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Channel Estimation of OFDM System using Real coded Genetic Algorithm

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Abstract

The paper demonstrates that the real coded or continuous Genetic Algorithm based Channel Estimation (RCGA) is capable of approaching optimal estimates compared to traditional Least Square (LS-CE) and minimum MSE (MMSE-CE) channel estimators. The real coded GA creates optimization parameters using integers rather than binary numbers. The simulation shows that the proposed scheme exhibits least $1.25X10^{-5}$ bit error Rate (BER) & 0.0014 mean square error (MSE) and better 6.6Mbps channel capacity.

Keywords—*BER, LE-CE, MMSE-CE, MSE, RCGA*

I. INTRODUCTION

The intensifying need for **S**peedier, **E**levated data rate and **T**rustworthy (SET) wireless multimedia services depends on optimal or near optimal channel estimates due to time varying multipath channel. The Orthogonal Frequency Division Multiplexing (OFDM) [1], a multiple subcarrier modulation technique with the aid of IFFT and FFT in its transceiver has been made a centre of attraction in fourth generation (4G) and fifth generation (5G) wireless standards

Channel estimation techniques [2] are used to explore channel characteristics in the multipath fading wireless environment. The fundamental channel estimate techniques are Least Squares (LS-CE) and Minimum Mean Square Channel Estimation (MMSE-CE) suffer from mean square error and complexity respectively.

Evolutionary algorithms [3] play an essential role in wireless communication for optimal channel estimates at an affordable cost and complexity. Deb [4] introduced GA to provide optimum solution with channel low bit error rate and high data rateThe need of Evolutionary aided Genetic Algorithm (GA) [5-8] in channel estimation is to apply the principle of natural genetics for the evolution of next gene ration wireless communication system with the better estimates. The current generation (Parent) from which future generation (offspring) is evolved through Variability and fertility (reproduction) process. Reproduction is an accountable for the selection of better channel estimates in a mating pool. Variation undergo mutation and crossover for surviving in the environment within partial resources.

The real coded GA (RCGA) differs from binary coded GA (BCGA) with respect to decision variables (either real or binary encoded real variables) for the computation of channel estimation. It works on the principle of identifying better estimates from a set of estimates (population) and eliminating the worst estimates to minimize the fitness function.

The fundamental Real Coded Genetic Algorithm (RCGA) flow chart shown in figure 1 describes the algorithm steps that undergo to generate better channel estimates. As the number of iterations increases, one can achieve the optimum channel estimate.

Initialization: Form a set of channel estimates (population) which are derived from traditional LS-CE and MMSE-CE.

Evaluation & Selection: Select best fit channel estimates for mating.

Crossover: Crossover is a variation operator responsible for generating offspring with a probability Pc. Select a random number (r) and if r>= Pc, then copy parent solutions as offspring else generate random numbers for each variable.

Mutation: Mutation is also a variation operator in which each of the population member undergo mutation and generates an offspring solution with a probability Pm.

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Replacement: Combine population members and offspring solutions for survival of best fit estimates.

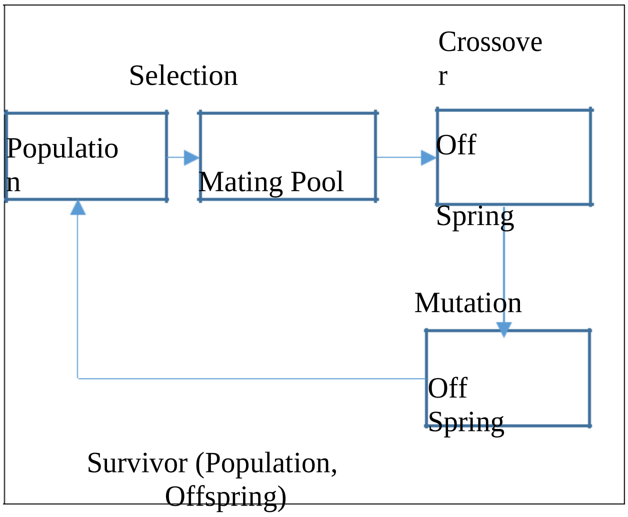

Fig 1. Genetic Algorithm flow chart

From figure 1, Genetic Algorithm (GA) operates through four steps by way of parent selection, cross over, mutation and survivor for next generation.

