Genetic Algorithm for Resource Allocation in WiMAX Network

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ABSTRACT
WiMAX offer a very demanding multiuser communication problem. To make resource allocation more practical, in mobile WiMAX subchannelization is used. The Resource Allocation is usually formulated as a constrained optimization problem for either fixed-rate applications such as voice or for variable rate applications such as data. In this paper we address Genetic Algorithm for Resource Allocation in downlink Mobile WiMAX networks. Objective of proposed algorithm is to optimize total throughput. Simulation results show that Genetic Algorithm performs better than methods proposed in [5] in terms of higher capacities.

Keywords
WiMAX, Subcarrier Allocation, power allocation, Genetic Algorithm.

1. INTRODUCTION
The resource allocation is usually formulated as a constrained optimization problem, either to (i) minimize the total transmission power with a constraint on the user data rate or (ii) maximize the total data rate with a constraint on total power [1-2]. The first objective is appropriate for fixed-rate applications such as voice, whereas the second is more appropriate for burst traffic applications such as data and other IP based applications [3]. In this paper we focus on the rate-adaptive algorithms based on second category which are more relevant to WiMAX systems. This paper is extension to our previous work in [5]. Objective of this paper is to compare Linear Algorithm [5], Root-Finding Algorithm [5] and Genetic algorithm with respect to channel capacity and complexity. System model and objective function formulation done in [5] and stated as follows.

$$\max_{c_{k,n},p_{k,n}} \frac{B}{N}\sum_{k=1}^{K}\sum_{n=1}^{N} c_{k,n}\log_2(1+p_{k,n}H_{k,n}) \qquad (3)$$

2. GENETIC ALGORITHM FOR RESOURCE ALLOCATION
Genetic algorithm (GA) uses three operators, selection, crossover and mutation to direct the population towards convergence at the global optimum. Naturally these initial guesses are held as binary strings of the true variables, although an increasing number of GAs use real-valued encodings. In Resource Allocation problem primary individuals are the element of the matrix Pk,n. For example if 10 subscribers with 1024 subcarriers on the network are available, then individuals matrix i.e. Pk,n is of the size 10 by 1024 but final optimize solution is a vector of only 1024 elements. Pk,n represents individual strings. Mutation is used to randomly flip the value of single bits within individual strings. After selection, crossover and mutation string applied to the initial population so that new population can form and the generational counter is incremented by one.

We use above algorithm [6] [7] for solving our Objective function (3), for simplicity we have solve smaller version of our problem as follows. There are two subscribers on the network hence K=2 with 8 subcarriers hence N=8, proportionality is 75% and 25% hence subscriber 1 got 6 subcarriers and subscriber 2 got 2 subcarriers. Total power assumed Ptot=1W hence

$$\sum_{n=1}^{N}\sum_{k=1}^{K} c_{k,n}p_{k,n} \le P_{tot} \qquad (29)$$

As 8 subcarriers are used total power distribution is 1/8=0.125 per subscriber per carrier. As 23=8 we can form binary string of 3 bits and pursue following sequence of steps.

- Form a population of eight random binary strings of length three (e.g. *000, 001, 010, 011, 100, 101, 110, 111*).
- Decode each binary string to a float $p_{k,n}$ (i.e. *000* implies $p_{k,n}=0$, *001* implies $p_{k,n}=0.125$, *010* implies $p_{k,n}=0.25$ etc).
- Test these numbers as solutions to the problem $\sum_{n=1}^{N}\sum_{k=1}^{K} c_{k,n}p_{k,n} \le P_{tot}$ and assign a fitness to each individual equal to the value of Objective function (e.g. the solution $p_{k,n}=0.25$ has a fitness of $1*0.25=0.25$ assuming $c_{k,n}=1$).
- Select the best half of the population to go forward to the next generation.
- Pick pairs of parent strings at random from these more successful individuals to undergo single point crossover. Taking each pair in turn, choose a random point between end points of the string, cut the strings at this point and exchange the tails, creating pairs of child strings. (e.g. *010* is the best string for subscriber *1* and *100* is the best string for subscriber *2*).
- Apply mutation to the children by occasionally means with the probability one in three flipping a *0* to a *1* or vice versa.
- Allow these new strings, together with their parents to form the new population, which will still contain only four members out of eight.
- Return to second step and repeat until *100* generations have elapsed.

