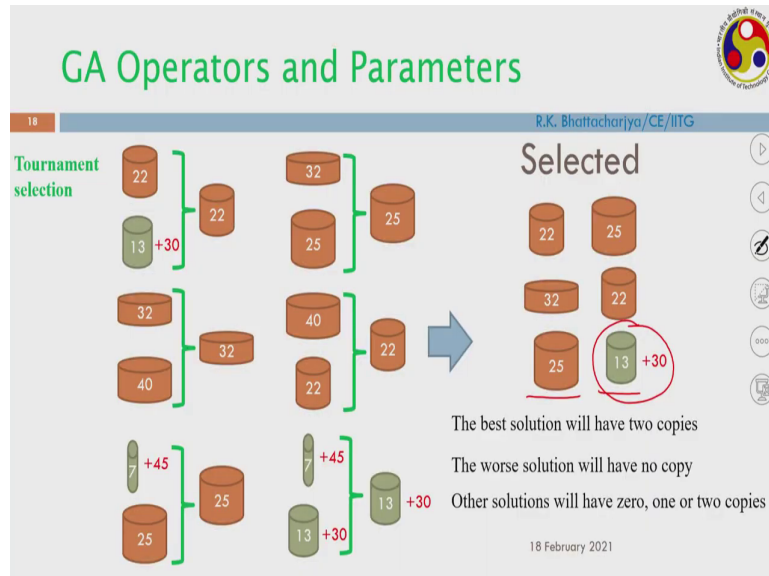


Optimization Methods for Civil Engineering
Dr. Rajib Kumar Bhattacharjya
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Indian Institute of Technology, Guwahati

Lecture - 18
Genetic Algorithms (Part II)

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Hello student. Welcome to the course again. So, in the last class we have discuss about Genetic Algorithm. So, I have introduced what is genetic algorithm, then I have also shown you the simple genetic algorithm flow chart. So, basically how we are solving a problem using genetic algorithm or how we approach a problem using genetic algorithm. So, I have shown you the flow chart and also, I have shown you the a pseudo code.

So, if we recall what we have done so far that the problem is starting with a set of solution we call it population ok. So, we have to generate initial solution and I have not discussed how to generate initial solution. So, that also I will show you how to generate initial solution or

initial population. And then, a fitness value will be assigned to each of the solution in the population ok.

So, I have discussed the fitness functions for a minimization problem or fitness function for a maximization problem. So, I can also convert a minimization problem to maximization problem. So, that I have discussed yesterday. And then, you will check for the termination criteria. So, if it is not terminated, then the solution will go through three genetic operators that is selection, crossover and mutation.

And in the last class, I discuss the selection operator and mainly we discuss the tournament selection ok. So, this is the slide where we have stop actually in the last class. So, as I said in this class, I can generate multiple copies of the better individual. So, if you have seen. So, here what I have done.

So, I have played the tournament two rounds and every tournament we have a tournament size of two; basically two individuals were selected randomly and they and there is a tournament between them and one of them is winning the tournament and then, he will go to the next generation.

So, as we have 6 solutions and then tournament size is two; that means, I have to play this tournament for twice in order to get 6 solutions. So, finally, I am getting the solution that is 22 32 and 25 and then, this is at the first round I am getting this solution. And in the second round, I am getting 25 22 and 13; 13 is a infeasible solution, but it he has played with another infeasible solution and the this solution is better than the other solution. So, that is why this solution was selected ok.

So, finally, I am getting 6 solution I also discuss. So, what will happen if the tournament size is three; that means, in that case I have to play this tournament for three rounds; that means, every round you will be selecting two solution and then. So, in three rounds, you will be selecting three solution.

Now, what will happen? In that case if you are taking a tournament size of three. So, in that case that the best solution will have three copies ok. So, best solution will have three copies; that means, out of 6 solution in the next your next generation, the three solution will be the best solution; that means, the best solution will have three copies ok and that is not a healthy situation.

I need the diversity here. I will also discuss what problem we may face if we have multiple copies of the best solution; that means, in that case, the crossover operator I have not discussed till now. So, I will discuss today what is crossover operator. The crossover operator will not create a new solution ok.

So, therefore, we want to avoid that situation; that means, I do not want that the best solution should have more copies ok. So, one two or three copies are fine, but if it is more than that that is not actually you are expected. So, you will miss the diversity. So, therefore, I do not want that tournament size should be more than two or three or something like that ok. So, I think this is clear to you.

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GA Operators and Parameters

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R.K. Bhattacharya/CE/IITG

Roulette wheel and proportionate selection

Parents are selected according to their fitness values

The better chromosomes have more chances to be selected

Chrom #	Fitness	% of RW	EC	AC
1	50	26.88	1.61	2
2	6	3.23	0.19	0
3	36	19.35	1.16	1
4	30	16.13	0.97	1
5	36	19.35	1.16	1
6	28	15.05	0.90	1
	186	100.00	6	6

ROULETTE WHEEL

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Let us discuss the other selection operators. So, one of them one of them is roulette wheel and another one is proportionate selection ok. So, these two are little bit interlinked. So, that is why we are discussing these two operators together. Now, what is roulette wheel? So, what you do basically. So, in this case the parents are selected according to their fitness values ok.

So, in this case a suppose a particular solution having higher fitness value. So, you will have the higher probability to be selected for the next generation. So, therefore, the better chromosome have more senses to be selected. So, let me explain this part. Suppose, we have 6 chromosome here ok 6 solution in a population. We have 6 solution and these are the fitness values. So, 50 then 6, 36, 30, 36 and 28.

Now, question is that in the last class, I discuss how to define fitness value. Suppose, if it is a maximization problem. So, it is a maximization problem. So, in that case, I can take this is a

fitness function. So, whatever objective function is there, objective function can be taken as a fitness function. So, in that case the objective function value more means that the solution is better, but if you have a minimization problem.