Step1: Parent Section: The first step, "parent selection" involves different types of methods such as Roulette wheel selection, Stochastic Universal Sampling, Tournament Selection and Rank based Selection used to select best parent automatically for the next generation.

Roulette Wheel Selection strategy (RWS): In RWS, each individual can be selected based on their fitness value. This technique is similar to Roulette wheel such that each region of wheel proportional to fitness. A random number is generated within the sum of their finesses. The best parent is selected if the partial sum of individual fitness and random number is greater than total sum else process repeats.

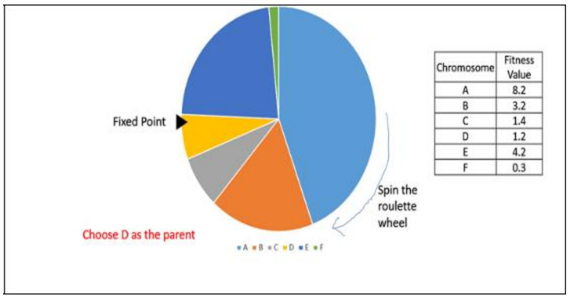

Fig 2. Process of Roulette Wheel Selection

The below figure 3 represents Roulette wheel selection implemented function in Python.

```
def roulette_wheel(items, n):
    total = float(sum(w.fitness for w in items))
    i = 0
    w, v =items[0].fitness, items[0]
    while n:
        x = total * (1- numpy.random.random() ** (1.0 /n))
        total -= x
        while x >w:
            x -= w
            i +=1
            w, v = items[i].fitness, items[i] w -= x
```

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```
yield v
n -= 1
```

Fig 3. roulette_wheel function

Stochastic Universal Sampling (SUS) Selection Strategy:

It is a process of conducting a selection strategy for which selected parents used to generate their offspring's by using Stochastic Universal Sampling wheel (SUS) with multiple fixed points as shown in figure 4. The wheel has 'n' pipes referred as number of members in a population and each member will get a part/portion in circle proportional to fitness value. For each spin of the wheel, the members appear at fixed point are referred as parents.

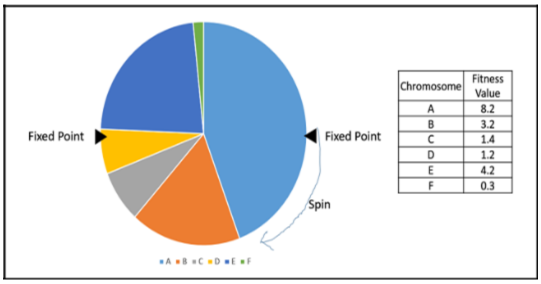

Fig 4. Process of Stochastic Universal Sampling

The figure 5 represents Stochastic Universal Sampling wheel selection implemented function in Python.

```
def NewChrIx = Sus_scheme(FitnV,Nsel):
        [Nind,ans] = size(FitnV)
         cumfit = cumsum(FitnV)
         trials = cumfit(Nind) / Nsel * (rand + (0:Nsel-1)')
         Mf = cumfit(:, ones(1, Nsel))
         Mt=trials(:, ones(1, Nind))'
        [NewChrIx, ans] = find(Mt < Mf & [zeros(1, Nsel); Mf(1:Nind-1, :)] <= Mt)
        [ans, shuf] = sort(rand(Nsel, 1))
        NewChrIx = NewChrIx(shuf)
```

Fig 5. Sus_scheme function

Truncation Selection Strategy (TSS): In TSS, the population members are sorted with respect to their fitness and the best individuals are selected as parents within 50-10% truncation threshold. The figure 6 represents truncation selection implemented function in Python.

```
def trunc_selec(self, threshold):
      for i in range(pop_size):
          gen_rand=random.randrange(threshold,100)
          individual=self.population[i]
           if individual.fit()>=gen_rand:
              individual.selec(True)
           else:
              individual.select(False)
         return
```

Fig 6. trunc_selec function

Random Selection Strategy (RSS): In RSS strategy is similar to TSS scheme without any threshold. Also, fixed number of individuals can be selected as parents randomly. The figure 7 represents random selection implemented function in Python.

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```
def rand_selec(self):
    for i in range(pop_size):
        gen_rand=random.randomrange(0,100)
        individual=self.population[i]
        if individual.fit()>=gen_rand:
            individual.selec(True)
        else:
            individual.select(False)
    return
```

Fig 7. rand_selec function

Step2: Crossover: Is a process used to create next generation offspring. Single point crossover selects a random gene and swap all genes from that point where as double point crossover selects two random genes and swap all genes after those points.