To further clarify the crossover operator, imagine two strings, *010* and *100*. Performing crossover between the first and second character produces two new strings as shown in Table 1.

TABLE 1

INITIAL STRINGS FOR PARENTS

Parents	Children
01-0	*11-0*
10-0	*00-0*

It is this process of crossover which is responsible for much of the power of this algorithm. This applied to our objective function in (3) assuming Hk,n is 3.5 and following are the initial population as shown in Table 2.

TABLE 2

FITNESS FUNCTION AFTER FIRST GENERATION

Population member	String	$P_{k,n}$	Fitness
1	*11-0*	*0.875*	*13.125*
2	*00-0*	*0.125*	*1.875*
3	*10-0*	*0.625*	*9.375*
4	*01-0*	*0.375*	*5.625*
5	*11-0*	*0.875*	*13.125*
6	*10-0*	*0.625*	*9.375*
7	*11-1*	*0.99*	*14.85*
8	*01-1*	*0.5*	*7.5*

The value of fitness function is highest at population member 1, 3, 5 and 7. Deleting those four with the least fitness provides a temporary reduced population ready to undergo crossover. Selecting again at random, a crossover point for each pair of strings, four new children are formed and the new population, consisting of parents and offspring as shown in Table 3.

TABLE 3

MAXIMUM VALUES FOR FITNESS FUNCTION AFTER SECOND GENERATION

Population member	String	$P_{k,n}$	Fitness
1	*11-0*	*0.875*	*13.125*
2	*10-0*	*0.625*	*9.375*
3	*11-0*	*0.875*	*13.125*
4	*11-1*	*0.99*	*14.85*
5	*10-0*	*0.625*	*9.375*
6	*11-0*	*0.875*	*13.125*
7	*11-1*	*0.99*	*14.85*
8	*11-1*	*0.99*	*14.85*

Any further populations will only contain the same, identical string. This is because the crossover operator can only swap bits between strings, not introduce any new -information. Mutation can thus be seen in part as operator charged with maintaining the genetic diversity of the population by preserving the diversity embodied in the initial generation. Rerunning the algorithm from the same initial population, but with mutation, allows the string 111 to evolve and the global optimum to be found. The progress of the algorithm with and without mutation, as a function of generation is shown in Fig.1. (A). Mutation has been included by visiting every bit in each new child string which throwing a random number between 0 and 1 if this number is less than 1/8 flipping the value of the bit. Best fitted individual shown in Fig.1. (B). although a Genetic Algorithm has now been successfully constructed and applied to a small version of our Objective function, it is obvious that many equations remaining with multiple constraints. In particular, how are problems with more than one unknown dealt with, and how are problems with real or complex valued parameters to be tackled? The approach has been shown to be successful over a growing range of difficult problems.

Above example is simulated for 100 iterations. Best fitness and Mean fitness shown in Fig.1. (A) against generations carried. As shown in Table 3 value of Best fitness is in the range of 14.85 and means fitness found in the range of 13.41. Fig.1. (B) shows number of variables versus current best individual as it is shown in Table 3, 3rd and 4th Individuals having optimized values i.e. 13.125 and 14.85. Hence problem of Resource Allocation tested and verified using simulated approach and theoretical approach.

Fitness value of each individual is shown in Fig.2. (A). Fitness of the optimum individual is ‘1’ hence after 1st iteration values of individuals is shown where it ranges from 0 to 0.2. Children populated by individual shown in Fig.2. (B).

