OPTIMIZATION OF SELECTION COMBINING DIVERSITY USING GENETIC ALGORITHM

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***Abstract*—This paper is focused on the optimization of number of receiver elements used in the selection combining receiver diversity of the base station along with the transmitter power and baud rate. The question of how many receiver antennas to employ in a diversity system operating in slow fading is examined. Genetic Algorithm (GA) which is a part of Evolutionary computing is used for optimization. It is a directed search algorithm based on the mechanics of biological evolution. The best number of antennas required for the fixed-size antenna array to achieve good compromise between system performance and its cost is investigated.**

Keywords- genetic algorithm, selection combining, baud rate, antenna

I. INTRODUCTION

WIRELESS antenna systems using multiple antennas at the receiver and/or the transmitter have attracted significant interest in recent years. Fundamental works [1], [2] show that the capacity of multiple antenna systems in independent Rayleigh fading reduces linearly with the increase in the number of transmitter antennas and receiver antennas. However designing of antenna array with many elements is complex and requires more space and cost. Therefore possible trade-off between design complexity and performance need to be made[3].

A. Receiver Diversity

Diversity is the technique which is used to mitigate the effect of multipath fading. Receiver diversity is the technique of using multiple antennas at the receiver. This exploits the fact that independent signals paths have low probability of experiencing deep fades simultaneously. Thus, the idea behind diversity is to send same data over independent fading paths. These independent paths are combined in such a way that the fading in the resultant signal is reduced. If the antennas are spaced sufficiently far apart, it is unlikely that they experience independent fading.

The Selection Combining (SC) diversity selects the strongest of all the paths and detects it thereby reducing the effect of the fading. It requires restricted CSI and does not require the estimation of channel coefficient. The Maximum Ratio Combiner (MRC) assumes higher weights to the paths with high SNR and lower weights to paths with low SNR. However it requires perfect CSI which requires additional overhead information that reduces the Spectral efficiency [5] and increases the system complexity. Thus Selection Combining (SC) arises as a most cost-efficient combining technique as it involves only one RF chain.

B. Genetic Algorithm

Genetic Algorithms (GA) are adaptive heuristic search algorithm based on the evolutionary ideas of natural selection and genetics and is widely used for optimization problems. Genetic algorithms (GA) are a part of Evolutionary computing, a rapidly growing area of artificial intelligence. They are inspired by Darwin's theory about evolution - ’’survival of the fittest”. GA, although randomized exploit historical information to direct the search into the region of better performance within the search space. In nature, competition among individuals for scanty resources results in the fittest individuals dominating over the weaker ones. Unlike older AI systems, the GA’s do not break easily even if the inputs changes slightly, or in the presence of reasonable noise. While performing search in large state-space, multi-modal state-space, or n-dimensional surface, a genetic algorithms offer significant benefits over many other typical search optimization techniques like linear programming, heuristic, depth-first, breath-first.

GA uses the process like Selection, Crossover and Mutation to evolve a solution to a problem. Initially the chromosomes are formed in random and their fitness is evaluated by using a fitness function which is formed by taking the characteristics of chromosomes into account. Based on the fitness value the chromosomes are selected for crossover. Higher the fitness value higher the probability of getting selected. When two organisms mate they share their genes; the resultant offspring may end up having half the genes from one parent and half from the other. This process is called recombination (cross over). The new created offspring can then be mutated. Mutation means, that the elements of DNA are a bit changed. The fitness of the new chromosome is measured and if its fitness value is more it will replace the chromosome with lower fitness values and the GA cycle will continue for further iterations till the fitness value reaches a maximum.