Step3: Mutation: Purpose of Mutation (exploration) is to avoid local minima. Select two random genes from a chromosome and swap them.

Step4: Survivor: This strategy decides which individuals are used for next generation and which are to be strike out of the populace.

The rest of the paper deals with system model in section II, simulation parameters and results in section III & conclusion in Section IV.

II. SYSTEM MODEL

The information bits are coded and mapped to a 16-QAM symbols and converted to time domain samples using OFDM modulator and directed through wireless channel. At the receiver, reverse procedure takes place. The figure 7 illustrates the OFDM functional block diagram.

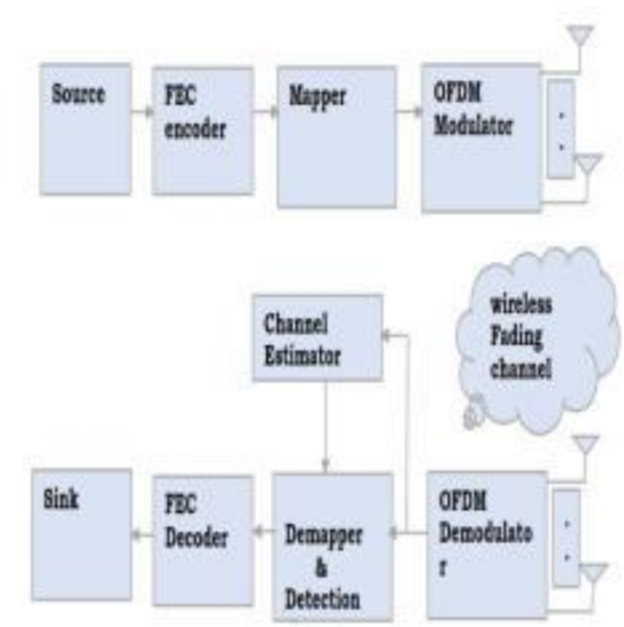

Fig 8. OFDM transceiver design

The received signal in vector domain can be expressed as,

$$= \;.\; + \qquad (1)$$

Where, H is channel matrix, H be input matrix, W be the Gaussian noise vector and Y be the output matrix.

Channel estimation block used to predict the channel's condition for the efficient detection of transmitted information at the receiver.

Least Square based Channel Estimation (LS-CE): The estimator provides minimum norm square of the error

$$\hat{H}_{LS} = \min \ ||Y - X\hat{H}||^2 \quad (2)$$

III. SIMULATION PARAMETERS

The proposed RCGA based optimization in the channel estimation of OFDM system equipped with 256 subcarriers with 16-QAM modulation scheme.

Table 1. Simulation Parameters

Parameter	**value**
# iterations	100
Mating Probability	0.7
Mutation rate	0.001
Crossover rate	0.9
#offspring per generation	20
Truncation threshold	50
Max population size	36

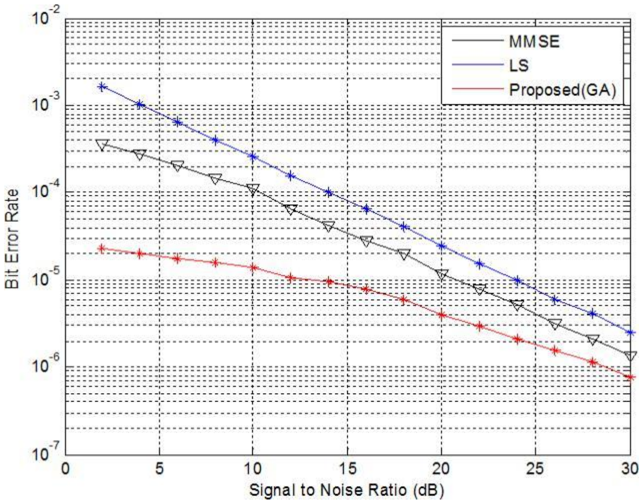

Fig 9. BER comparison of LS, MMSE and GA

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The figure 8 depicts the BER performance comparison of LS, MMSE and GA. The GA method requires 1.25X10^{-5} BER at 10 dB SNR under 16-QAM modulation