So, if you have a minimization problem minimization of $f(x)$. So, in that case what will happen, if the function value is less so, that will be the better solution. So, if you have some confusion so what I can do. I can convert this minimization problem to a maximization problem. So, what I can do. I can convert this problem to a maximization problem. Suppose maximization of $F(x)$ which is equal to $1/(1 + f(x))$ ok.

So, I can convert it. So, now, in this case, if capital $F(x)$ is more; that means, the solution is better. So, for this example problem. So, I have calculated the fitness just like a maximization problem. So, in that case the value if the value is more. So, in that case; that means, that is a better solution.

So, in that case suppose the chromosome 1; that is first solution fitness value is 50. So, so that is the best solution in the population. So, out of this 6 solution, the first solution is the best solution. Then, the second solution, fitness value is 6; that is the worst solution in this population ok. So, that is the worst solution and the other solutions are between the best and the worst. So, this is 36 and then 30 36 twice and then, 28. So, these are the solution.

Now, case. Now, we have to apply the roulette wheel concept to find out the multiple copies of the best solution and I would like to eliminate the worst solution or inferior solution. So, next what we will do. We will calculate the percent of percentage of roulette wheel. I will explain that one. So, now, what I am doing just calculate the percentage. So, total is 186. So, 186 the fitness value if I add it. So, I am calculating this value.

So, this is basically 50 divided by 186 into 100 ok. So, I am getting 26.88. Then, second one, 6 divided by 186 into 100 so, I am getting 3.23. Then for third one I am getting 19.35 and fourth one 16.13, then 19.35 15.05 and total is 100 percent ok. So, what we can do basically. So, I can create a roulette wheel.

So, and this area occupied by each of the solution; that is 1st solution if you look at this is 26. So, it is if you round it up. So, this is 27 percent. So, 1st solution is occupying 27 percent in this wheel. Similarly, 2nd solution is 3 percent or 3.23 and then, 3rd one is 20 percent and then, 16 percent 19 percent and 15 percent.

So, now they are occupying an area equal to their fitness value in proportion basically ok. So, they are suppose, 1st solution 27 like that other is occupying different area in the roulette wheel. So, now, that means, this is the perimeter the contribution of this solution one.

Now, what will happen? If this portion is more; that means, the solution to be selected or probability of selection of that particular solution is more. Now, what I can do basically. So, I can play this roulette wheel. So, I have to select 6 solution and to select 6 solution. So, I will rotate this roulette wheel and those suppose, when this roulette wheel will stop the. So, that whatever solution is indicated by this arrow line. So, I will select that particular solution.

So, idea is that algorithm is very simple. So, what I will do. I will play the roulette wheel for 6 time, because I have to select 6 solution. So, according to what solution you are selecting. So, basically this solution will go to the next generation. So, this is the idea of roulette wheel. Now, what is the probability is that that the worst solution because it is occupying only 3 percent that selection of that particular solution is the is very less probability of selection is very less.

So, this is again I as I said this is an unbiased roulette wheel ok. So, in that case, but the best solution will have higher probability. So, its probability is 26.88. So, similarly other solution will also be selected. So, this is the concept of roulette wheel. So, I can write a computer program to implement this concept and based on that, I can select the solution for the next generation.

So, I will create the multiple copies of the better individual and the worst solution will be eliminated and inferior solution will also be eliminated from the population pool. Now, in the proportionate selection what I do basically. So, I can calculate the expected count. So, what is

the expected count that this expected count is based on the probability of that your fitness of that particular solution the.

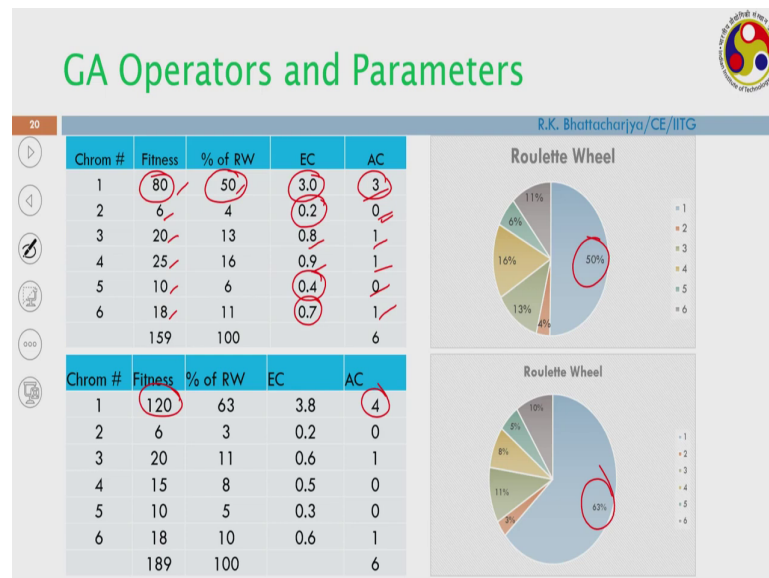
So, here this is 26.88 percent; that means, the out of 6 solution 26.88 of that will be your expected count. So, in that case this is 1.61. So, how I am getting 1.61. So, 1.61 I am getting you just multiply 6 with 26.88 percent. So, you will be getting 1.61. And then, this is 3.23 into 2 percent 3.23 percent into 6 you are getting 0.19, then 1.61 0.97 1.16 0.90 and if you add it. So, you are getting total 6 solution.

