

VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.



LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING



B.M.S. COLLEGE OF ENGINEERING

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CERTIFICATE

This is to certify that the Lab work entitled “ Bio Inspired Systems (23CS5BSBIS)” carried out by **Tamanna Barman (1WA23CS006)**, who is bonafide student of **B.M.S. College of Engineering**. It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum. The Lab report has been approved as it satisfies the academic requirements of the above mentioned subject and the work prescribed for the said degree.

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|---|--|

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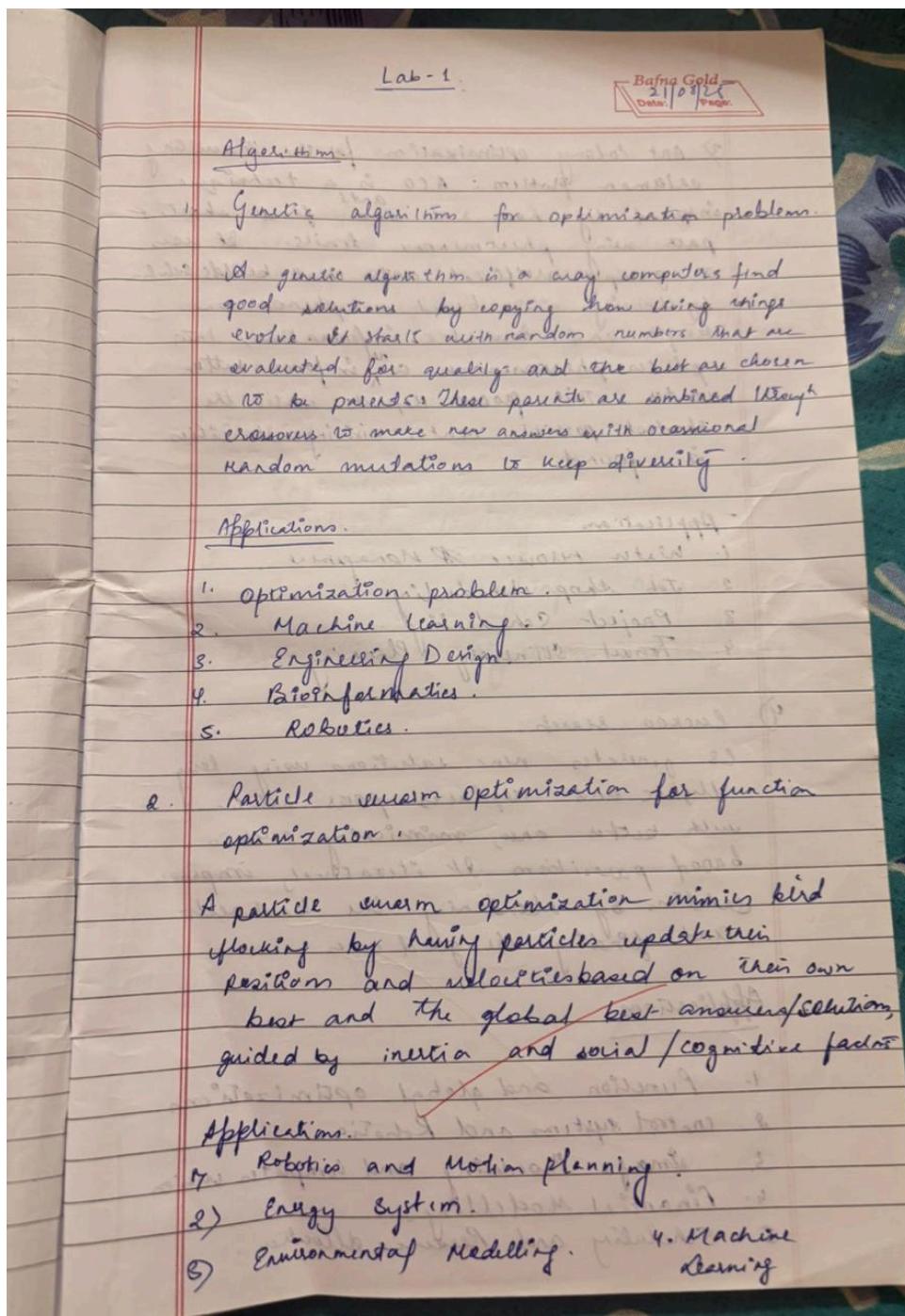
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(88/2011)

Github Link: <https://github.com/1WA23CS006/bio-inspired-systems-lab-programs>

Program 1 Genetic Algorithms (GA) are inspired by the process of natural selection and genetics, where the fittest individuals are selected for reproduction to produce the next generation. GAs are widely used for solving optimization and search problems. Implement a Genetic Algorithm using Python to solve a basic optimization problem, such as finding the maximum value of a mathematical function.



3) Ant Colony Optimization for the Travelling Salesman Problem: ACO is a technique inspired by how real ants find shortest path using pheromone trails. It uses a group of artificial ants that builds solution by choosing cities based on pheromone strength and heuristic information, then updates pheromones on ^{new} ~~old~~ in force better routes. This process repeats until the shortest possible route visiting all cities is found.

- Applications

1. Water resource Management.
2. Job shop scheduling.
3. Project Scheduling.
4. Travel itineraries Planning.

4) Cuckoo Search:

CS generates new solutions using Levy flights and replaces poor solutions with better ones, mimicking cuckoo brood parasitism. It iteratively improves solutions by abandoning the dead nests and finding the good ones.

Applications

1. Function and global optimizations
2. control systems and Robotics.
3. Image Processing and Computer vision
4. Financial Modelling
5. Scheduling and Resource allocation

5) Grey Wolf Optimizer.

Grey wolf optimizer mimics how grey wolves hunt, with alpha, beta and delta wolves leading the search with other followers. The wolves update their positions by following their leaders to gradually find the best solution.

Applications

1. Engineering Design.
2. Machine Learning.
3. Renewable Energy.
4. Medical Imaging & Diagnosis.

6) Parallel Cellular Algorithms and Programs:

21.08.2025

LAB-2

Genetic algorithm (a)

→ A genetic algorithm is an optimization and search technique based on the principle of natural selection and genetics. It belongs to the class of evolutionary algorithms and is widely used to solve complex optimization problems.

- select initial population.
- calculate the fitness.
- selecting mating pool.
- crossover.
- Mutation.

The initial population for individual changing from

0 to B1

| Stage no. | Initial population | (x) value | fitness function $f(x^2)$ |
|-----------|--------------------|-----------|---------------------------|
| 1 | 01100 | 12 | 144 |
| 2 | 11001 | 25 | 625 |
| 3 | 00101 | 5 | 25 |
| 4 | 10011 | 19 | 1361 |
| | Sum | | 1155 |
| | Average | | 288.75 |
| | Maximum | | 625 |

Prob.

$$\text{Prob} = \frac{f(x)}{\sum f(x)}$$

0.1247.