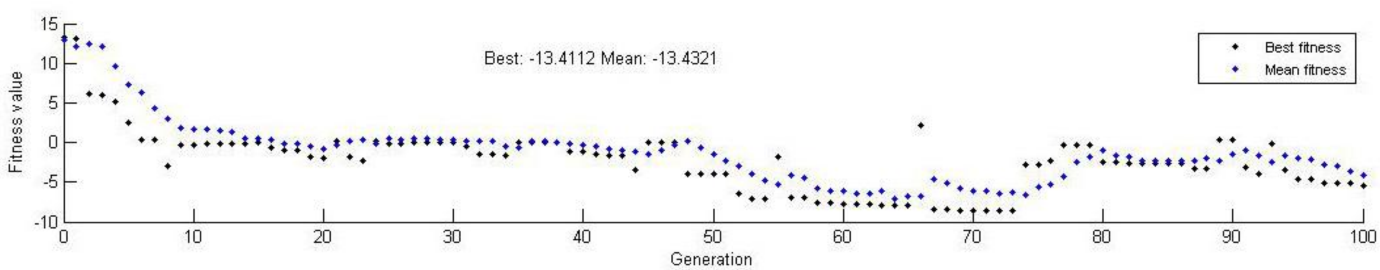

Fig.1. (A) Fitness value versus number of generations

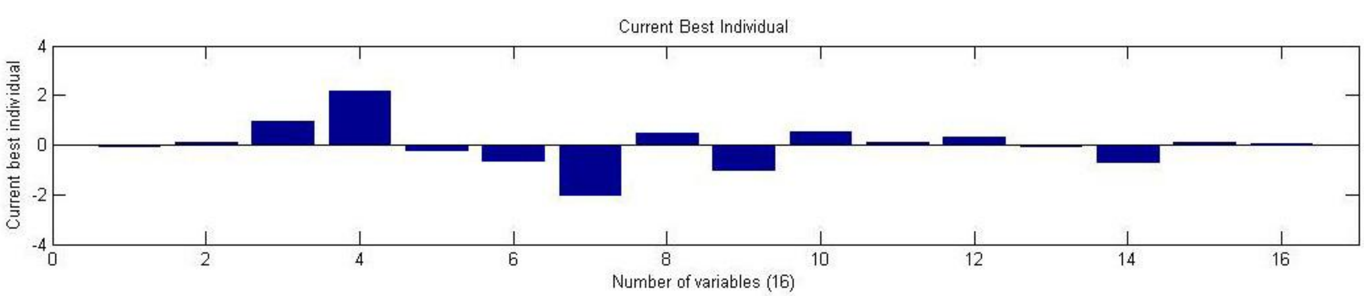

Fig.1. (B) Best fitted Individual versus Number of variables

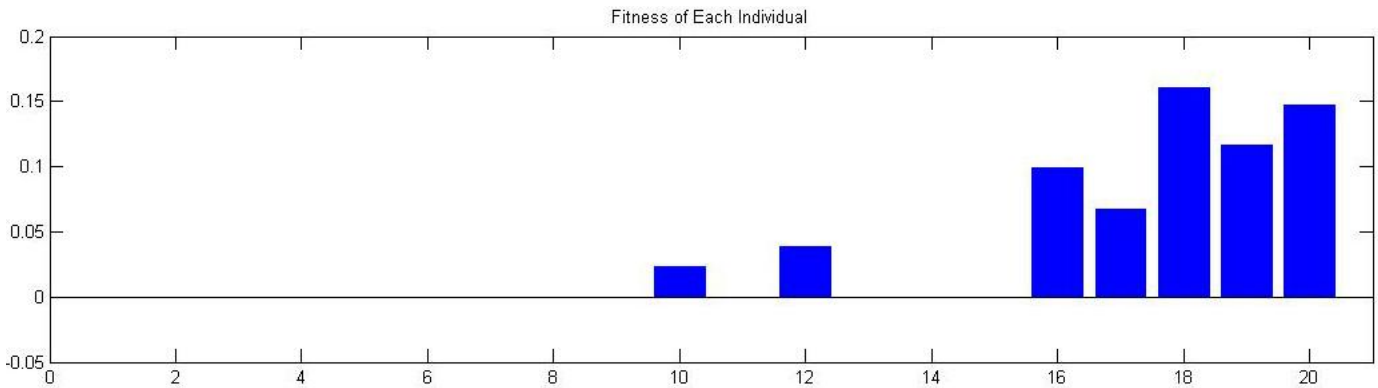

Fig.2. (A) Fitness of each Individual

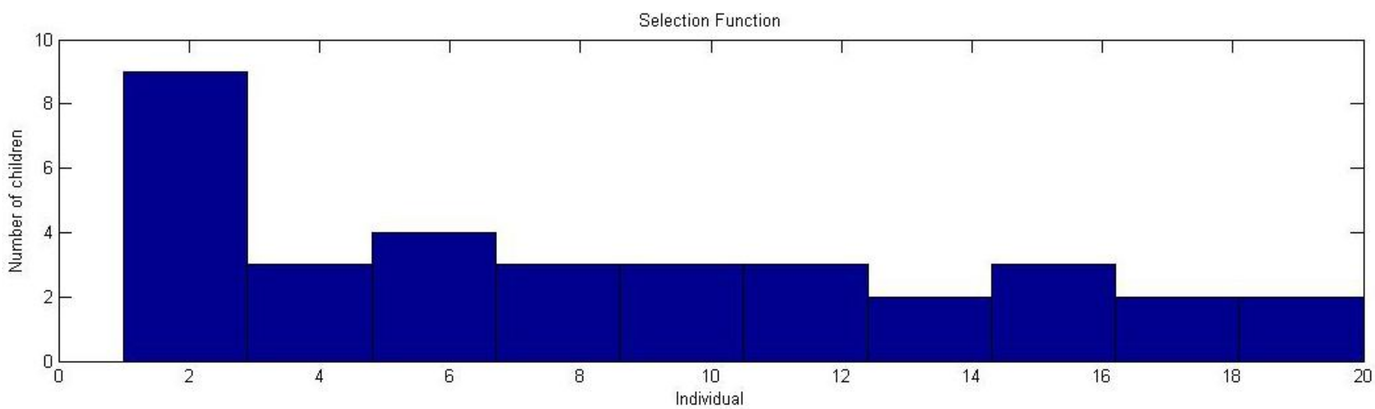

Fig.2. (B) Number of children versus number of Individual

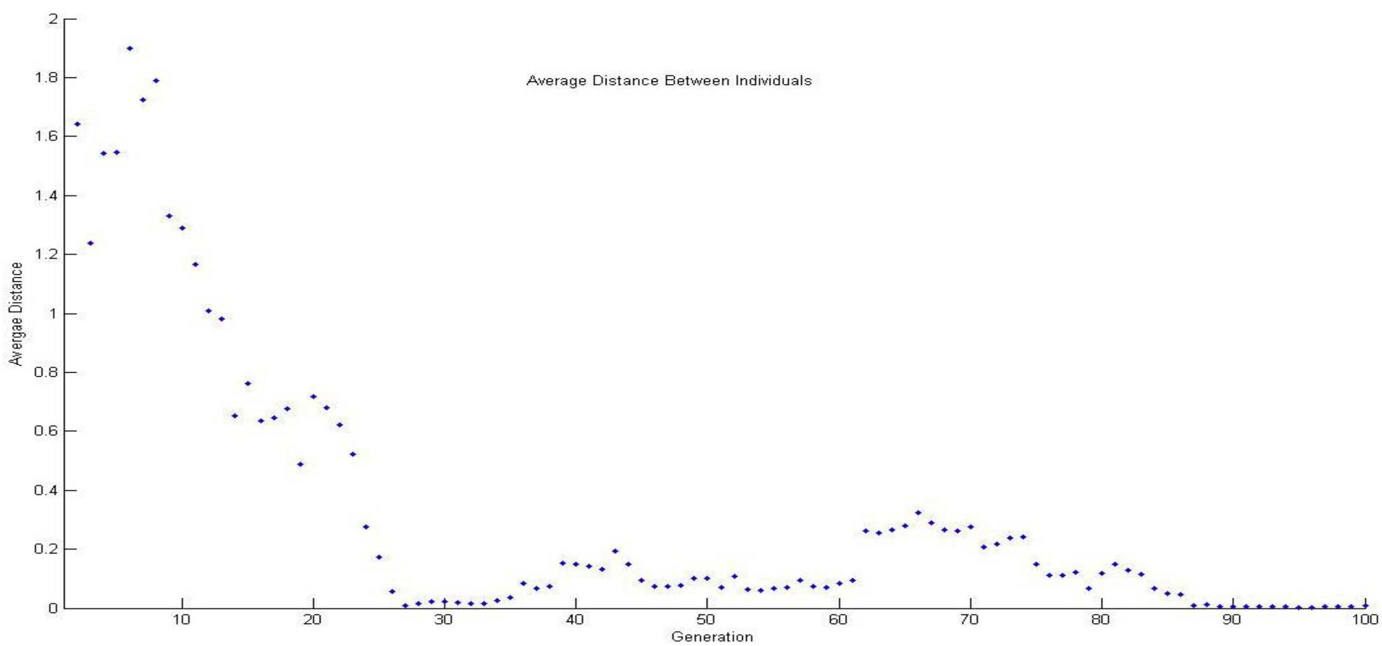

Fig.3. Number of Generation carried out versus Average Distance between individual.

Fig.3. shows the generations taken by algorithm versus average distance between two optimum values of the individuals. As number of generations increases per iteration average distance between first two individuals reduces and once the difference is equal to 0 and till few iterations remaining for stopping criteria set for the algorithm fitness functions value is calculated. We can say that if value of average distance is 0 then we got the Optimum value or desired value for our fitness function.