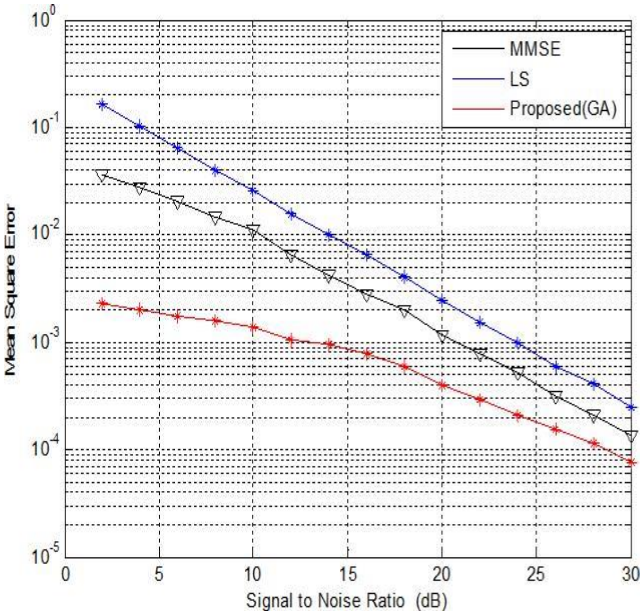
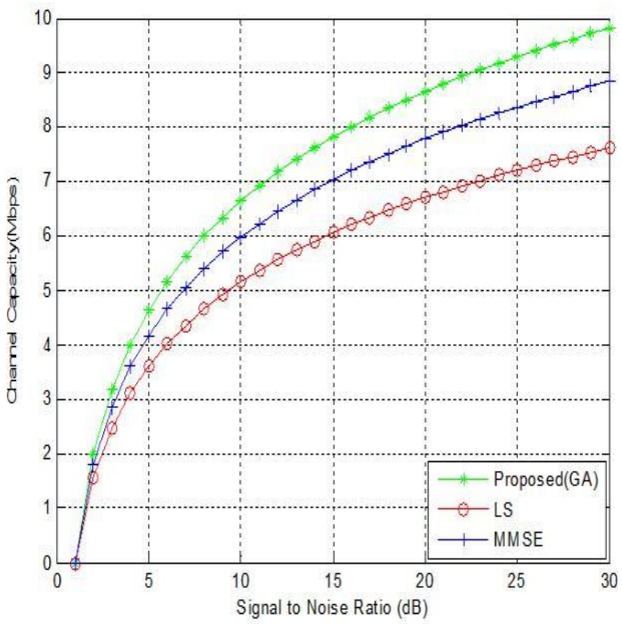


Fig 10. MSE comparison of LS, MMSE and GA

From figure 10, it is observed that GA method provides better MSE 0.0014 at 10 dB SNR.



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The figure 10 demonstrates that the maximum fitness is reached at 6.6439 Mbps within 10 dB SNR using proposed genetic algorithm (GA), whereas 5.9795 Mbps using MMSE and 5.1490 Mbps using LS based channel estimation.
If trinc_selec function is selected, encountered 10 mutations in 9507 offsprings. If sus_strategy function is selected, 5 mutations are encountered in 4779 offspring. If roulette_wheel function is selected, 9 mutations are encountered in 9037 offspring. In rand_selec, 0 mutations are encountered in 290 offspring

IV. CONCLUSION

The real coded Genetic Algorithm analyzed under different selection methods such as Roulette wheel, Statistical Universal sampling, Truncation method and Random Selection. Also analyzed single point cross over and double point crossover. The RCGA optimizer performs better improvement in terms of minimal error performance and better channel capacity over LS and MMSE channel estimation schemes. If trinc_selec function is selected, encountered 10 mutations in 9507 offsprings. If sus_strategy function is selected, 5 mutations are encountered in 4779 offspring. If roulette_wheel function is selected, 9 mutations are encountered in 9037 offspring. In rand_selec, 0 mutations are encountered in 290 offspring

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