0.5411

0.0216

0.3126

% Prob

1. 12.47

2. 54.11

3. 2.16

Expected count

1. 0.49 → 1

2. 2.1625 → 2

3. 0.0866 → 0

1. Single point crossover.

after crossover

| | |
|----------------------------------|-------------------------|
| P ₁ - 11 <u>100</u> | P ₁ 11 101 |
| P ₂ - 10 <u>101</u> | P ₂ 10 100 |

2. Multipoint crossover.

3. Uniform crossover.

Children

$$\begin{aligned} c_1 &= 11 + 101 = 11101 \text{ (27) } \text{ offspring.} \\ c_2 &= 10 + 100 = 10100 \text{ (20) } \end{aligned}$$

Two pt crossover.

$$P_1 = 01010 \text{ (10)}$$

$$P_2 = 11001 \text{ (25)}$$

after 3rd and 9th bit

$$P_1 = 01\cancel{0}1\cancel{0}$$

$$P_2 = 1\cancel{1}00\cancel{1}$$

swap the middle part.

$$c_1 = 0 + 100 + 0 = 01000 \text{ (8)}$$

$$c_2 = 1 + 101 + 1 = 11011 \text{ (27)}$$

New offspring : 8 and 27

Uniform crossover

bits \rightarrow 50% from P₁

50% from P₂.

$$\text{expected} = f(x_i)$$

$$\text{avg } (\bar{f}(x))$$

Selecting mating pool

| String no. | Mating pool members | remove pt | offspring after crossover | x | $f(x) = x^2$ |
|------------|---------------------|-----------|---------------------------|-----|--------------|
| 1 | 011001 | 4 | 001101 | 13 | 169 |
| 2 | 11001 | 4 | 11000 | 24 | 576 |
| 3 | 11001 | 2 | 11011 | 27 | 729 |
| 4 | 100011 | 2 | 10001 | 12 | 289 |

$$\text{total} = 1283$$

$$\text{avg} = 440.75$$

max: 729

Mutation

| String no. | offspring after crossover | mutation chromosome for offspring | offspring after mutation | value | $f(x) = x^2$ |
|------------|---------------------------|-----------------------------------|--------------------------|-------|--------------|
| 1 | 01101 | 10000 | 11101 | 29 | 841 |
| 2 | 11000 | 00000 | 11000 | 24 | 576 |
| 3 | 11011 | 0000001 | 11011 | 27 | 729 |
| 4 | 10001 | 00100 | 10100 | 20 | 400 |

(is) \neq parents

((A+B)) \neq A+B

Genetic Algorithm.

```

import random, math
pop, GENES = 50, 16
MUT-RATE, CROSS-RATE = 0.01, 0.8
OFNS = 5
X-MIN, X-MAX = -1.8, 1.8
def fitness(x):
    return x * math.sin(x) / (math.pi * x) + 1
def decode(chromo):
    val = int(chromo, 2)
    return X-MIN + (X-MAX - X-MIN) * val / (2**GENES - 1)
def init_pop():
    return [".join(random.choice('01') for _ in range(GENES)) for _ in range(pop)]
```

```

def evaluate(pop):
    return [fitness(decode(ind)) for ind in pop]
```

```

def select(pop, fits):
    selected = []
    for _ in range(pop):
        i, j = random.sample(range(pop), 2)
        if fits[i] > fits[j]:
            selected.append(pop[i])
        else:
            selected.append(pop[j])
    return selected
```

```

def crossover (P1, P2):
    if random.random() < cross-RATE:
        point = random.randint (1, GENES - 1)
        return P1[:point] + P2[point:], P2[:point] + P1[point:]
    return P1, P2

def mutate(chromo):
    return ''.join('1' if bit == '0' else '0'
                  if random.random() < MUT-RATE
                  else
                  + random.choice(['0', '1']) for bit in chromo)

def ga():
    pop = [random.getrandbits(GENES) for _ in range(POP)]
    for gen in range(GENS):
        fits = evaluate(pop)
        best = max(fits)
        best_ind = pop[fits.index(best)]
        print(f"Generation {gen+1} Best fitness = {best:.5f}, x = {decode(best_ind):.5f}")
        selected = select(pop, fits)
        pop = []
        for i in range(0, POP, 2):
            c1, c2 = crossover(selected[i], selected[i+1])
            pop.append(mutate(c1))
            pop.append(mutate(c2))
        fits = evaluate(pop)
        best = max(fits)
        best_ind = pop[fits.index(best)]
        print(f"Best solution: x = {decode(best_ind)}")

```

$sf \{ f(x) = \{ \text{best} : sf \}$)

if name == "main":
go()

output:

Gen1 : Best fitness = 2.831219500, x = 1.85512

Gen2 : Best fitness = 1.69346, x = 1.81250

Gen3 : Best fitness = 2.24999, x = 1.24999

Gen4 : Best fitness = 2.24999, x = 1.24999

Gen5 : Best fitness = 1.69346, x = 1.81250

Best solution: x = 2.00000, f(x) = 1.00000

Initial population: [101100, 110111, 100101, 1111,
[12, 25, 5, 19]]

Generation 1

x = 12, bin = 01100, fit = 144, prob = 0.136, exp-count = 0.5

x = 25, bin = 10111, fit = 529, prob = 0.500, exp-count = 2.00

x = 5, bin = 00101, fit = 25, prob = 0.024, exp-count = 0.09

x = 19, bin = 10011, fit = 361, prob = 0.313, exp-count = 1.25

Generation 2

x = 28, bin = 11100, fit = 784, prob = 0.635, exp-count = 2.54

x = 9, bin = 01001, fit = 81, prob = 0.066, exp-count = 0.26

$X=3$, bin = 00011, fit = 9, prob ≈ 0.007 , exp-count
 $= 0.03$

$X=19$, bin = 10011, fit = 361, prob ≈ 0.292 ,
exp-count ≈ 1.17

Generation 3.

$X=25$, bin = 11001, fit = 625, prob = 0.334, exp-count = 1.33

$X=8$, bin = 01000, fit = 64, prob = 0.034, exp-count = 0.14

$X=28$, bin = 11100, fit = 484, prob = 0.419, exp-count = 1.64

$X=20$, bin = 10100, fit = 900, prob = 0.214, exp-count = 0.85

Generation 4.

$X=21$, bin = 10101, fit = 441, prob = 0.252, exp-count = 1.01

$X=24$, bin = 11000, fit = 546, prob = 0.330, exp-count = 1.32

$X=21$, bin = 10101, fit = 441, prob = 0.252, exp-count = 1.01

$X=17$, bin = 10001, fit = 287, prob = 0.165, exp-count = 0.66

Generation 5.

$X=21$, bin = 10101, fit = 441, prob = 0.208, exp-count = 0.83

$X=20$, bin = 10100, fit = 400, prob = 0.188, exp-count = 0.78

$X=29$, bin = 11101, fit = 841, prob = 0.396, exp-count = 1.54

$X=21$, bin = 10101, fit = 441, prob = 0.208, exp-count = 0.83

Final best solution : 29 11101 fitness = 841

Code:

```
import random

CHROM_LENGTH = 5
CROSS_RATE = 0.8
MUT_RATE = 0.1

def fitness(x):
    return x**2

def encode(x):
    return format(x, f'0{CHROM_LENGTH}b')

def decode(b):
    return int(b, 2)

def roulette_selection(pop, fitnesses):
    total_fit = sum(fitnesses)
    pick = random.uniform(0, total_fit)
    current = 0
    for i, f in enumerate(fitnesses):
        current += f
        if current > pick:
            return pop[i]
    return pop[-1]

def crossover(p1, p2):
    if random.random() < CROSS_RATE:
        point = random.randint(1, CHROM_LENGTH-1)
        c1 = p1[:point] + p2[point:]
        c2 = p2[:point] + p1[point:]
        return c1, c2
    return p1, p2

def mutate(chrom):
    chrom_list = list(chrom)
    for i in range(CHROM_LENGTH):
        if random.random() < MUT_RATE:
            chrom_list[i] = '1' if chrom_list[i] == '0' else '0'
    return ''.join(chrom_list)

def genetic_algorithm():
    user_input = input("Enter initial population values (space-separated, e.g. 12 23 5 19): ")
    values = list(map(int, user_input.split()))
```

```

generations = int(input("Enter number of generations to run: "))

POP_SIZE = len(values)
population = [encode(x) for x in values]

print("\nInitial Population:", population, [decode(c) for c in population])

global_best = population[0]
global_best_fit = fitness(decode(global_best))

for gen in range(1, generations + 1):
    decoded = [decode(c) for c in population]
    fitnesses = [fitness(x) for x in decoded]

    best_idx = fitnesses.index(max(fitnesses))
    if fitnesses[best_idx] > global_best_fit:
        global_best = population[best_idx]
        global_best_fit = fitnesses[best_idx]

    total_fit = sum(fitnesses)
    probs = [f / total_fit for f in fitnesses]
    expected = [p * POP_SIZE for p in probs]

    print(f"\nGeneration {gen}")
    for i in range(POP_SIZE):
        print(f"x={decoded[i]}, bin={population[i]}, fit={fitnesses[i]}, "
              f"prob={probs[i]:.3f}, exp_count={expected[i]:.2f}")

    new_pop = [global_best]

    while len(new_pop) < POP_SIZE:
        p1 = roulette_selection(population, fitnesses)
        p2 = roulette_selection(population, fitnesses)
        c1, c2 = crossover(p1, p2)
        c1, c2 = mutate(c1), mutate(c2)
        new_pop.extend([c1, c2])

    population = new_pop[:POP_SIZE]

    decoded = [decode(c) for c in population]
    fitnesses = [fitness(x) for x in decoded]
    best_idx = fitnesses.index(max(fitnesses))
    print("\nFinal Best Solution:", decoded[best_idx], population[best_idx], "fitness=", fitnesses[best_idx])