But question is that I cannot select 1.5 solution. So, either I have to select the solution or I will not select the solution, either it is 0 or 1 you are selecting the solution or you are not selecting the solution. So, therefore, the actual count will be in will be an integer value. So, it is 1.61. So, I have round it up and I am getting 2 and this is 0.19 it will not be selected 0. 1.61 so, it will 1, 0.97 it will 1, 1.6 1.16 ok so, you will get 1 and 0.09 you will get 1.

So, what you are doing; that means, the first solution that is the best solution. So, it will have 2 copies and another solution. So, worst solution will have 0 copies and other solution will have 1 copies and all together I am getting 6 solution. So, I am I can implement either roulette wheel concept or I can implement the proportionate selection in order to select this 6 solution.

So, as I said the idea of selection operator is that. So, you are selecting the better solution. So, you will have multiple copies of the better solution and or and you are eliminating the inferior solution and overall that population size should be maintained. So, in this case it was you had 6 solution. Now, also after implementation of the operator, you are again getting 6 solution, but you are getting multiple copies of some of the solutions ok.

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I hope this is clear to you. The next is now, what is the disadvantage of your select this proportionate selection ok. So, disadvantage is that if suppose the fitness value of a particular solution is very high compared to the other solution. So, in this case that if you look at in this table that the solution 1; the fitness value is 80 and other solution you just see that this is 6 20 25 10 18. So, means one solution is very good compared to the other solution.

Then, what will happen it will occupy a large area in the roulette wheel ok. So, it will occupy a very large area. In this case, you can see that it is occupying 50 percent of the roulette wheel; that means, the probability of your selection of that particular solution is again 50 percent ok.

So, therefore, expected count you are getting 3. So, actual count is also 3, then 2nd solution is the worst solution expected count is 0.2 and so, it is not selected, then the 3rd one expected

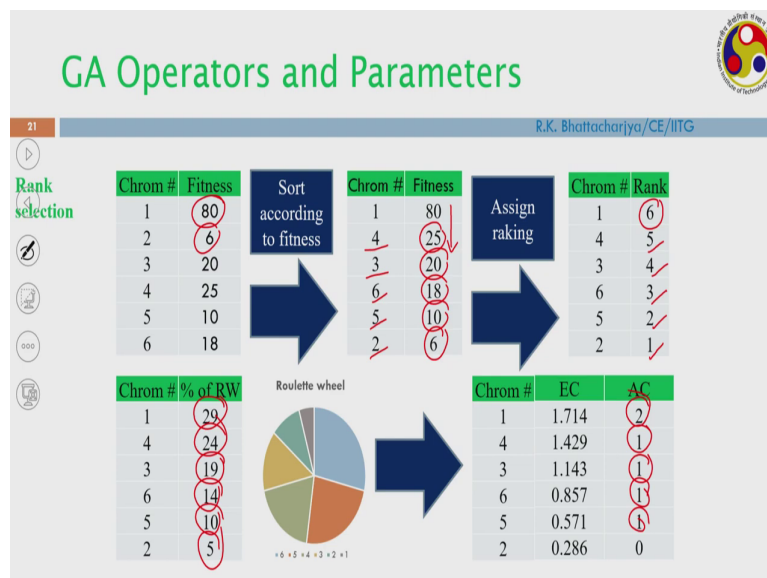
count is 0.8 you are selecting one, then the 4th one 0.9 you are selecting one then the 5th one this is 0.4. So, it is a actual count is 0 and the last one it is 0.7 and actual count is 1.

So, in this case what is happening that if a particular solution is the fitness value of a particular solution is very high in that case, it will have more copies ok for an in the next generation like that. So, in this case so, you are getting that your first solution will have 3 copies. Now, let us see that the fitness value is again very high suppose, 120 compared to the other solution in that case, it will have 4 copies out of 6. 4 copies will be the first solution ok and that is as I said that is not a healthy situation I we should avoid that one, because I would like to maintain the diversity.

Otherwise, what will happen in what has happened in this case if the fitness value of a particular solution is very large. So, it will have multiple copies and then population will be saturated with that particular solution and you will not have any diversity and in that case, crossover operator will not create new solution ok.

I will explain that one when I will discuss crossover operator. So, in this case so, I would like to avoid this one. So, how to avoid. So, it is having 63 percent is occupying by this the best solution in this case this is 50 percent and I would like to avoid this situation. So, how to avoid this situation? So, I can apply Rank selection ok.

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So, by applying Rank selection so, I can avoid that one. So, what is this rank selection? So, in this case what I am doing, I have taken the same example problem the fitness value is 80 here, the best solution worst solution is 6 another solution is 20, 25, 10 and 18. So, what I am doing. I am sorting this solution; sorting this solution in descending order. The best solution is at the top and then in the descending order, I am sorting this solution.

So, first best is this one the best solution is the solution 1, then second is solution 4 it has 25 fitness value then solution 3 that is 20 then solution 6 18 then fifth that is 10 and the worst solution is 6 ok. Now, what I am doing. So, we are assigning rank to each of the solution how we are assigning rank. The best solution we will get the highest rank.

So, in this case suppose total I have 6 solution. So, I am putting rank 6 to solution 1 this is the best solution. And then I am reducing the rank by 1; that means, the next best solution will

have a rank of 5 then 4 then 3 then 2 and then 1 ok that the worst solution is getting a rank 1 ok.

So, now what I will do. I will create the area based on this rank not based on the original fitness value. So, you create you calculate the percentage of roulette wheel. The 1st solution is now occupying 29, then the 4th one the 4th solution is occupying 24 percent then 19 then 14 then 10 then 5. So, this is the roulette wheel now.

So, in that case what will happen? The best solution ok anyway he is occupying more area. So, probability of selection of that particular solution is very high. So, anyway so, you will get multiple copies, but situation whatever we have actually we discussed that it will not be saturated with the best solution.