II. SYSTEM MODEL

A. Hata Model

The optimization of SNR for indoor optical communication is discussed in [4]. In this paper the Hata model [5] for calculation of theoretical path loss for free space environment is used. The equations for it are given by,

$$L(dB) = \begin{cases} A + B\log d & \text{Urban} \\ A + B\log d - c & \text{Sub urban} \\ A + B\log d - d & \text{Open} \end{cases} \quad (1)$$

where,

$$A = 69.55 + 26.16\log f_c - 13.82\log(h_b) - a|h_m| \quad (2)$$

$$B = 44.9 - 6.55\log|h_b| \quad (3)$$

$$C = 5.4 + 2[\log(fc/28)]^2 \quad (4)$$

$$D = 40.94 + 4.78[\log(f_c)]^2 - 19.33|fc| \quad (5)$$

where f_c is the carrier frequency, h_m is the height of the mobile, h_b is the height of the base station and d is the distance between the base station and mobile receiver. The distance d is also taken as the maximum area of coverage of the base station.

B. GA Cycle

The chromosomes are formed initially using transmitted power (P), baud rate (b) and number of receiver elements (N) of the selection combiner. The type of area is selected based on the Hata model and the path loss is calculated by using f_c, h_m and h_b. The value of P_t ranges from 8 to 17W, b from 40 to 60Mbps and N from 2 to 10. The chromosomes are initiated only using the above range.

1) Encoding: Before a genetic algorithm can be put to work on any problem, a method is needed to encode potential solutions to that problem in a form so that a computer can process. The encoding technique used for this model is binary encoding in which the chromosomes are represented as streams of zeros and ones.

TABLE I
Binary Encoding

	Pt(W)	b(Mbps)	N
chromosome	12	52	6
Binary	1100	110100	0110

2) Fitness Evaluation: The fitness of the chromosome is evaluated based on theoretical path loss, baud rate, transmitted power and number of receiver elements. It is given as,

$$Fitness = F(P_t, N, b, L) \quad (6)$$

Where L is theoretical loss calculated by Hata model.

3) Selection: Selection is usually the first operator applied on population. From the population, the chromosomes are selected to be parents to crossover and produce offspring. The selection process employed for this model is Roulette wheel selection. It is also called fitness proportionate selection in which the chromosomes that has higher fitness values have higher probability of selection. It is given as,

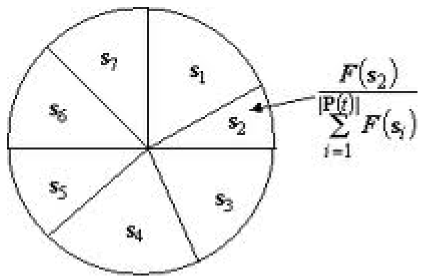

Fig.1 Roulette Wheel Selection

4) *Crossover:* The crossover employed for the methodology is Three Parent crossover[11][12]. In this technique, the child is derived from three parents. They are randomly chosen. Each bit of first parent is checked with bit of second parent whether they are same. If same then the bit is taken for the offspring otherwise the bit from the third parent is taken for the offspring. And it is given as,

TABLE II
Three Parent Cross Over

parent1:	11010001
parent2:	01100100
parent3:	11011010
offsprin	11010000

5) Mutation: The mutation operation is important to the success of the GA since it diversifies the search direction and prevents a population prematurely converging at local minima. Flipping technique is used for this system.

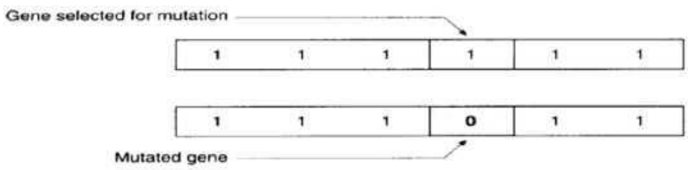

Fig. 2. Flipping

II. EXPERIMENTAL RESULTS AND DISCUSSIONS

This section will present the validation of the effectiveness of the proposed optimization model. The theoretical loss is calculated for urban, sub urban and open areas for f_c=1.8GHz, h_m=10m h_b=100m and d=1.2km. Different optimization is achieved for three different areas based on the theoretical losses respectively. Further the optimized results can be used as a template for mobile base station design based on their coverage area. The flow chart for the methodology is given in Fig.3.