```

```
genetic_algorithm()
```

```
OUTPUT:
```

```
==== RESTART: C:/Users/student/AppData/Local/Programs/Python/Python313/gene.py ===
Initial Population: ['01100', '11001', '00101', '10011'] [12, 25, 5, 19]

Generation 1
x=12, bin=01100, fit=144, prob=0.125, exp_count=0.50
x=25, bin=11001, fit=625, prob=0.541, exp_count=2.16
x=5, bin=00101, fit=25, prob=0.022, exp_count=0.09
x=19, bin=10011, fit=361, prob=0.313, exp_count=1.25

Generation 2
x=19, bin=10011, fit=361, prob=0.211, exp_count=0.85
x=19, bin=10011, fit=361, prob=0.211, exp_count=0.85
x=25, bin=11001, fit=625, prob=0.366, exp_count=1.46
x=19, bin=10011, fit=361, prob=0.211, exp_count=0.85

Generation 3
x=17, bin=10001, fit=289, prob=0.137, exp_count=0.55
x=19, bin=10011, fit=361, prob=0.171, exp_count=0.68
x=25, bin=11001, fit=625, prob=0.295, exp_count=1.18
x=29, bin=11101, fit=841, prob=0.397, exp_count=1.59

Generation 4
x=9, bin=01001, fit=81, prob=0.050, exp_count=0.20
x=25, bin=11001, fit=625, prob=0.384, exp_count=1.54
x=9, bin=01001, fit=81, prob=0.050, exp_count=0.20
x=29, bin=11101, fit=841, prob=0.517, exp_count=2.07

Generation 5
x=29, bin=11101, fit=841, prob=0.517, exp_count=2.07
x=25, bin=11001, fit=625, prob=0.384, exp_count=1.54
x=9, bin=01001, fit=81, prob=0.050, exp_count=0.20
x=9, bin=01001, fit=81, prob=0.050, exp_count=0.20

Final Best Solution: 29 11101 fitness= 841
```

Problem 2

Gene Expression Algorithms (GEA) are inspired by the biological process of gene expression in living organisms. This process involves the translation of genetic information encoded in DNA into functional proteins. In GEA, solutions to optimization problems are encoded in a manner similar to genetic sequences. The algorithm evolves these solutions through selection, crossover, mutation, and gene expression to find optimal or near-optimal solutions. GEA is effective for solving complex optimization problems in various domains, including engineering, data analysis, and machine learning.

LAB-3
28.08.2025
Bafna Gold
Date: _____
Page: _____

Optimization via Gene Expression.

```
import random

CHROM_LENGTH = 18 // 5 codons x 3 bits
CODON_LENGTH = 3
POP_SIZE = 4
CROSS_RATE = 0.8
MUT_RATE = 0.1
GENES = 5

def fitness(phenotype):
    return sum(x ** 2 for x in phenotype)

def encode(codons):
    return ''.join(format(c, f'0{CODON_LENGTH}b')
                  for c in codons)

def decode(chrom):
    return [int(chrom[i:i + CODON_LENGTH], 2)
            for i in range(0, CHROM_LENGTH, CODON_LENGTH)]

def roulette_selection(pop, fits):
    pick = random.uniform(0, sum(fits))
    current = 0
    for c, f in zip(pop, fits):
        current += f
        if current > pick:
            return c
    return pop[-1]
```

```
def crossover(p1, p2):
    if random.random() < CROSS_RATE:
        point = random.randint(1, CHROM_LENGTH)
        return p1[:point] + p2[point:], p2[:point] + p1[point:]
    return p1, p2
```

```
def mutate(chrom):
    return ''.join('1' if (bit == '0'
                           and random.random() < MUT RATE)
                  else '0' if (bit == '1' and
                               random.random() < MUT RATE)
                  else bit for bit in chrom)
```

```
def GEA():
    population = [encode([random.randint(0, 1)])
                  for _ in range(CHROM_LENGTH // CODON_LENGTH)]
    for _ in range(POP_SIZE):
        if _ in range(GENS):
            phenotypes = [decode(c) for c in population]
            fitnesses = [fitness(p) for p in phenotypes]
            new_pop = []
            while len(new_pop) < POP_SIZE:
                p1 = roulette_selection(population,
                                         fitnesses)
                p2 = roulette_selection(population,
                                         fitnesses)
                c1, c2 = crossover(p1, p2)
                new_pop += [mutate(c1), mutate(c2)]
            population = new_pop[-POP_SIZE:]
```

phenotypes = [decode(c) for c in population]

fitness = [fitness(p) for p in phenotypes]

best = fitness[0].index(max(fitness))

print("Best phenotype:", phenotypes[best])

"fitness", fitness[best])

chromosome

print("Final Best Solution:",

GGA() decode(best_idx), population[best_idx], "fitness =", fitness(best_idx))

output Genetic algorithm

output

Enter 4 chromosomes (each 5 bits, only 0 or 1)

chromosome 1 : 00100

chromosome 2 : 10111

chromosome 3 : 00101

chromosome 4 : 1+10011 + 1+1 = 10011

Initial population: ['00100', '10111', '00101', '10011']

Gen 1: Best Chromosomes : 10111, Expected - value = 23,

Fitness = 1058

Gen 2: Best Chromosomes : 11111, Expected value : 31

fitness = 1922.

Gen 3: Best Chromosomes : 11111, Expected - value : 31,

Gen 4: Best Chromosomes : 10111, Fitness = 1922

Gen 5: Best Chromosomes : 11011, Expected value : 23, Fitness = 1058

Expected - value : 27

Fitness = 1458.

~~Best Solution : 11111 expected - value : 31, fitness = 1922~~

```

import random

POP_SIZE = 4
CHROM_LENGTH = 5
MAX_GENERATIONS = 5
MUTATION_RATE = 0.1

def gene_expression(chromosome):
    return int(chromosome, 2)

def fitness(chromosome):
    x = gene_expression(chromosome)
    return x * 2 * x

def get_population_from_input():
    population = []
    print(f"Enter {POP_SIZE} chromosomes (each {CHROM_LENGTH} bits, only 0 or 1):")
    while len(population) < POP_SIZE:
        chrom = input(f"Chromosome {len(population) + 1}: ").strip()
        if len(chrom) == CHROM_LENGTH and all(c in '01' for c in chrom):
            population.append(chrom)
        else:
            print(f"Invalid chromosome! Please enter exactly {CHROM_LENGTH} bits (0 or 1).")
    return population

def select(population):
    fitnesses = [fitness(chrom) for chrom in population]
    total_fitness = sum(fitnesses)
    pick = random.uniform(0, total_fitness)
    current = 0
    for i, chrom in enumerate(population):
        current += fitnesses[i]
        if current > pick:
            return chrom

def crossover(parent1, parent2):
    point = random.randint(1, CHROM_LENGTH - 1)
    child1 = parent1[:point] + parent2[point:]
    child2 = parent2[:point] + parent1[point:]
    return child1, child2

def mutate(chromosome):
    mutated = ""
    for bit in chromosome:
        if random.random() < MUTATION_RATE:
            mutated += str(1 - int(bit))
        else:
            mutated += bit
    return mutated