So, you apply this thing and finally, you are getting. So, earlier what happens? So, you got 3 copies. Now, you are getting 2 copies of the best solution ok. And similarly, you are getting for 4th solution you are getting 1 and then 1, then 1 and then 1 and worst solution it has been eliminated.

So, using rank selection so, I can avoid that type of situation and certainly this is a better method than the normal proportionate selection ok. So, this is one of the method for implementing selection operator. So, there are some other methods. So, I am not discussing here. So, you can use one of them or you can have your own your selection operator.

So, basic idea is that you have to create or it is just like acting as a filter; that means, the better individual will have multiple copies or some copies or single copies and the worst solution inferior solution will be eliminated from the population. And at the same time, you have to maintain some diversity and also, what you have to do the population size should be same.

So, if you have 6 solution, after operating this selection operator you should get another 6 solution ok. So, these are the properties of this particular function of this selection operator. So, you can have your own selection operator which will basically fulfil this function.

Otherwise, as I have discussed so, you can implement you can use one of them for as a one of them as a selection operator.

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GA Operators and Parameters

R.K. Bhattachariya/CE/IITG

Crossover

The crossover operator is used to create new solutions from the existing solutions available in the mating pool after applying selection operator.

This operator exchanges the gene information between the solutions in the mating pool.

Centromere holds 2 chromatids together

Chromosome

Gene segment of DNA that codes for a trait

Chromatids identical copies

Encoding of solution is necessary so that our solutions look like a chromosome

Source: <http://www.biologycorner.com/bs1/cell/division-chromosomes.html>

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Now, the next operator is the crossover operator. So, what is the function of crossover operator? The function of crossover operator is to create new solution. As you have seen the selection operator is actually not creating any new solution. So, what we are doing we are getting multiple copies of the better individual or and or you are eliminating the inferior solution, but you are not getting a new solution by you are applying the selection operator.

So, therefore, this crossover operator is implemented or the function of the crossover operator is to create new solution. So, I will explain the crossover operator now. So, as I said the crossover operator is used to create new solution used to create new solution from the existing solution available in the mating pool after applying selection operator.

So, what is mating pool? So, mating pool is that whatever solution you are getting after applying the selection operator and that is basically now, mating pool and we can apply crossover operator on that particular solution. This operator extends the gene information ok. I will explain what is gene information. As of now, we have not seen any gene information between the solution in the mating pool ok. So, this is the function of this operator. So, this operator exchanges the gene information between the solution in the mating pool ok.

This is a biological chromosome. So, this chromosome is consist of gene ok. And then, what is happening during reproduction, this chromosome they exchange the gene information and they are transferring the characteristics of the parents to their offspring ok. So, this is the function of crossover. In order to implement this concept. So, we have to convert our solution to a chromosome type structure.

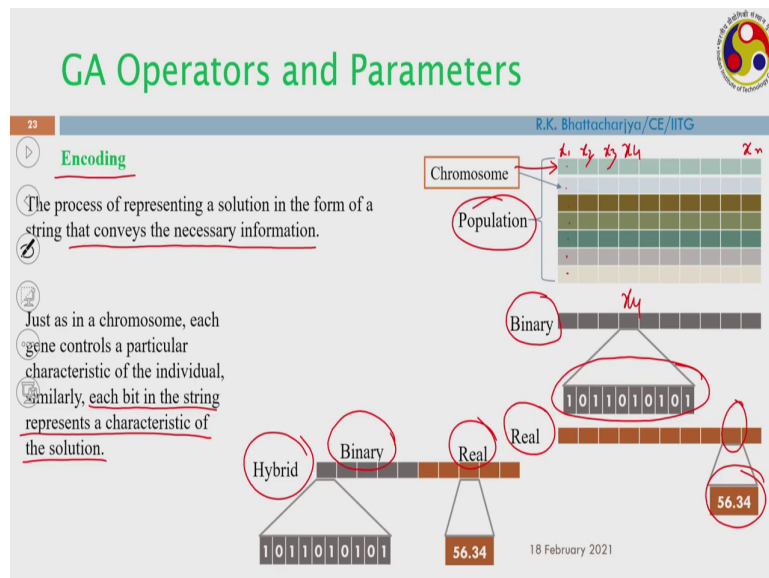
So, here this is just like a simple chromosome. So, if I say this is a chromosome ok. So, if I say this is a chromosome and this is basically the gene of this particular chromosome ok this is gene. Now, just like your biological chromosome. So, here also gene is carrying the characteristics of that particular solution. So, the value in this particular chromosome. So, we will basically carrying characteristics of the solution just like the biological chromosome ok.

So, now how to do that basically so, I can convert whatever solution I have to a binary bit. So, once you are converting the solution to a binary bit. So, in that case, this is acting as a gene. So, this is acting as a gene and all together this is basically we can say a chromosome and its value. So, this gene value are bearing the characteristics of that particular solution. I will explain that one how it is bearing that characteristics.

So, now I can say that this is a simple your chromosome and then we have the gene information and once we converting our solution just like in chromosomes. So, in that case, I can apply the crossover operator in order to in order to create a new solution. So, for that what I need.

Encoding of solution is necessary. So, that our solution solutions look like a chromosome. So, you have to encode. So, whatever solution whatever that solution you have that you have to means you have to do the encoding. So, that it looks like a chromosome.

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So, how to do that what is encoding. The process of representing a solution in the form of a string that conveys the necessary information is called encoding. Just as in a chromosome, each gene controls a particular characteristics of the individual; similarly, its bit in the string represent a characteristics of the solution so, ok.

So, what I am what we want to do basically here. So, using encoding so, I would like to convert this solution just like a string and in that case just like in chromosome that gene is

actually bearing the characteristics of that particular solution. And here also, its bit will you would carry the information or characteristics of that solution.