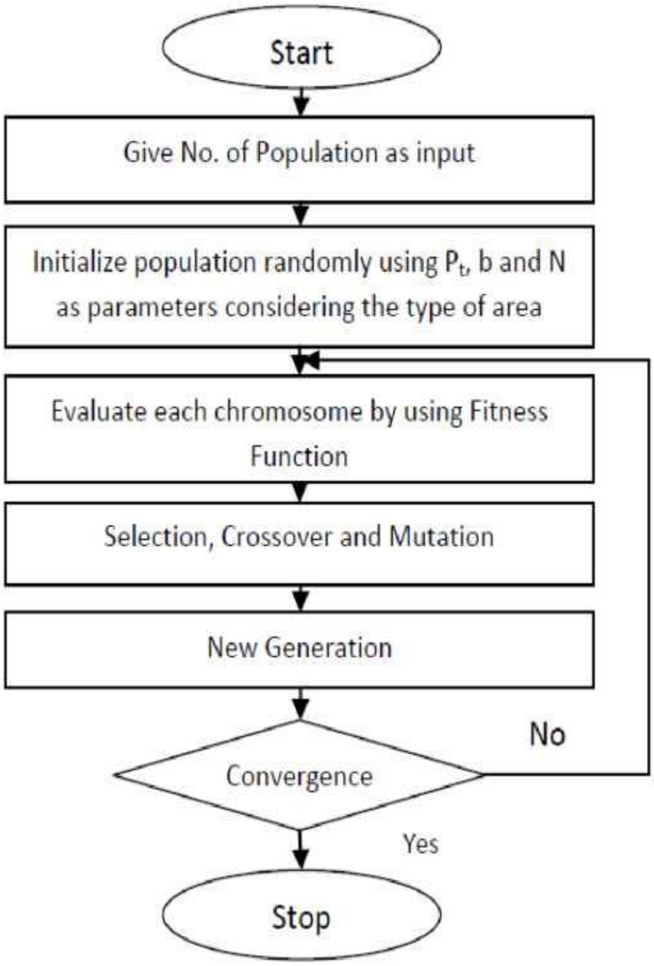

Fig. 3. GA Flow chart

A)Simulation Results

The simulated results for different areas using MATLAB as follows:

1) Urban Area:

TABLE III
Urban Area

No. of Generation=1 | Initial Population=10000 | No. of rounds=1000				
Roulette Wheel Selection				
N	Pt	b	Probability	Actual Count
7	11	45	0.0891	12
6	11	56	0.0811	11
7	11	49	0.0719	11
Crossover				
N	Pt	b		
7	11	57		
Mutation				
N	Pt	b		
7	11	56		

2) Sub Urban Area:

TABLE IV
Sub Urban Area

No. of Generation=1 | Initial Population=10000 | No. of rounds=1000				
Roulette Wheel Selection				
N	Pt	b	Probability	Actual Count
7	13	47	0.0819	15
6	13	48	0.0711	13
6	13	46	0.0691	11
Crossover				
N	Pt	b		
6	13	46		
Mutation				
N	Pt	b		
6	12	47		

3) Open Area:

TABLE V
Open Area

No. of Generation=1 | Initial Population=10000 | No. of rounds=1000				
Roulette Wheel Selection				
N	Pt	b	Probability	Actual Count
4	11	54	0.0919	16
5	10	49	0.0811	14
5	11	52	0.0796	14
Crossover				
N	Pt	b		
5	11	52		
Mutation				
N	Pt	b		
5	11	52		

III. CONCLUSION

In this paper, the investigation about how many antenna elements to employ for varying channel conditions was examined. Further the number of iterations will be increased and will be analyzed for better optimization of the above parameters. The optimized results will be substituted in the selection combining diversity and will be evaluated for better performance.

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