```

```

if random.random() < MUTATION_RATE:
    mutated += '1' if bit == '0' else '0'
else:
    mutated += bit
return mutated

def genetic_algorithm():
    population = get_population_from_input()
    print(f"Initial Population: {population}")

    best_overall = None
    best_fitness = float('-inf')

    for generation in range(MAX_GENERATIONS):
        new_population = []
        while len(new_population) < POP_SIZE:
            parent1 = select(population)
            parent2 = select(population)
            child1, child2 = crossover(parent1, parent2)
            child1 = mutate(child1)
            child2 = mutate(child2)
            new_population.extend([child1, child2])

        population = new_population[:POP_SIZE]

        best = max(population, key=fitness)
        best_fit = fitness(best)
        if best_fit > best_fitness:
            best_fitness = best_fit
            best_overall = best

        print(f"Generation {generation + 1}: Best Chromosome = {best}, "
              f"Expressed Value = {gene_expression(best)}, Fitness = {best_fit}")

    print(f"\nBest solution after {MAX_GENERATIONS} generations: {best_overall} "
          f"with expressed value = {gene_expression(best_overall)} and fitness = {best_fitness}")

if __name__ == "__main__":
    genetic_algorithm()

OUTPUT:

```

```
Enter 4 chromosomes (each 5 bits, only 0 or 1):
Chromosome 1: 11001
Chromosome 2: 01101
Chromosome 3: 00110
Chromosome 4: 10011
Initial Population: ['11001', '01101', '00110', '10011']
Generation 1: Best Chromosome = 11101, Expressed Value = 29, Fitness = 1682
Generation 2: Best Chromosome = 11011, Expressed Value = 27, Fitness = 1458
Generation 3: Best Chromosome = 11001, Expressed Value = 25, Fitness = 1250
Generation 4: Best Chromosome = 11010, Expressed Value = 26, Fitness = 1352
Generation 5: Best Chromosome = 11011, Expressed Value = 27, Fitness = 1458

Best solution after 5 generations: 11101 with expressed value = 29 and fitness = 1682
```

Problem 3

Particle Swarm Optimization (PSO) is inspired by the social behavior of birds flocking or fish schooling. PSO is used to find optimal solutions by iteratively improving a candidate solution with regard to a given measure of quality. Implement the PSO algorithm using Python to optimize a mathematical function.

Lab - 4.

11-09-25

> Particle swarm optimization
algorithm parameters
for objective function.
 x_i : position of the particle / agent.
 v_i : velocity of the particle / agent.
 A : population of the agent.
 w : inertia weight.
 c_1 : cognitive constant.
 r_1, r_2 : Random numbers.
 c_2 : social constant.

Updating particle's velocity: personal influence

$$v_i^{t+1} = v_i^t + c_1 w_i^t (p_{best}^t - p_i^t) + c_2 w_s^t (g_{best}^t - p_i^t)$$

$p_i^{t+1} = p_i^t + v_i^{t+1}$ social influence

0 → inertia
 → personal influence
 → social influence.

PSO velocity update formula.

$w * \text{velocities} \rightarrow \text{inertia term}$

$c_1 * c_1 * (\cancel{g_{best}} p_{best} - positions) \rightarrow \text{particle's best}$

$c_1 * c_2 * (g_{best} - positions) \rightarrow \text{group's best}$

Position update formula
 $x_i(t+1) = x_i(t) + v_i(t+1)$
 positions + 1 = velocities.

Job Scheduling - Application

Code:

```

import numpy as np
processing-times = input ("Enter job processing
times separated by spaces: ")
processing-times = np.array([float(x) for x
in processing-times.strip().split()])
num-particles = 30
num-iterations = 100
w = 0.8
c1 = 1.5
c2 = 1.5
positions = np.random.uniform(0, 1, (num-particles,
num-jobs))
velocities = np.random.uniform(-0.1, 0.1,
(num-particles, num-jobs))
    
```

```

def fitness(priority-vector):
    job-order = np.argsort(priority-vector)
    completion-time = 0
    total-completion = 0
    for job in job-order:
        completion-time += processing-time[job]
    
```

total-completion + = completion time
within total-completion

pbest - positions = positions - copy()
pbest - scores = np.array([fitness(p)
for p in positions])

gbest_idx = np.argmax(pbest_scores)

gbest_position = np.copy(pbest_positions
[gbest_idx].copy())

gbest_score = pbest_scores[gbest_idx]

for iteration in range(num_iterations):
z1 = np.random.rand(num_particles, num
jobs)

MR = np.random.rand(num_particles, num
jobs)

velocities = (w * velocities + c1 * z1 *
egene(pbest_positions - positions)
+ c2 * z2 * (gbest_positions
- positions))

positions += velocities.

positions = np.clip(positions, 0, 1)

scores = np.array([fitness(p) for p in
positions])

better_mask = scores < pbest_scores

pbest_positions[better_mask] =

positions[better_mask]

pbest_scores[better_mask] =

scores[better_mask]

min_idx = np.argmax(pbest_scores)

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```

if pbest_scores == pbest_scores [min_idx]
    < gbest-score :
        gbest-score = pbest_scores [min_idx]
        gbest-position = pbest_positions [min_idx]
        - copy)
        if (iteration + 1) % 10 == 0 or iterations
            = 0;
        print(f" Iteration {iteration + 1} : Best
        Total completion time = {gbest-score :.2f}
        ")
    best_schedule = np.argsort (gbest-position)
    print(f"\n Optimal job order (0-based) :",
        best_schedule)
    print(" Processing time in optimal order :")
    processing_times [best_schedule] )
    printf "Minimum total completion time:
    {gbest-score :.2f}")

```

Output:

Enter job processing times separated by spaces
: 1 2 3 4 5 6 17 8 9 10

Iteration 1 : Best Total completion Time = 243.00
Iteration 2 : Best Total completion Time = 236.00
:
Iteration 100: Best Total completion Time = 236.00

~~Optimal~~ Optimal job order (0-based) : [0 2 3 4 5 7
8 9 6]
Processing time in order : [1. 2. 3. 4. 5. 6. 8. 9. 10. 17.]
Minimum Total completion time : 236.00

```

import numpy as np

num_drones = 5
area_size = 20
num_particles = 30
iterations = 10

w = 0.5
c1 = 1.5
c2 = 1.5

dim = num_drones * 2

particles = np.random.uniform(0, area_size, (num_particles, dim))
velocities = np.zeros((num_particles, dim))

pbest_positions = particles.copy()
pbest_scores = np.full(num_particles, -np.inf)

gbest_position = None
gbest_score = -np.inf

def fitness(position):
    x = np.sum(position)
    return (x*2 + 5*x + 20)

for iter in range(iterations):
    for i in range(num_particles):
        score = fitness(particles[i])

        if score > pbest_scores[i]:
            pbest_scores[i] = score
            pbest_positions[i] = particles[i].copy()

        if score > gbest_score:
            gbest_score = score
            gbest_position = particles[i].copy()

    r1, r2 = np.random.rand(), np.random.rand()
    for i in range(num_particles):
        velocities[i] = (w * velocities[i] +
                        c1 * r1 * (pbest_positions[i] - particles[i]) +
                        c2 * r2 * (gbest_position - particles[i]))

```