Here, so, I am represent this a population. So, population as I said. So, it is a set of solutions. So, I can say what is solution. Solution means this is one chromosome so, one chromosome I can also say that is one solution. Suppose here, we have an population is consist of chromosome.

So, here I have 1, 2, 3, 4, 5, 6, 7 chromosomes in the population. So, now, this is basically so, this is a chromosome and these are all gene information just like the biological chromosome. And once you have the gene information. So, you can apply the crossover concept on this particular your chromosome.

Now, what we do suppose this is, this is representing a variable. So, this is variable one. Suppose, x_1 and this is x_2 this is x_3 something like that and this is x_n . Now, this may be a real value or this may be a binary value. So, if it is a binary value. So, suppose this is x_4 and this is x_4 here and x_4 may be a binary value. I will discuss how you can convert to a binary string. So, a real value I can convert or decimal value I can convert it a binary value.

So, this is a binary bit; that means, all values all variables are converted to a binary bit ok. Or otherwise, what I can do I can also take the real values ok decimal values I can take. So, in that case this is suppose real value. So, here, I will say this is binary bit and here, I will say this is real bit.

Sometime what you do basically some of the bit basically or some of the variable I am taking as a real variable and some of them are I am taking as a binary variable and in that case, this is known as hybrid string basically. So, what I have seen here or what we have seen here. So, I can consider a binary bit I can consider a real your string or I can consider that a part of the string is real and part of the string is binary.

So, in that case what will happen if you are using binary. So, we call it binary coded G A ok. So, BGA binary coded G A, if your string is binary. And if you are using real values decimal

values the in that case, what I say that we are calling real coded G A. So, I will also discuss real coded G A, but we will start with binary coded G A ok. And sometimes what we do that we are using hybrid string; that means, part of the string is real and part of the string is binary ok.

So, depending upon the requirement of the problem. Sometime, what happen I would like to represent a particular variable suppose a mixed integer problem. So, in case of mixed integer problem a variable may be a integer variable. So, I would like to keep it as a binary variable and maybe other variable I can consider as a continuous variable. So, it may be a real value. So, I can have a hybrid string like that. So, but we will discuss initially the binary coded G A.

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GA Operators and Parameters

R.K. Bhattacharjya/CE/IITG

Encoding Methods

Most common method of encoding is binary coded. Chromosomes are strings of 1 and 0 and each position in the chromosome represents a particular characteristic of the problem

1st variable 2nd variable

3 1 1 0 1 0 0 1 1 1 0 1 0

Decoded value 52 26

Mapping between decimal and binary value

$$x_i = x_i^{\min} + \frac{x_i^{\max} - x_i^{\min}}{2^{l_i} - 1} DV(S_i)$$

$$\begin{array}{r}
 1 \quad 0 \quad 1 \quad 1 \quad 0 \quad 1 \quad 0 \quad 1 \\
 2^6 \quad 2^5 \quad 2^4 \quad 2^3 \quad 2^2 \quad 2^1 \quad 2^0 \\
 32 \quad 16 \quad 8 \quad 4 \quad 2 \quad 1
 \end{array}$$

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The encoding method ok so, most common method of encoding is binary coded. So, as I said this is a binary coded. Chromosomes are string of 0 and 1 1 or 0 and each position of the

chromosome represents a particular characteristics of the problem. So, I have shown here a string. So, this is a string and we have two variable; variable 1 and variable 2. And suppose the variable 1 is so, here it is 6-bit string. So, 1 2 3 4 5 6 that this first 6 bit that represent the variable 1 and the next 6 bits represent the variable 2 ok.

So, variable second variable and here 1 1 0 1 0 0. So, if we decoded decode that one. So, what I am getting I am getting 52. I think you know that one how to decode this one and for the second one, I am getting 26 ok. Now, what I can do basically, then I can do the mapping. So, as per my requirement ok and my precision whatever precision you as per the requirement of the precision I can do the mapping and this mapping is done using this equation ok.

So, what is this that x_i which is equal to $x_{i \min} + (x_{i \max} - x_{i \min}) \times \frac{\text{decoded value}}{2^{\text{length of string}}}$ and this portion is known as precision ok. So, depending upon that length of the string suppose, if you are increasing the length of the string, then your precision will increase. And if you look at that if suppose if it is between suppose I would like to have this variable the lower bound is 0 and upper bound is suppose 10. So, depending upon what type of string you are using.

So, if you are using all 0s then you will get the lower bound and if you are getting all 1s, then you will get the upper bound if you are using this mapping ok. Now, if you look at. So, I would like to explain one thing here. Suppose, you are taking a string 0 then 1, then 1, then 0, then 1 and 0. Now, what is happening here?

So, if I decode this one. So, this is 2^0 this is 2^1 this is 2^2 this is 2^3 this is 2^4 and this is 2^5 . So, what I am getting. So, this is 1 this is 2 this is 4 this is 8 this is 16 and this is 32 ok. Now, if you look at.

So, if suppose this particular bit is change; that means, the right-hand side this bit I if I change from 0 to 1, then what will happen then there is a change in just the change in corresponding

will the change will be just 1, but if you are changing this from 0 to 1, then what will happen then you are adding 32 to that new string.

So, therefore, if you look at this that this, the left-hand side bits are more significant bits if there is any change in the left-hand side bit. So, the corresponding change in the decoded value will be very large. Similarly, the right-hand side bit if you are changing that corresponding change in the decoded value will be very less.

So, I will use this concept when I discuss about crossover and mutation. So, you just remember if you are changing the right-hand side bit. So, that are not very sensitive what is happening the corresponding change in the decoded value is very less, but if somehow the left-hand side bits are change. So, in that case what will happen, there will be a huge change in the decoded value.

