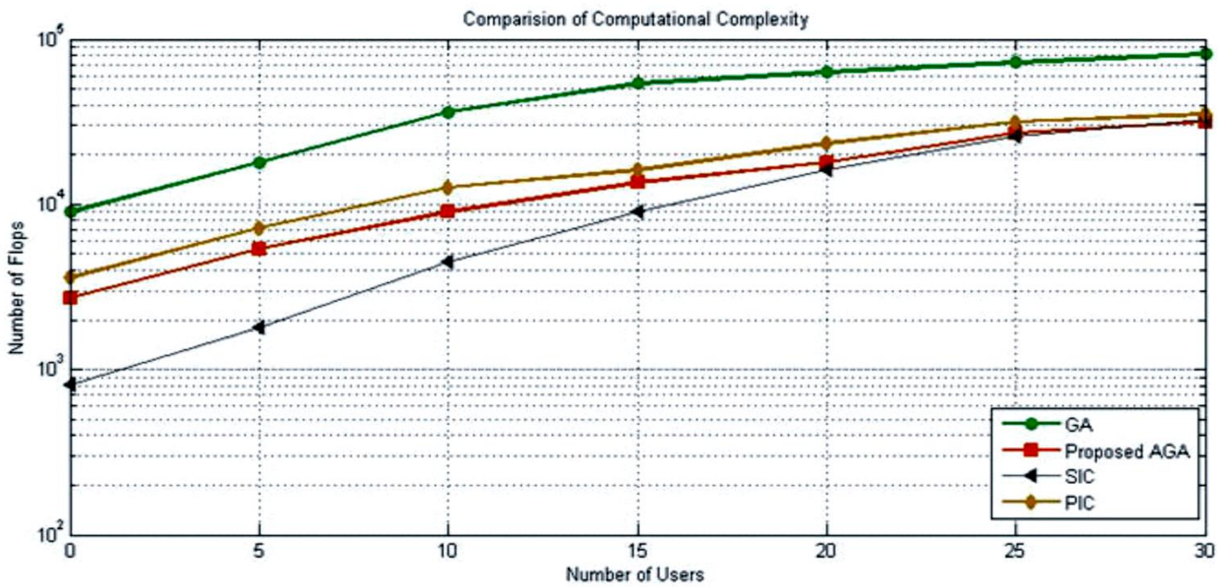

Fig.6. Comparison of Computational Complexity of Suggested AGA assisted MUD with existing MUD schemes

The fig.6 shows the computational complexity analysis of the suggested AGA technique with number of operators. From the figure 7, it is evident that as the individuals are increasing, the computational complexity is also growing, but compared to GA aided MUD, the computational complexity of recommended AGA aided MUD is less. At less quantity of individuals, the computational complexity of PIC is better compared to SIC, GA and AGA. As the individuals increasing, the computational complexity of suggested method outperforms the earlier approaches. Table.5 gives the computational complexity comparative analysis of SIC, PIC, GA, suggested AGA.

Number of Users	Complexity (Number of Flops)			
	SIC	PIC	GA	Suggested AGA
0	800	3,800	10,000	3,000
5	1,800	7,000	18,000	5,000
10	4,500	12,000	38,000	7,500
15	7,500	17,000	52,000	15,000
20	9,000	22,000	60,000	18,000
25	17,000	30,000	70,000	26,000
30	30,000	35,000	80,000	30,000

Table.5 the computational complexity comparative analysis of suggested AGA with SIC, PIC and GA.

7. CONCLUSION:

In this paper, an adaptive GA aided MUD of FD-MC-CDMA in frequency selective fading channels is suggested, this system is experimented in MATLAB version and implementation of suggested AGA aided MUD is matched with prevailing SIC, PIC and Traditional GA depending on MUD. From experimental it is demonstrated that the BER of the suggested AGA dependent MUD is greater when compared with the performance of the prevailing MUD. Additionally the computational intricacy of traditional GA aided MUD is matched with the suggested ADA aided MUD. From the Experimental outcomes guaranteed the computational complexity of suggested AGA dependent MUD is very low whenever matched with traditional GA aided MUD.

The suggested approach is experimented in MATALAB version and its efficiency is matched with prevailing MUD approaches in Rayleigh fading channel. From the Experimental results it is shown that suggested AGA aided MUD method outstripped prevailing MUD methods.

8. ACKNOWLEDGMENT

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