```
particles[i] += velocities[i]
particles[i] = np.clip(particles[i], 0, area_size-1)

print(f"Iteration {iter}, Best Fitness: {gbest_score:.2f}")

print("\nOptimized drone waypoints (x,y):")
optimized_coords = gbest_position.reshape((num_drones, 2))
for idx, coord in enumerate(optimized_coords):
    print(f"Drone {idx+1}: {coord}")
```

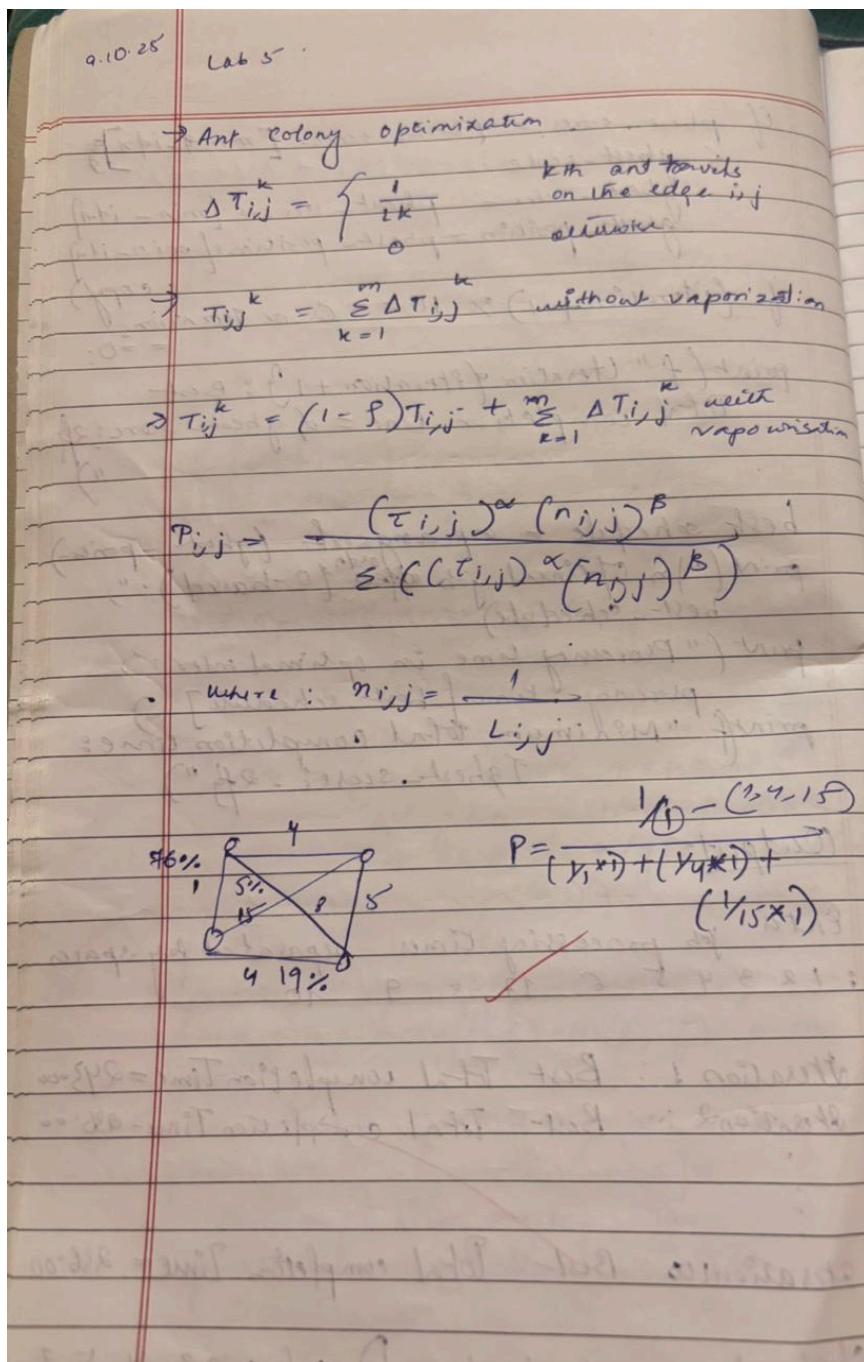
OUTPUT:

```
Iteration 0, Best Fitness: 995.60
Iteration 1, Best Fitness: 995.60
Iteration 2, Best Fitness: 995.60
Iteration 3, Best Fitness: 1062.14
Iteration 4, Best Fitness: 1109.77
Iteration 5, Best Fitness: 1126.03
Iteration 6, Best Fitness: 1131.01
Iteration 7, Best Fitness: 1143.85
Iteration 8, Best Fitness: 1151.87
Iteration 9, Best Fitness: 1155.98

Optimized drone waypoints (x,y):
Drone 1: [19. 19.]
Drone 2: [13.47083229 13.14074042]
Drone 3: [ 9.53393196 19.        ]
Drone 4: [19. 19.]
Drone 5: [19.          12.13802119]
```

Problem 4

The foraging behavior of ants has inspired the development of optimization algorithms that can solve complex problems such as the Traveling Salesman Problem (TSP). Ant Colony Optimization (ACO) simulates the way ants find the shortest path between food sources and their nest. Implement the ACO algorithm using Python to solve the TSP, where the objective is to find the shortest possible



Algorithm - and optimization travel salesman

steps:

1. Initialization

initialize pheromone levels T_{ij} on all edges to a small positive constant.

$$T_{ij} = T_0$$

2. Repeat for each iteration

$$t = 1, 2, \dots, T$$

a) for each $k = 1, 2, 3, \dots, m$

$$\begin{aligned} P_{ijk}^k &= (T_{ij})^\alpha (n_{ij})^\beta \\ &\in ((T_{inj})^\alpha (n_{inj})^\beta) \end{aligned}$$

b) evaluate the length of each ant's tour L_k .

3. update pheromones.

a) Evaporation:

$$T_{ij} = (1 - \rho) \cdot T_{ij}$$

b) Deposit pheromone:

if for each k and edge (i, j) in i 's tour.

$$T_{ij} = T_{ij} + \Delta T_{ij}^k$$

where

$$\Delta T_{ij}^k = \frac{\phi}{L_k}$$

ϕ is constant representing the total pheromone amount deposited.

4. keep track of the best tour found so far.

5. After 'T' iterations output the best tour.

-End

import numpy as np

class AntColony:

def __init__(self, distance, n_ants,
n_iterations, decay,
alpha=1, beta=2):

self.distance = distances

self.pheromone = np.ones((distances.shape[0],
distances.shape[1])) /

len(distances)

self.n_ants = n_ants

self.n_iterations = n_iterations

self.decay = decay

self.alpha = alpha

self.beta = beta

def run(self):

best_path, best_length = None, float('inf')

for i in range(self.n_iterations):

paths = [self.construct_path(j) for j in
range(len(self.n_ants))]

paths_with_length = [(self.path
(p), p)
for p in paths]

self.evaporate_pheromone()

self.deposit_pheromone(paths_with_
length)

current_best = min(paths_with_length,
key=lambda x: x[0])

if current_best[0] < best_length:

best_length, best_path = current_
best

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print(f "Iteration {i+1} gives shortest-path length
 = {best-length} y")
 return best-path, best-length

```

def construct-path(self, start):
    path, visited = [start], set()
    for _ in range(len(self.city.distance) - 1):
        current = path[-1]
        move = self.pick-move(current, visited)
        path.append(move)
        visited.add(move)
    return path

```

```

def path-length(self, path):
    return sum(self.city.distances[path[i],
                                   path[i+1]] for i in range(len(path)-1))
    + self.city.distances[path[-1], path[0]]

```

```

def evaporate-pheromone(self):
    self.pheromone *= self.decay

```

```

def deposit-pheromone(self, path-with-length):
    for length, path in path-with-lengths:
        for i in range(len(path) - 1):
            self.pheromone[path[i], path[i+1]] += 1 / length
        self.pheromone[path[-1], path[0]] += 1 / length
    self.pheromone[path[0], path[-1]] += 1 / length

```

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```

if name == "main":
    distances = np.array([
        [0, 2, 2, 5, 7],
        [2, 0, 4, 8, 2],
        [2, 4, 0, 1, 3],
        [5, 8, 1, 0, 2],
        [7, 2, 3, 2, 0]
    ])

```

ant-colony = AntColony(distances, m-ants=10,
 m-iterations=5, decay=0.5)

best-path, best-length = ant-colony.
 run()

Output

Iteration 1: Shortest path length = 9

Iteration 2: shortest path length = 9

Iteration 3 : shortest path length = 9

Iteration 4: shortest path length = 9

Iteration 5: shortest path length = 9

Iteration

Best path found : [0, np.int64(2),
 np.int64(3), np.int64(4),
 np.int64(1)].

