# IMPLEMENTATION OF AN OPTIMIZATION TECHNIQUE: GENETIC ALGORITHM

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***Abstract—*** **We are encountered with various optimization problems in real life situations. During solving these problems, a problem of local optima is raised. There are various optimization algorithms that are used to solve these kinds of mathematical problems either discrete or continuous from which Genetic Algorithm is one and presented in this paper. It was formally introduced in the United States in the 1970s by John Holland at University of Michigan. It repeatedly modified a population of individual solutions and selects individuals of better fitness from the current population to be parents and used them to produce the children of the best fitness for the next generation and remove the worst one. After successive generations, the population turned out towards an optimal solution. Genetic algorithm does not stuck out to local optima and give the global optimum solution.**

**Keywords- Genetic Algorithm; Nature Inspired Meta-Heuristics; Optimization; Mutation; Crossover; Roulette Wheel; Population.**

## I. INTRODUCTION

For optimization problems, various algorithms based on nature-inspired concepts [1] are developed. Evolutionary algorithms (EA) and swarm optimization algorithms are two different classes in which nature inspired algorithms are classified. Evolutionary algorithms like Genetic algorithm (GA) and Differential evolution (DE) attempt to carry out the phenomenon of natural evolution [2]. However, a swarm like ant colony, a flock of birds can be described as collection of interacting agents and their intelligence lie in their way of interactions with other individuals and the environment [3]. Here we are discussing about Genetic Algorithm this is a meta-heuristic algorithm inspired from the process of natural evolution and include population, inheritance, mutation, crossover and selection. Some important characteristics of Genetic algorithms that make it attractive are:

1. Quite simple and flexible.
2. Fast convergence speed.
3. Easily integrated with other optimization algorithms.

Genetic Algorithm is very popular nature-inspired algorithm i.e. used in various applications like Robotics, Travelling Salesman problem, Optimized telecommunications routing, computer gaming, clustering etc [4].

## II. GENETIC ALGORITHM

Genetic algorithm was formally introduced in the United States in the 1970s by John Holland at University of Michigan. It simulates the behavior of natural evolution i.e. always best fit survives. In this algorithm each population (collection of chromosomes taken in one generation) is represented by character strings that may be of binary digits called chromosome and each chromosome represents a point in a search space of possible solutions of the problem. We have to find the optimum solution among them by generating a chromosome of maximum fitness through a process of evolution called number of generations. In each generation a chromosome of better fitness propagates in the next generation and the poor one left behind. Always a better fit population gives better offspring and propagates in next generation. Offspring are calculated by applying operators on the chromosomes namely mutation and crossover. After selecting best fit chromosome in each successive generation we achieved a best fit chromosome among several. Genetic algorithm is explained step by step below:

### *A. Initialization*

For finding out the solution of a problem, firstly initialize a population of possible solutions of the problem. Population is a collection of chromosome (possible solution) and each chromosome is represented by a character string let's take binary vector in some domain.

Example: Find the solution of a function $f(x) = x*x$



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Where x= [-1,2]

Population size= No. of possible solutions we are taking in one generation.

Let Population size=5

Now generate each chromosome. Firstly calculate no. of bits required to represent a chromosome. It depends on a required precision which is in this example, six places after the decimal point. Domain of variable x has length 3 and with precision it must represent -1.000000 to 2.000000.

Therefore we required 3000000 equal size ranges. Hence number of bits required is:

2097152=2^21 < 3000000 < 2^22 = 4194304

Hence we choose the maximum value i.e. 22 bit to represent a single chromosome and then its actual value is found out by using below formula:

x= lower bound + x' * (domain length/(2^22 -1))

x= -1+x'*(3/(2^22-1))

= -1+x'*(3/4194303)

Example: let a chromosome= 1000101110110101000111

Its decimal value=2288967

I.e. x'= 2288967

Now, x = -1+2288967*(3/4194303)

=0.637197

Hence, 0000000000000000000000 and 1111111111111111111111 represents -1 and 2 and Initial Population:

TABLEI INITIAL POPULATION

| S.No. | Chromosome | Decimal value | Actual value in [-1,2] |
|---|---|---|---|
| 1 | 1000101110110101000111 | 2288967 | 0.637197 |
| 2 | 0000001110000000010000 | 57360 | -0.958973 |
| 3 | 1110000000111111000101 | 3674051 | 1.627888 |
| 4 | 0000000000011100001111 | 1807 | -0.001092 |
| 5 | 0011100000000000100001 | 917537 | -0.343726 |

## *B. Calculate fitness value:*

Now the fitness value is calculated of each chromosome according to given function:
F(X) = X*X
Example:
Fitness value of 1st chromosome (0.637197) = 0.637197 * 0.637197 =0.406020

TABLEII POPULATION WITH FITNESS VALUE

| S.No. | Chromosome | Actual value in [-1,2] | Fitness value |
|---|---|---|---|
| 1 | 1000101110110101000111 | 0.637197 | 0.406020 |
| 2 | 0000001110000000010000 | -0.958973 | 0.919629 |
| 3 | 1110000000111111000101 | 1.627888 | 2.650019 |
| 4 | 0000000000011100001111 | -0.001092 | 0.000001 |
| 5 | 0011100000000000100001 | -0.343726 | 0.118148 |

Clearly, the 3rd chromosome is the best, since its evaluation returns maximum and the chromosome 4th is the weakest one.

## *C. Selection using roulette wheel*

Now the system constructs a roulette wheel to select the population for the next generation. Steps to select the chromosome are:

*1) Find out the total fitness of the population:*

F= $\sum_{i=1}^{5} fitness(i)$



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F= 0.406020+0.919629+2.650019+0.000001+0.118148

=4.093817

*2) Find out the probability of a selection $p_i$ for each chromosome as: .*

$P_i$ = fitness(i)/F

Example: $P_1$= fitness(1)/4.093817

=0.406020/4.093817

=0.099179

TABLEIII POPULATION WITH PROBABILITY OF SELECTION

| S.No. | Chromosome | Actual value in [-1,2] | Fitness value | Probability of selection |
|---|---|---|---|---|
| 1 | 1000101110110101000111 | 0.637197 | 0.406020 | 0.099179 |
| 2 | 0000001110000000010000 | -0.958973 | 0.919629 | 0.224638 |
| 3 | 1110000000111111000101 | 1.627888 | 2.650019 | 0.647322 |
| 4 | 0000000000011100001111 | -0.001092 | 0.000001 | 2.4427e-7 |
| 5 | 0011100000000000100001 | -0.343726 | 0.118148 | 0.028860 |

*3) Find out Cumulative probability $q_i$ for each chromosome as: .*

$q_i = \sum_{i=1}^{i} p_i$

$q_1$ = 0.099179

$q_2$ = 0.099179+0.224638=0.1216428

TABLEIV POPULATION WITH CUMULATIVE PROBABILITY

| S.No. | Chromosome | Fitness value | Probability of selection | Cumulative probability |
|---|---|---|---|---|
| 1 | 1000101110110101000111 | 0.406020 | 0.099179 | 0.099179 |
| 2 | 0000001110000000010000 | 0.919629 | 0.224638 | 0.323817 |
| 3 | 1110000000111111000101 | 2.650019 | 0.647322 | 0.971139 |
| 4 | 0000000000011100001111 | 0.000001 | 2.4427e-7 | 0.971140 |
| 5 | 0011100000000000100001 | 0.118148 | 0.028860 | 1.000000 |

*4) Now, spin the roulette wheel 5 times equal to population size and its value turn out to be in [0,1]:*

TABLEV ROULETTE WHEEL VALUES

| S. No. | Roulette wheel values |
|---|---|
| 1 | 0.550011 |
| 2 | 0.642682 |
| 3 | 0.728654 |
| 4 | 0.320586 |
| 5 | 0.039637 |

Now we check roulette wheel $1^{st}$ value is greater than $q_2$ and less than $q_3$ therefore select $3^{rd}$ chromosome and similarly others. We will see better fitness value chromosome are selected more number of times then worst chromosomes of lowest fitness value. Chromosomes selected corresponding to roulette wheel:

TABLEVI SELECTED CHROMOSOMES ACCORDING TO ROULETTE WHEEL

| S. No. | Roulette Wheel Value | Chromosome Selected | Chromosomes |
|---|---|---|---|
| 1 | 0.550011 | $3^{rd}$ | 1110000000111111000101 |
| 2 | 0.642682 | $3^{rd}$ | 1110000000111111000101 |
| 3 | 0.728654 | $3^{rd}$ | 1110000000111111000101 |
| 4 | 0.320586 | $2^{nd}$ | 0000001110000000010000 |
| 5 | 0.039637 | $1^{st}$ | 1000101110110101000111 |



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### *D. Apply Genetic Operator*

Now we will apply genetic operator on selected population. There are two operator crossover and mutation. Both of them need a parameter $p_c$ (probability of crossover) and $p_m$ (probability of mutation) respectively. They are needed to tell on how many chromosomes from all operators is applied. Crossover operator provide the properties of two chromosomes that belongs to the population i.e. search near about a point, no newly genetic material is used (only exploitation). Crossover operator try to find out the solution best in near about space but sometime only through crossover operator we reached at local optima so there is a need of exploration in search space. Mutation operator is one of those which help in exploration by providing new genetic material. So, to get best solution we need a better balance between exploration and exploitation and the need of probability of mutation and crossover arises.

#### *1) Crossover operator:*

Let the $p_c$ = 0.25 i.e. one-fourth of population goes under crossover operator.

- Firstly generate a random number between 0 and 1 equal to population size and select the chromosome for crossover operator if its value is less than 0.25.
- Randomly generated number:

  0.822951

  0.245861

  0.756943

  0.896341

  0.054789
- Only 2nd and 5th chromosome is selected for crossover operator as only two values 2nd (0.245861) and 5th (0.054789) is less than 0.25.
- For applying crossover operator select a position of crossover (pos) between 1 and 21 as size of a chromosome is 22. Let pos=6

TABLEVII SELECTED CHROMOSOMES FOR CROSSOVER

| **S.No.** | **Chromosome Selected for Crossover** | **Pos selected** | **Chromosome after crossover operator** |
|---|---|---|---|
| 1 | 111000\|0000111111000101 | 6 | 111000\|1110110101000111 |
| 2 | 100010\|1110110101000111 | 6 | 100010\|0000111111000101 |

TABLEVIII NEW CHROMOSOMES AFTER CROSSOVER

| **S. No.** | **Chromosome** |
|---|---|
| 1 | 1110000000111111000101 |
| 2 | 1110001110110101000111 |
| 3 | 1110000000111111000101 |
| 4 | 0000001110000000010000 |
| 5 | 1000100000111111000101 |

#### *2) Apply Mutation Operator*

Let the $p_m$= 0.02 i.e. 2 bit among 100 is mutated.

Total number of bits= Number of bits in a chromosome * population size

= 22 * 5 =110

Hence, there are 2 numbers among 110 (randomly generated numbers between 0 and 1) which is less than 0.02. Let Bit positions are 48 and 91.

TABLEIX BIT SELECTED FOR MUTATION

| **Bit Position** | **Chromosome Number** | **Bit Number Within Chromosome** |
|---|---|---|
| 48 | 3 | 4 |
| 91 | 5 | 3 |


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TABLEX NEW POPULATION AFTER MUTATION

| S. No. | Chromosome |
|---|---|
| 1 | 1110000000111111000101 |
| 2 | 1110001110110101000111 |
| 3 | 1111000000111111000101 |
| 4 | 0000001110000000010000 |
| 5 | 1010100000111111000101 |

