1. Solution Approach (Genetic Algorithms)

The genetic algorithm workflow consists of following main steps:

- (a) Defining/Initializing the problem instance (e.g. users, servers, server capacity, constraints etc.)
- (b) Defining the objective function to be maximized/minimized. Also known as Fitness in GA lingo
- (c) Individual (aka Chromosome aka solution) representation & population initialization
- (d) Selection Strategy– Based on the fitness of individuals
- (e) Crossover Strategy How to do reproduction of parents for next generation
- (f) Mutation Strategy How to do some random changes in an individual/chromosome

Explanation of Solution (Assume num_users = N, num_servers = M)

(1.a) Defining/Initializing the problem instance

- set whatever users/servers etc. you want on **lines 5 23 in configuration_users_servers.py**
- whatever number of users & servers you set, select or set appropriate parameters for genetic algorithm computation in the if-else logic on **line 29/39/49 in configuration_users_servers.py**
- constraint (eqn 1.3 in the pdf) is defined on line 69 in UserServerResourceAllocation.py

(1.b) Objective/Fitness function (to judge a solution/individual's quality)

The objective function is given in eqn (1.1) in the provided pdf. But there are two constraints also. So to get an optimal solution we define a hybrid objective function:

- defined as eqn (1.1) penalty*constraint_violations
- this means that when we don't have any constraint violations we'll not be penalized & our hybrid_objective will be maximum of true objective
- the constraint eqn 1.3 is a hard constraint which can not be violated
- the constraint 1.2 is automatically followed because the way we represent an individual/solution each user is by default assigned only one server or no server. So there is no violation here. But it's preferable to allocate a user some/any server rather than not allocating him at all. So we define it as a soft constraint with soft penalty etc.

(more comments/illustration included in line 27 in the definition of function getHybridObjectiveFunction in the UserResourceAllocation.py file)

(1.c) Individual (aka Chromosome) representation & population initialization

I represent a tentative solution (aka individual or chromosome):

- a list of length N
- each element of the list can take any value between 0 to M.
- each element of the list means which server was allocated to that index (or user). Last number M just means no allocation, other numbers from 0 to M-1 are represent the M servers

(more comments/illustration included in line 46-62 in the main.py file)

(1.d) Selection Strategy (line 75 in main.py)

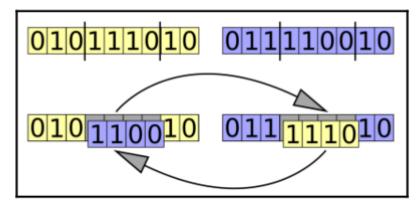
I use a tournament selection strategy of size 3

Individual	Fitness
Α	8
В	12
С	27
D	4
Е	45
F	17

Tournament selection example with a tournament size of three

(1.e) Crossover Strategy (line 76 in main.py)

I use a two point crossover strategy. We select any two points in each parent & reproduce by interchanging the parts between them



(1.f) Mutation Strategy (line 77 in main.py)

Just as in a binary mutation (below pic) we interchange between integers 0 to 1 & vice versa,



I use a mutation such that any integer between 0-M can be changed to any other between 0-M as above

2. Parameter Selection Strategy

Most of the parameters come by testing & seeing what gives better solution. Generally experienced modelers use their previous experience. There is no exact/exclusive thumb rule for parameter selection & it'll vary from problem to problem & modeler to modeler experience.

I am including some comments about what the parameters signify & how they are chosen.

[*Note: Optimal Solution was found in each Case 1-3 without any constraint violation but with different parameters]

[Case 1: 20 Users, 3 Servers] [Case 2: 1000 Users, 7 Servers] [Case 3: 10000 Users, 100 Servers]

	Comments	Case 1	Case 2	Case 3
POPULATI ON_SIZE	the optimal solution/individual is going to come from the previous generation of POPULATION_SIZE number of parents. So more population means better chances of finding an optimal/fittest offspring from that population. Generally something between 100-500 works for easy/hard problems. Use more for big/hard problems. The more the better, but more will take more time. So time/optimality trade-off	100	500	500
HALL_OF_ FAME_SIZ E	This basically means how many best individuals to keep as it is without crossover/reproduction in next generation. This helps is retaining/remembering some good individuals for a longer time. Generally neither too low nor too high is good & something in range 20-50 works good for population size of 100-500. Needs to be tried & seen	20	30	30
MAX_GEN ERATIONS	number of iterations/loops GA will run to find the optimal solution. The more the better but generally around 100-500 works for easy/hard (small/big) problems. Try & see	50	100	100
TOURNAM ENT_SIZE	This means how to select from current most fit individuals for next generation. TOURNAMENT_SIZE individuals are selected based on objective/fitness value & out of that one is randomly selected. This is repeated POPULATION_SIZE times. Needed as explained in fig of sec 1.d (selection strategy). Generally 2-5 needs to be tried but most of the time 2 or 3 works.	3	3	3
P_CROSSO VER	Consecutive pairs of individuals form last generation of size POPULATION_SIZE are selected with probability P_CROSSOVER for crossover/reproduction. Generally .8 or .9 works but any value between 0-1 can be tried. But the higher the better & preferably around .995 Needed as in Sec 1.e	.9	.9	.9
P_MUTATI ON	Probability of mutating an individual. This helps in exploring new solution . But sometimes too high value can slow down convergence as we will be changing even good individuals too much. Generally .1, .2, .3 works but sometimes might need higher values. Try higher values like .4, .5 to explore more/new solutions if not getting optimality Needed as in Sec 1.f	.2	.2	<mark>.5</mark>

IND_PB	Probability with which each attribute of the individual (chosen for mutation) is mutated. Generally most common value is 1/length(individual) but something between .011 might also work.	.01	.01	.01
HARD_CO NSTRAINT _PENALTY	Used to guide algorithm go in right direction so that no constraints of this sort are violated. Generally arbitrary high numbers are chosen/tried. e.g. eqn 1.3 in our case shouldn't be violated. Increase till no/less violation.	1000	10000	10000
SOFT_CON STRAINT_ PENALTY	Used to guide algorithm go in right direction so that no constraints of this sort are also violated but they can be violated without making solution infeasible. Generally some number <= HARD_CONSTRAINT_PENALTY is chosen/tried. e.g. eqn 1.2 in our case can be 0 (it'd be <=1, so it's not violation but but its better to not have 0) which means that user wasn't allocated any server. Increase till no/less violation.	100	1000	1000

3. Running Code & Analyzing Results on Some Test Cases

Case 1 [20 Users, 3 Servers] [code running time < 5 seconds]

parameters – line 28-37 configuration_users_servers.py

[Optimality Found, No Constraint Violation]

Case 2 [1000 Users, 7 Servers] [code running time 130 seconds]

parameters – line 38-47 configuration_users_servers.py

[Optimality Found, No Constraint Violation]

I increased the POPULATION_SIZE & also increased the Penalty compared to Case 1 as I was not getting optimal value with parameters of Case 1

Case 3 [10000 Users, 100 Servers] [code running time 1260 seconds ~ 21 Minutes]

parameters – line 48 - 57 configuration_users_servers.py

[Optimality Found, No Constraint Violation]

I increased the P MUTATION from .2 used previously in Case 1,2 to .5