Length of best path : 9

✓
 ✓
 ✓

```

import numpy as np
import random

NUM_ANTS = 2
NUM_ITERATIONS = 50
ALPHA = 1.0
BETA = 5.0
EVAPORATION = 0.5
Q = 100

def input_matrix(name):
    print(f"Enter the {name} matrix row by row (space-separated). Type 'done' when finished:")
    matrix = []
    while True:
        row = input()
        if row.strip().lower() == 'done':
            break
        row_values = list(map(float, row.strip().split()))
        matrix.append(row_values)
    return np.array(matrix)

print("Input Cost Matrix (Distance Matrix):")
dist_matrix = input_matrix("cost")
NUM_CITIES = len(dist_matrix)

print("\nInput Initial Pheromone Matrix:")
pheromone = input_matrix("pheromone")

assert dist_matrix.shape == (NUM_CITIES, NUM_CITIES), "Cost matrix must be square."
assert pheromone.shape == (NUM_CITIES, NUM_CITIES), "Pheromone matrix must be square."

best_distance = float('inf')
best_path = []

for iteration in range(NUM_ITERATIONS):
    all_paths = []
    all_distances = []

    for ant in range(NUM_ANTS):
        path = [random.randint(0, NUM_CITIES - 1)]

        while len(path) < NUM_CITIES:
            current_city = path[-1]

```

```

probabilities = []

for next_city in range(NUM_CITIES):
    if next_city not in path:
        tau = pheromone[current_city][next_city] ** ALPHA
        eta = (1 / dist_matrix[current_city][next_city]) ** BETA
        probabilities.append(tau * eta)
    else:
        probabilities.append(0)

probabilities = np.array(probabilities)
probabilities_sum = probabilities.sum()
if probabilities_sum == 0:
    break
probabilities /= probabilities_sum

next_city = np.random.choice(range(NUM_CITIES), p=probabilities)
path.append(next_city)

if len(path) < NUM_CITIES:
    continue

path.append(path[0])
distance = sum(dist_matrix[path[i]][path[i + 1]] for i in range(NUM_CITIES))
all_paths.append(path)
all_distances.append(distance)

if distance < best_distance:
    best_distance = distance
    best_path = path

pheromone *= (1 - EVAPORATION)

for i in range(len(all_paths)):
    for j in range(NUM_CITIES):
        from_city = all_paths[i][j]
        to_city = all_paths[i][j + 1]
        pheromone[from_city][to_city] += Q / all_distances[i]
        pheromone[to_city][from_city] += Q / all_distances[i]

if iteration % 10 == 0 or iteration == NUM_ITERATIONS - 1:
    print(f"Iteration {iteration}: Best Distance = {best_distance:.2f}")

print("\nBest Path Found:")

```

```
print(" -> ".join(map(str, best_path)))
print(f"Total Distance: {best_distance:.2f}")
OUTPUT:
```

```
0 5 15 4
5 0 4 8
15 4 0 1
4 8 1 0
done
```

Input Initial Pheromone Matrix:

Enter the pheromone matrix row by row (space-separated). Type 'done' when finished:

```
0 4 10 3
4 0 1 2
10 1 0 1
3 2 1 0
done
```

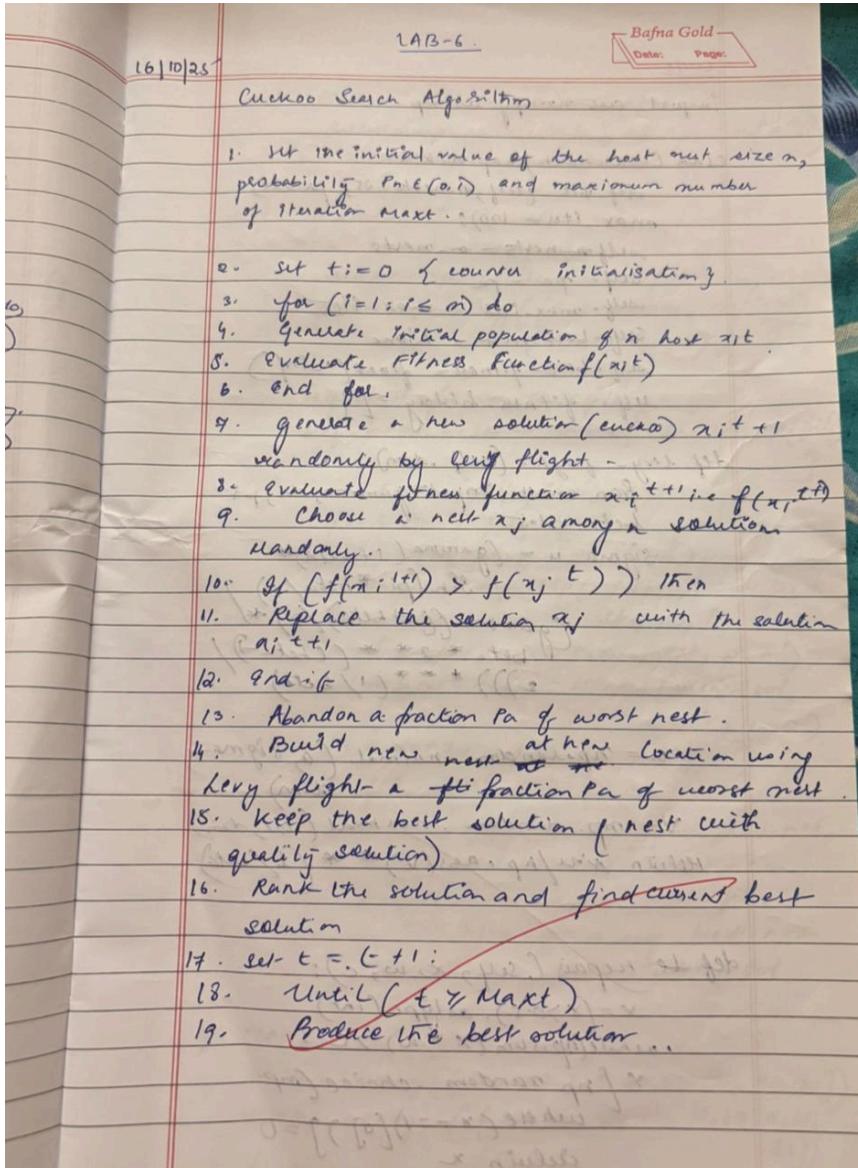
```
Iteration 0: Best Distance = 14.00
Iteration 10: Best Distance = 14.00
Iteration 20: Best Distance = 14.00
Iteration 30: Best Distance = 14.00
Iteration 40: Best Distance = 14.00
Iteration 49: Best Distance = 14.00
```

Best Path Found:

```
3 -> 2 -> 1 -> 0 -> 3
Total Distance: 14.00
```

Problem 5

Cuckoo Search (CS) is a nature-inspired optimization algorithm based on the brood parasitism of some cuckoo species. This behavior involves laying eggs in the nests of other birds, leading to the optimization of survival strategies. CS uses Lévy flights to generate new solutions, promoting global search capabilities and avoiding local minima. The algorithm is widely used for solving continuous optimization problems and has applications in various domains, including engineering design, machine learning, and data mining



code.

import numpy as np

```
class CuckooSearchKnapsack:  
    def __init__(self, m_nests=25, pa=0.25,  
                 max_iter=100):  
        self.m_nests = m_nests  
        self.pa = pa  
        self.max_iter = max_iter  
        self.best_nest = None  
        self.best_fitness = float('inf')  
        self.fitness_history = []
```

```
    def levy_flight_(self, dim):  
        from math import gamma, sin, pi  
        beta = 1.5  
        sigma_u = (gamma(1 + beta) **  
                   sin(pi * beta / 2) /  
                   (gamma((1 + beta) / 2) *  
                    beta ** 2 * ((beta - 1) /  
                                 2))) ***(1 / beta)
```