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GA Operators and Parameters

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R.K. Bhattacharjya/CE/IITG

Encoding Methods

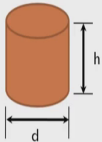
Minimize $f(d, h) = c \left(\frac{\pi d^2}{2} + \pi dh \right)$

Subject to $g(d, h) = \frac{\pi d^2 h}{4} \geq 300$

$d_{min} \leq d \leq d_{max}$

$h_{min} \leq h \leq h_{max}$

Defining a string



Solⁿ

[0100001010]

(d, h) = (8, 10) cm

Chromosome = [0100001010]

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So, now let us take an example problem encoding method. I would like to take the same problem that is minimization of the cost of the can and then, subject to that volume of the can should be greater than 300. And the dimension that is diameter and height of the can should be between d minimum and d maximum and h minimum and h maximum.

Let us define a string here. So, what I am doing. So, I am using total five bit here to represent the variable d another five bit to represent the variable h ok. So, this is the solution string basically. So, this is your solution string. So, now, I am defining just like a chromosome here. So, this is a chromosome and these are the gene of this particular chromosome ok.

Ah when we will decode that one. So, then what will happen. I will consider the five first five-bit for d and the second five bit for h . So, if you do that. So, what you are getting then this d this is for 0 1 0 0 0. So, you are getting 8 and 4 0 1 0 1 0. So, you are getting 10. So, decoded value is 10. So, I am not using any mapping here. Directly we are using decoded value and this is representing a particular your solution string ok.

So, now once you are defining this chromosome ok. So, in that case when we will apply crossover. So, we will apply the crossover in the entire string not based on individual variables. So, I will discuss this part when I will show you the crossover method. So, here this is a chromosome here.

So, this is a chromosome here, the chromosome is 0 1 0 0 0 0 1 0 1 0. So, this is the chromosome. And I can decode this chromosome and if I decode this, I will be getting the d equal to 8 and h equal to 10. And I know and putting that value in the objective function, I can also find out for this particular chromosome what will be the fitness value.

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GA Operators and Parameters

Crossover operator

The most popular crossover selects any two solutions strings randomly from the mating pool and some portion of the strings is exchanged between the strings.

The selection point is selected randomly.

A probability of crossover is also introduced in order to give freedom to an individual solution string to determine whether the solution would go for crossover or not.

R.K. Bhattacharya/CE/IITG

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Now, crossover operator; so, what is crossover operator. The most popular crossover select any two solutions string randomly from the mating pool and some portion of the string is exchanged between the strings ok. So, what we do basically. So, we select two solution we select two solution string randomly from the mating pool.

Suppose, these are two solution that is solution 1 and solution 2 you are selecting from the mating pool. This is solution 1 and this is solution 2. And then, you are selecting a crossover side ok. So, I am selecting this crossover side and after that you are just swapping the information ok.

So, what is happening that this portion, this portion is coming here and this portion is going there. So, you are getting a new child that is from the solution 1 and solution 2, the one

portion from the solution 1 this is this portion is from the solution 1 and this portion from solution 2.

So, this is coming from solution 1 and this is coming from solution 2. And similarly for the 2nd solution, this is coming from your solution 2 and this is coming from solution 1 ok. So, I can write a code to implement that one. So, what we are doing here. So, we are exchanging the gene information.

So, part of the chromosome actually exchange in this particular process and you are getting two new solution. So, what you have done. So, I am taking two solution and then, I have applied this crossover operation and you are getting two children ok child 1 and child 2 you are getting.

Now, question is that the concept is very simple. So, what I am doing here. From the mating pool, you are selecting two chromosome and this chromosome will go for crossover and crossover means a crossover site will be selected randomly and then, you are swapping the gene information and you are getting a new solution.

Now, question is that what do you do basically. So, a probability is concept is you or a probability value is used or we call it crossover probability. So, what we are doing here, a probability of crossover is also introduced in order to give freedom to an individual solution string to determine whether the solution would go for crossover or not basically.

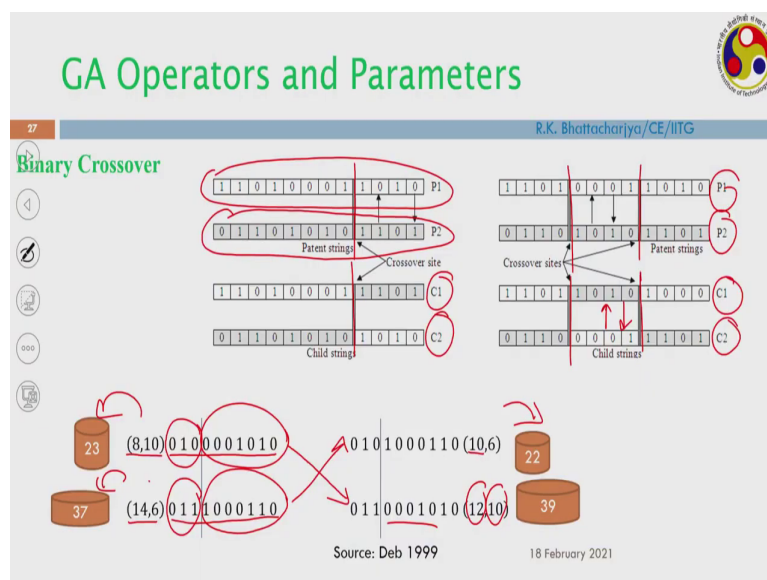
So, what we are doing here. A probability value is assigned here this is we call it crossover probability based on the crossover probability. So, that an individual solution will either go for crossover or will not go for crossover; that means, without going crossover that particular solution will go to the next generation. So, we are putting a crossover probability.