As compared to reduced complexity Linear Approach [5] for Resource Allocation for WiMAX system, Genetic Algorithm seems especially attractive as the number of subscribers increases.

2.1 Simulation Experiment:

Experiment is done on two subscribers only with 50% proportionality for each user; total subcarrirers available are 8, hence 4 subcarriers allotted to each user. We noted results shown in Table 4 for capacity for the two subscribers for 8 iterations or generations.

TABLE 4.

CAPACITY ACHIEVED USING GA FOR TWO SUBSCRIBERS

Iteration Number	Capacity (bits/s/Hz)	
	User 1	User 2
1	*5.0254*	*2.9410*
2	*3.0452*	*4.3337*
3	*4.3129*	*4.7474*
4	*5.6984*	*4.3495*
5	*6.0764*	*5.6382*
6	*6.2318*	*6.0812*
7	*6.2412*	*6.1012*
8	*6.3098*	*6.1113*

Capacity achieved using Genetic Algorithm is highest as compared to Root-Finding [5] and Linear Algorithm [5]. It is also observed that power allocation proportionality complexity of Genetic algorithms is quiet high hence time taken to execute it more as compared to Linear and Root-Finding Algorithms.

3. SIMULATION RESULTS AND COMPARISON

3.1 Simulation Parameters

Network under test is downlink multi user Mobile WiMAX. Rayleigh multi path channel model considered with exponentially decaying profile. Delay spread of 5ms with Doppler frequency of 30Hz. The channel information is sampled every 0.2ms, algorithms update information of subcarrier allocation and power allocation within that period. For simplicity total subcarriers took 64 instead of 1024. The average subchannel SNR is 50dB and Bit Error Rate (BER) is 10-6. Total power at base station is 10W. This simulation is for 8 subscribers only. Performance is evaluated on the basis of overall capacity of the channel in bits/sec/Hz.