$u = np.random.normal(0, \sigma_u, dim)$

$v = np.random.normal(0, 1, dim)$

~~return u / np.abs(v) ***(1 / beta)~~

~~def __repairs(self, x, w, c):~~

~~x = (x > 0.5).astype(int)~~

~~while np.sum(x ** w) > c:~~

~~* [np.random.choice(np.~~

~~where(x == 1)[0]) == 0]~~

~~return x~~

```
def fitness(self, x, v, w, c):
    return np.sum(x * v) / np.sum(x * w)
    L = c else 0
```

```
def optimize(self, v, w, c):
    n_items = len(v)
    nests = np.random.randint(0, n_items)
    fits = np.array([self.fitness(self.repair((n, w, c), v, w, c)) for n in
                    nests])
    self.best_fit = max(fits)
    self.best_nest = nests[np.argmax(fits)]
```

```
i = 0
for i in range(n_items):
    for j in range(n_items):
        step = self.repair((n - i, w))
        new_nest = np.clip(nests[i] + 0.01 * step, 0, 1)
        new_sol = self.repair(new_nest, w, c)
        fit_new = self.fitness(new_sol, v, w, c)
```

```
j = np.random.randint(n_items)
if fit_new > fits[j]:
    nests[j], fits[j] = new_nest, fit_new
```

```
if fit_new > self.best_fit:
    self.best_fit, self.best_nest =
        fit_new, new_nest
```

```
if __name__ == "__main__":
    v = np.array([60, 100, 120, 80, 50, 70, 90, 100])
    w = np.array([[10, 20, 30, 15, 12, 18, 8, 25,
                  22]])
```

c = 80

```

os = CuckooSearch(30, 0.25, 100)
sol, val = os.optimize(v, w, c)
c1 = np.where([sol == 1], [0])
print("selected: " + str(c1))
print("f" + " Value : " + str(val))
weight = sum((c1 * w) + " " + str(w))

```

Output:

== Cuckoo search for 0/1 Knapsack
Problem ==

Number of items: 8

Knapsack capacity: 80

Items (value, weight):

Item 1: (\$60, 10kg)

Item 2: (\$100, 20kg)

Item 3: (\$120, 30kg)

Item 4: (\$20, 10kg)

Item 5: (\$50, 12kg)

Item 6: (\$70, 12kg)

Item 7: (\$90, 25kg)

Item 8: (\$110, 12kg)

--- solution ---

Selected items: [1 2 4 5 8]

Total value: \$400

Total weight: 79kg / 80kg

Item Details:

Item 1: value = \$ 60, weight = 10 kg

Item 2: value = \$ 100, weight = 20 kg

Item 3: value = \$ 80, weight = 15 kg

Item 4: value = \$ 50, weight = 12 kg

Item 5: value = \$ 110, weight = 22 kg

Convergence (after 20 iterations)

Iter 1: Best Value: \$ 370

Iter 21: Best Value: \$ 400

Iter 41: Best Value: \$ 400

Iter 61: Best Value: \$ 400

Iter 81: Best Value: \$ 400

~~Best Value: \$ 400~~

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$$\Delta x = 100 - x$$

$$x \leftarrow x + \Delta x \cdot (\text{target} - x) + \epsilon \text{ noise}$$

```

import random
import math

weights = [10, 20, 30, 40, 15, 25, 35]
values = [60, 100, 120, 240, 80, 150, 200]
capacity = 100

n_items = len(weights)
n_nests = 15
max_iter = 50
pa = 0.25

def fitness(solution):
    total_weight = sum(w for w, s in zip(weights, solution) if s == 1)
    total_value = sum(v for v, s in zip(values, solution) if s == 1)
    if total_weight > capacity:
        return 0
    else:
        return total_value

def generate_nest():
    return [random.randint(0, 1) for _ in range(n_items)]

def levy_flight(Lambda=1.5):
    sigma_u = (math.gamma(1 + Lambda) * math.sin(math.pi * Lambda / 2) /
               (math.gamma((1 + Lambda) / 2) * Lambda * 2 ** ((Lambda - 1) / 2))) ** (1 / Lambda)
    u = random.gauss(0, sigma_u)
    v = random.gauss(0, 1)
    step = u / (abs(v) ** (1 / Lambda))
    return step

def get_cuckoo(nest, best_nest):
    new_nest = []
    for xi, bi in zip(nest, best_nest):
        step = levy_flight()
        val = xi + step * (xi - bi)

        s = 1 / (1 + math.exp(-val))
        new_val = 1 if s > 0.5 else 0
        new_nest.append(new_val)
    return new_nest

def cuckoo_search():
    nests = [generate_nest() for _ in range(n_nests)]

```

```

fitness_values = [fitness(nest) for nest in nests]

best_index = fitness_values.index(max(fitness_values))
best_nest = nests[best_index][:]
best_fitness = fitness_values[best_index]

for iteration in range(1, max_iter + 1):
    for i in range(n_nests):
        new_nest = get_cuckoo(nests[i], best_nest)
        new_fitness = fitness(new_nest)
        if new_fitness > fitness_values[i]:
            nests[i] = new_nest
            fitness_values[i] = new_fitness

    for i in range(n_nests):
        if random.random() < pa:
            nests[i] = generate_nest()
            fitness_values[i] = fitness(nests[i])

    current_best_index = fitness_values.index(max(fitness_values))
    current_best_fitness = fitness_values[current_best_index]

    if current_best_fitness > best_fitness:
        best_fitness = current_best_fitness
        best_nest = nests[current_best_index][:]

if iteration % 10 == 0:
    print(f"Iteration {iteration}: Best value so far = {best_fitness}")

return best_nest, best_fitness

if __name__ == "__main__":
    best_solution, best_value = cuckoo_search()
    total_weight = sum(w for w, s in zip(weights, best_solution) if s == 1)
    print(f"\nBest packing solution (1 = selected): {best_solution}")
    print(f"Total value of supplies packed: {best_value}")
    print(f"Total weight: {total_weight}")