So, now what should be the value of crossover probability? So, crossover probability is generally we consider little bit large; that means, 60 percent to 95 percent or something like that. So, what does it mean? 60 percent means that whatever solution you have 60 percent of

that solution will go for crossover and 40 percent of them will not go for crossover and they will directly go to the next generation.

So, if it is 95 percent; the 95 percent of the solution will solution in the mating pool will go for crossover and 5 percent will directly go to the next generation. Generally, what we do. We consider a very high crossover value as I said that 0.6 to 0.95 ok. So, 60 percent to 95 something like that. So, high value of. So, our idea is that the most of the solution will go for crossover maybe, few solution; they will not go for crossover they will directly go to the next generation.

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In a binary crossover what we do. So, we have converted this string to a binary bit. So, this is parent 1 and this is parent 2 ok. And these are bits and bits are bits values are either 0 or 1. And then a crossover site is selected here. This is the crossover site and then exchange of this

information will happen and finally, you are getting child 1 and child 2 basic. So, this is your binary your crossover.

So, what we are doing here. We are converting the solution to a binary bit and then, we are selecting a cross over side and this crossover side is also selected randomly ok. So, also selected randomly between one and $n - 1$ so, where n is the your number of bits. So, it is selected and after that you are exchanging the gene information. So, taken just look an example sometime what happen we are also taking two crossover site.

So, in this case, this is one site and this is another site and then exchange of gene information is happening ok. So, you are getting from these two parents. So, parent 1 and parent 2; you are getting two solution that is C 1 and C 2. Let us take this example problem that can design problem. So, this is one solution 8, 10 and if I encode this solution. So, I will be getting this 1 0 1 0 0 0 1 0 1 0. So, this is this will represent 8 and 3 and corresponding decoded value is 23.

Now, there is another solution that is 14 6. So, this solution these two solutions we are picking randomly and this is 14 and 6. So, corresponding chromosome is 0 1 1 1 then 0 0 0 1 1 0. So, this is the string and corresponding the decoded value is 14 and 6 and then corresponding cross value is 37.

Now, if you take this as a crossover site so; that means, crossover site is 3 and then, you are exchanging the gene information. So, what is happening that this portion of the first string and this portion of the second string will create the children or child 1. And similarly, this portion of the second string and this portion of the first string will create the another solution.

So, you are getting two new solution and this solution if you decode it, then you are getting 10 and 6 and corresponding objective function value is 22 and for this solution if you decode it. So, you are getting 12 and 10 and the corresponding solution you are getting is 39 ok.

So, you just see so, you have applied crossover. And in this case, the parent solution is 23. So, objective function will is 23 and 37 and here, you are getting 22 and 39. So, what you are

doing here. So, using crossover so, you are getting two new solution, but look at this solution. So, earlier solution was 23 and 37 and whatever new solution you are getting that is 22 and 39; objective function value is just near to whatever their parents value.

So, if you look at this thing you are getting the solution near to the parent. So, earlier solution what 8 and 10 and now, new solution is 10 and 6. Similarly here, earlier solution is 14 and 6 and new solution is 12 and 10. So, whatever solution you are getting you are getting near to their parents. Is not it the children whatever new offspring you are getting, they are near to the parents.

So, what does it mean that, crossover operator is basically creating a new solution near the parents. So, it means that thus that crossover is actually doing the local search. It is searching near to the parents ok. So, this is so, for all the population. Suppose you have 100 population and after crossover what you will get. So, you will just you will say is there any improved value near to the current solutions ok.

So, near the current solution is there any improved value; that means, you are doing the local search using crossover. Now, I would like to mention another point here. So, when we discuss the selection operator. So, I said that once you are increasing selection pressure; that means, you are getting multiple copies of a particular solution.

Now, I think we will appreciate that one that if you are getting multiple copies and suppose the solution is saturated by a particular solution. So, out of 6 solution, 4 solution is the best solution then what will happen. If you are picking up two solution for the crossover and because this these two solutions are same. And in that case, if you apply crossover and what you will get you will get the same solution. So, you will not get a different solution.

So, therefore, the crossover operator will not be able to produce a new solution in that case. So, we do not want that one. And therefore, we do not want that our population is saturated with particular solution ok. So, I would like to avoid that one and that is why we have applied rank method or we will not you increase the selection pressure.

If you are increasing selection pressure so, in that case, a particular solution will have multiple copies. And in that case, the crossover operator will not work crossover will not create a new solution that means, both the strings are same. So, if you exchange the gene information. So, you are not getting a new solution. So, I would like to avoid that one and therefore, I need multiple copies, but with some limited number.

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GA Operators and Parameters

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Mutation

Mutation is the occasional introduction of new features in to the solution strings of the population pool to maintain diversity in the population.

Though crossover has the main responsibility to search for the optimal solution, mutation is also used for this purpose.

Before mutation **After mutation**

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The diagram shows a bit string of length 10. In the 'Before mutation' state, it is all zeros. In the 'After mutation' state, the 1st, 4th, and 9th bits have been flipped to 1. Red circles and arrows highlight these changes. A small red 'x' is also visible to the right of the 'After mutation' string.

The next portion is mutation. So, what is mutation? So, as you have seen that crossover is creating a new solution, but what crossover is doing crossover is just doing the local search ok. So, it means that it is searching near the parents ok. So, whatever new solution you are getting, these new solutions are near the parent.

So, you are not exploring the other region in the search space. So, mutation is doing that one how mutation is doing let me check that one. So, what is the what is mutation first. So,

mutation is the occasional introduction of new features in the solution string of the population pool to maintain diversity in the population. So, what you want to do you want to create diversity; that means, you want to maintain diversity in the population. So, we are using mutation ok.