### *E. Fitness Evaluation*

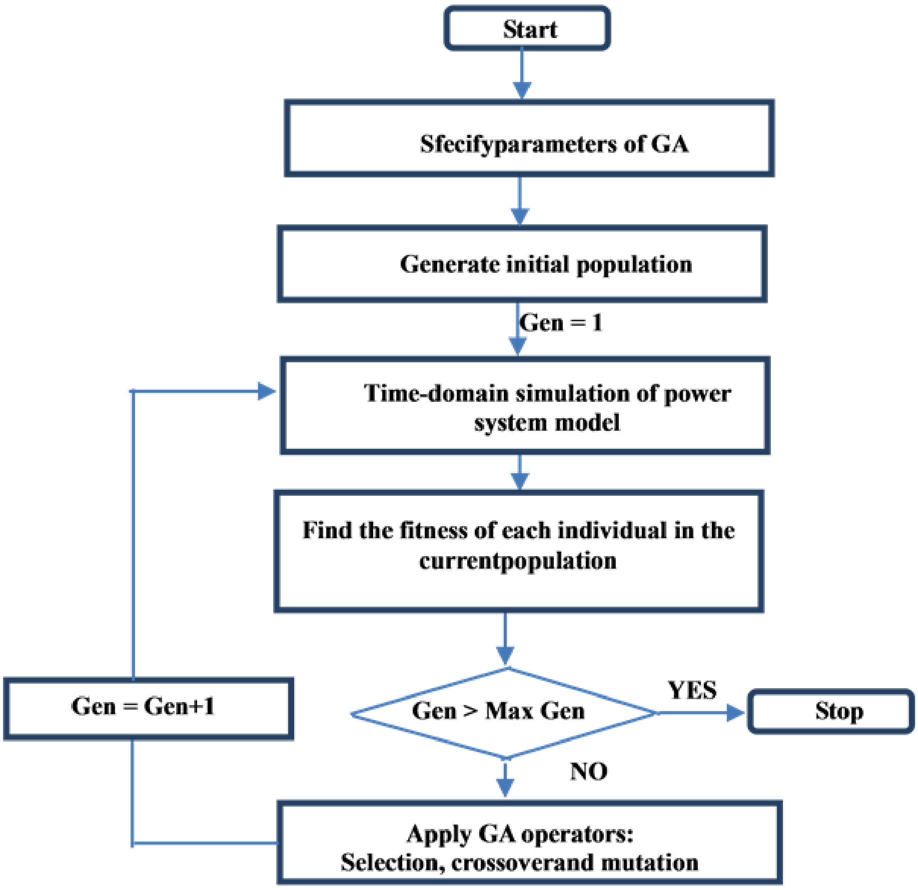
Now, we have completed 1st iteration and generated the new population for next generation. Let us compare the fitness of the 1st population that is initialized and the newest one:

TABLEXI NEW POPULATION AFTER FIRST ITERATION

| S. No. | Chromosome | Decimal Value | Actual Value | Fitness Value |
|---|---|---|---|---|
| 1 | 1110000000111111000101 | 3674051 | 1.627888 | 2.650019 |
| 2 | 1110001110110101000111 | 3730759 | 1.668447 | 2.783715 |
| 3 | 1111000000111111000101 | 3936197 | 1.815388 | 3.295634 |
| 4 | 0000001110000000010000 | 57360 | -0.958973 | 0.919630 |
| 5 | 1010100000111111000101 | 2756549 | 0.9716380 | 0.944080 |

Now on comparing it with the initialized population i.e. population of previous generation we get, Best fitness value of previous generation is 2.650019 and that of new generation is 3.295634 and the worst fitness of old population is 0.000001 and that of new one is 0.919630. So, we can see on successive generation Genetic Algorithm give better fitness value and approached toward optimal solution by improving the chromosomes and removing the worst ones. On repeating iterations for 100 generations (maximum generation stopping criteria) we will get the chromosome having value=2 and fitness value =4 i.e. the best chromosome in a given search space of the problem.

## III. FLOWCHART OF GENETIC ALGORITHM





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## IV. CONCLUSION

In this paper, Genetic algorithm is presented. Genetic algorithm moves from number of generations and each generation select the best fit chromosome and generate a new chromosome (solution) by applying genetic operators to get optimal solution and remove the worst one. It can be applied in different fields of optimization either discrete or continuous efficiently.

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