3.2 Overall Capacity

Fig.4. shows the comparison of total capacities between the Root-Finding, Linear Approach and Genetic Algorithm. Notice that the capacities increase as the number of users increases. This is the effect of multiuser diversity gain, which is more prominent in WiMAX systems with larger number of users. It is observed through simulation that the system using Genetic Algorithm performs better than Linear Approach and ROOT-FINDING algorithms in terms of capacity while being applicable to a more general class of systems.

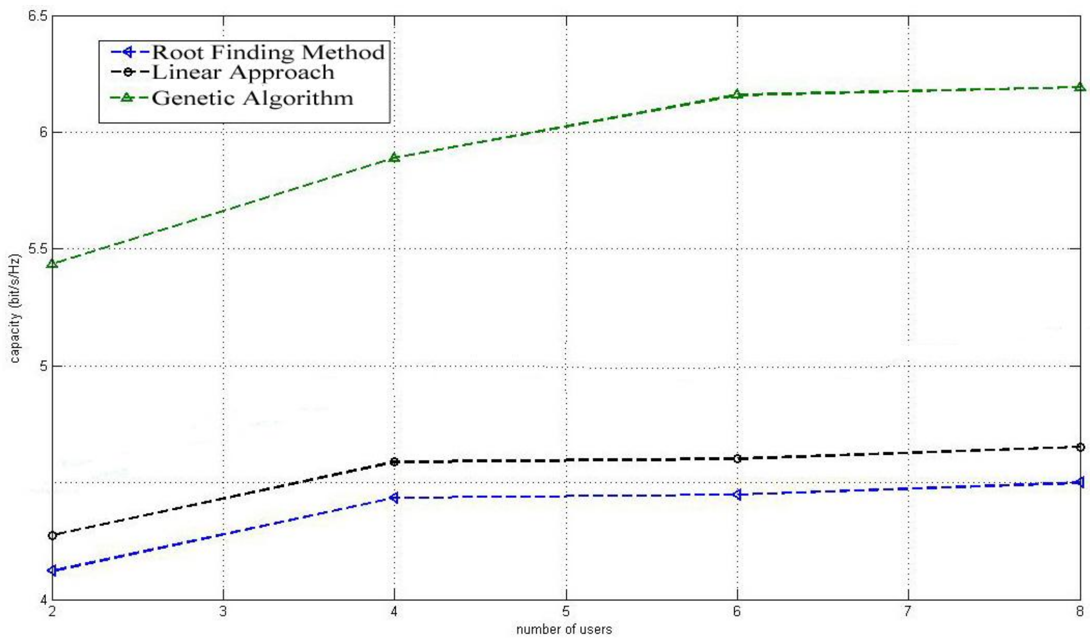

Fig.4. Total capacity versus number of users in downlink WiMAX network with N=64 and subchannel SNR=50dB. The capacity achieved by Root-Finding method, Linear Approach and Genetic Algorithm Optimization technique for 1 to 8 subscribers.

4. CONCLUSION AND FUTURE SCOPE

Though using Genetic Algorithm we achieve highest capacity due to its stochastic processing it didn't offer highest results shown in Fig.4. Also latency period plays a vital role in real time applications handled by WiMAX systems. Base station should decide and assign priorities and resources within framed time duration. On the network if all subscribers are using same service like voice or data then we suggest using Linear Approach for allotting resources. In hybrid scenario and off line decision making there is no option for Genetic Algorithm as we can compromise on latency period. This work is done as a partial fulfillment of our research; future scope is that we can test these techniques for particular QoS like Real Time Polling Service (rtps), Live Video Streaming, served by WiMAX.

We found that Linear Programming is one of the most versatile, powerful and useful technique for making decisions from the perception of Base Station. One more future direction is to design wireless devices in such a way that they can execute Linear Programming algorithms more efficiently. Also we want to extend our research for extended real time application services like video streaming on WiMAX network. Resource Allocation for Video signals can be good current research area.

5. REFERENCES

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