So, though crossover has the main responsibility to search for optimal solution, mutation is also used for this purpose. So, what we do basically. Suppose, this is a particular string and then, you are this string per that the fourth one is mutated. So, now, you are getting a new value in this particular bit ok or in this particular gene. So, once you are getting a new value, the decoded value of this one will also bit different.

But now, question is that what is happening if you are using binary bit. If you recall that if suppose this value is 0 and after mutation it become 1; that means, what is happening you are adding 1 to the decoded value. So, whatever decoded value earlier it was. So, you are adding another 1 to that 1, but if this value was 0 and if you are putting it 1 or if it is 1, if you are putting is 0, there will be huge change in the decoded value.

Therefore, the right-hand side bit ok. So, they are less significant bit; that means, if there is a change in this bit. So, corresponding change in the decoded value is very less, but if there is a change in that particular bit, the corresponding change will be very high. Suppose, if it is suppose, this is the solution if the right-hand side this bit is change.

So, you are getting a new solution somewhere here, but if the leftmost bit is change. So, in that case, what will happen, you will get the new solution maybe at far distance. So, that way what you can do basically you can explore the other unexplored region of the search space using mutation ok.

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GA Operators and Parameters

Binary Mutation

- ✓ Mutation operator changes a 1 to 0 or vice versa, with a mutation probability of P_m .
- ✓ The mutation probability is generally kept low for steady convergence.
- ✓ A high value of mutation probability would search here and there like a random search technique.

Diagram illustrating binary mutation:

Before mutation: 1 1 0 0 0 0 1 1 1 0 1 1

After mutation: 1 1 0 0 0 0 1 1 1 0 1 1

Handwritten formula: $P_m = \frac{1}{L} = \frac{1}{10}$

Source: Deb 1999 18 February 2021

So, binary mutation. So, mutation in this case, the mutation operator changes a 1 to 0 or 0 to 1 with a mutation probability of P_m . So, with a mutation probability of P_m ok. So, we are just like crossover probability. Here also, we are defining a mutation probability, but the mutation probability is generally kept very low.

So, the mutation probability is generally kept very low for steady convergence. Otherwise, what will happen you are moving here and there and you may not get the you may not converge towards the optimal reason. So, therefore, the mutation probability is generally kept very low. So, what I do basically. So, the a high value of mutation probability would search here and there like a random search technique ok.

So, I will explain that one. Suppose, this is the bit before mutation and this particular bit is muted mutated, then it will change from 1 to 0 ok. So, this is the new bit whatever this is the

new solution after mutation. So, let me take this example problem. So, here this is the solution. The solution is 10 6 and this is the chromosome this is the chromosome we have. And then, suppose you are mutating the fourth bit and then, this bit will change the fourth it was 1 then it will be 0 now.

And whatever new solution you are getting. So, this is your the objective function value is or cost is 16. So, you are getting some better solution after mutation. Now, what is happening that as I said that this bit is now change. So, what we got it. So, this is for the first one 1 2 3 4 so, up to this is first the variable 1 that is your diameter and this is your h. So, in this case the diameter the portion is mutated. So, therefore, whatever you are getting that it was 10 and now, it is it the value is 8 ok.

Now, just see that if 1 is mutated ok. So, this particular bit is mutated. So, then, there will be huge change in the diameter value. So, there will be huge change in the diameter value and you are going towards a different region. So, therefore, if you are applying mutation, you will be able to explore the entire search space ok. So, if there is any other solution in some areas. So, that can also be explored using mutation, but you will not be able to do that by using cross only crossover operator.

Now, as I said the mutation probability should be very low. The thumb rule is you consider that P_m equal to $1/L$. So, what is L . L is the string length. So, in that case, we have total five bits. So, in this case the mutation probability should be $1/10$ ok. So, $1/10$ should be the mutation probability.

So, generally we are taking very low mutation probability. And if I take $1/10$ in this case, what is it means that out of 10 bits, 1 will be mutated. So, I do not want that more than one-bits or something like that. So, idea is that out of 10 bits. So, 1 will be mutated. So, you have to use mutation, but with some control manner. So, I am not using very high probability of mutation.

So, generally as I said it is $1/L$ generally, we use but you can also use a very small one, but the crossover probability should be very large 60 percent to 95 percent or something like that

even you can use hundred percent crossover probability also. So, if you summarize now, we have discussed selection operator. So, selection operator is not producing any new solution. It is not searching. It is only creating multiple solution of the better individual.

Then, crossover operator is creating new solution, but it is acting as a local search. It is just searching near the parents. To summarize what we have discussed today. So, we have discussed selection operator. The selection operator is creating multiple copies of the better individual. And we are eliminating the inferior solution and while keeping the population size constant. So, we are not creating new solution, using selection operator.

Crossover operator is creating new solution, but what we are doing. We are try we are basically doing the local search; that means, the crossover operator will create new solution near the parents, then we have seen that mutation. So, what mutation is doing? Mutation operator can explore the unexplored region of the search space ok. So, if there is any solution in or any better solution in some other region. So, you can actually explore using mutation so, but you have to use in a control manner. So, mutation probability should be very low and crossover probability should be large.

Now, if we see the difference between crossover and mutation. So, crossover is convergence in nature so; that means, you are converging towards the optimal solution and mutation is divergence in nature. So, you are going away from the optima to explore some other unexplored region. So, this is the difference between crossover and mutation. So, we have to use both of them in a control manner to guide the search towards optimal solution.

Let us stop here. Tomorrow we will solve a problem simple problem. And basically, I would like to show you the hand calculation and how these operators are working, how to generate how to generate initial solution then, how to apply crossover, how to apply selection operator, how to apply mutation using hand calculation so, that we will discuss tomorrow.

Thank you.