```

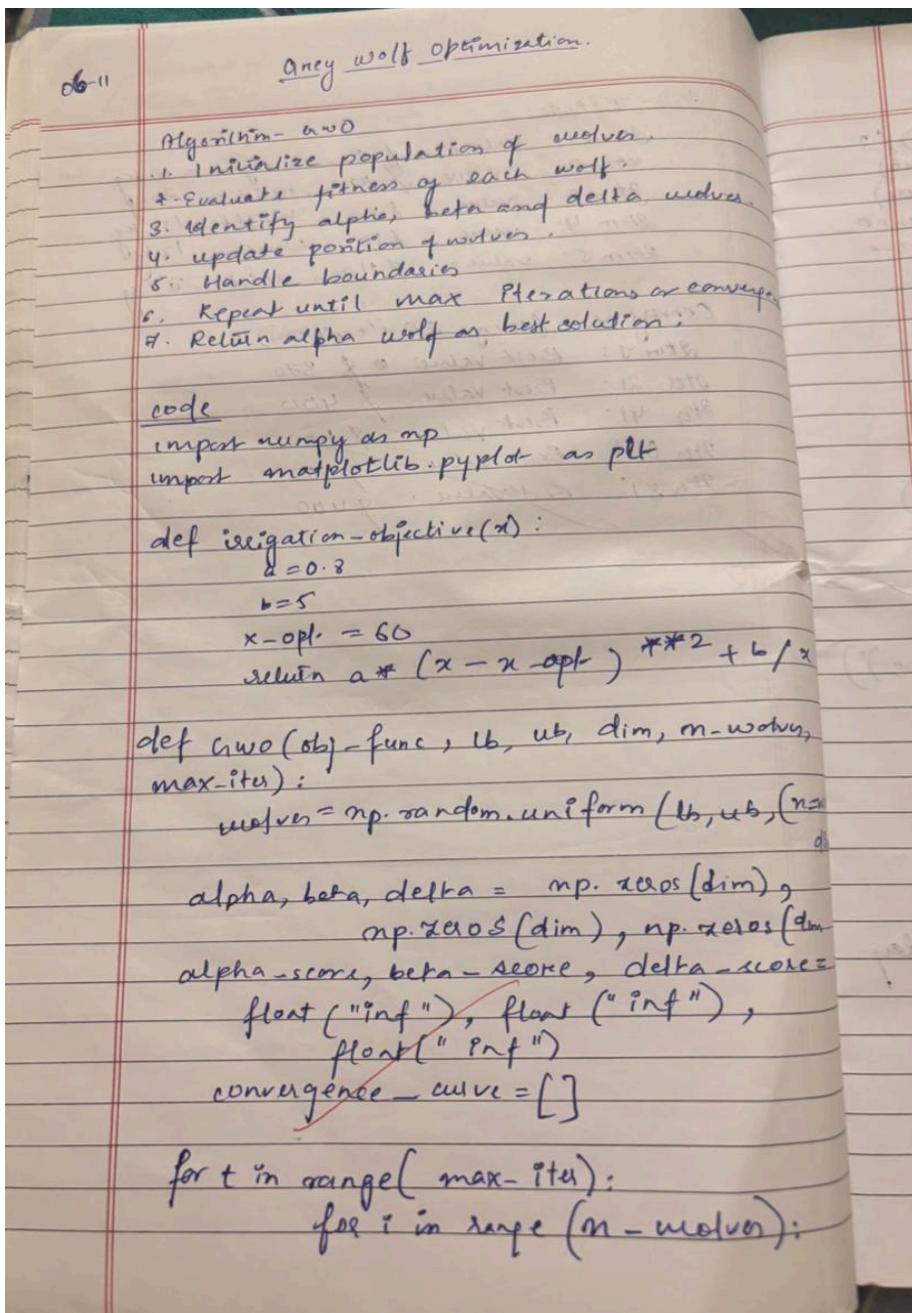
OUTPUT:

```
Iteration 10: Best value so far = 570
Iteration 20: Best value so far = 570
Iteration 30: Best value so far = 590
Iteration 40: Best value so far = 590
Iteration 50: Best value so far = 590
```

```
Best packing solution (1 = selected): [0, 0, 0, 1, 0, 1, 1]
Total value of supplies packed: 590
Total weight: 100
```

Program 6

The Grey Wolf Optimizer (GWO) algorithm is a swarm intelligence algorithm inspired by the social hierarchy and hunting behavior of grey wolves. It mimics the leadership structure of alpha, beta, delta, and omega wolves and their collaborative hunting strategies. The GWO algorithm uses these social hierarchies to model the optimization process, where the alpha wolves guide the search process while beta and delta wolves assist in refining the search direction. This algorithm is effective for continuous optimization problems and has applications in engineering, data analysis, and machine learning.



$\text{fitness} = \text{obj_func}(\text{m}, \text{wolves}[i])$

if fitness < alpha_score:

alpha_score = alpha = fitness,
 $\text{wolves}[i].\text{copy}()$

elif fitness > beta_score:

beta_score = beta = fitness, $\text{wolves}[i].\text{copy}()$

elif fitness < delta_score:

delta_score = delta = fitness,
 $\text{wolves}[i].\text{copy}()$

$$\alpha = \alpha - t * (\alpha / \max_iter)$$

for i in range(0, n_wolves):

for j in range(dim):

$a_1, s_2 = \text{np.random.rand}(), \text{np.}$

$\text{random.rand}()$

$$A_1, C_1 = 2 * a_1 * r_1 - \alpha, 2 * s_2$$

$$D_{\text{alpha}} = \text{abs}(C_1 * \alpha) [j] \\ - \text{wolves}[i][j]$$

$$x_1 = \alpha[j] - A_1 * D_{\text{alpha}}$$

$$r_1, s_2 = \text{np.random.rand}(), \text{np.}$$

$\text{random.rand}()$

~~$$A_2, C_2 = 2 * a * r_1 - \alpha, 2 * s_2$$~~

~~$$D_{\text{beta}} = \text{abs}(C_2 * \beta) [j] \\ - \text{wolves}[i][j]$$~~

$$x_2 = \beta[j] - A_2 * D_{\text{beta}}$$

$$r_1, s_2 = \text{np.random.rand}(), \text{np.}$$

random.

$\text{rand}()$

$$A_3, C_3 = 2 * a * r_1 - \alpha, 2 * s_2$$

$$D_{\text{delta}} = \text{abs}(C_3 * \delta) [j] - \text{wolves}[i][j]$$

$$x_3 = \delta[j] - A_3 * D_{\text{delta}}$$

```

def mutation(i):
    mu1 = (x1 + x2 + x3) / 3
    mu2 = np.clip(mu1, l, u)
    convergence_curve.append(alpha - side)
    return alpha, alpha - score, convergence_curve

```

```

print("Optimal irrigation level:
      [best_pos[0]]: {} mm/day")

```

```

print("Minimum cost Function value:
      [float(best_score)]: .4f")

```

```

plt.plot(Curve, linewidth=2)
plt.title("Two convergence curve for
          irrigation optimization")

```

```

plt.xlabel('Iteration')

```

```

plt.ylabel('Fitness (Objective Value)')

```

```

plt.grid(True)

```

```

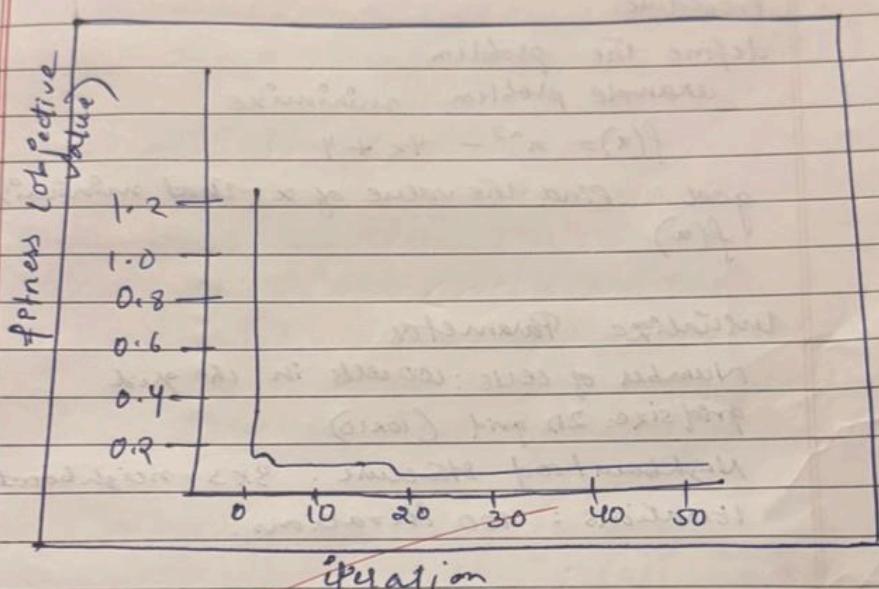
plt.show()

```

Output:

Optimal Irrigation level: 59.991 mm/day
 Minimum cost Function value: 0.083

GWO convergence curve for virginia optimization



iteration

~~80~~
~~60~~

```

import numpy as np
import matplotlib.pyplot as plt

def irrigation_objective(x):
    # Parameters for irrigation problem
    a = 0.8    # yield penalty factor
    b = 5      # water cost factor
    x_opt = 60 # optimal irrigation level (e.g., mm/day)
    return a * (x - x_opt)**2 + b / x

def GWO(obj_func, lb, ub, dim, n_wolves, max_iter):
    # Initialize wolves randomly within bounds
    wolves = np.random.uniform(lb, ub, (n_wolves, dim))
    alpha, beta, delta = np.zeros(dim), np.zeros(dim), np.zeros(dim)
    alpha_score, beta_score, delta_score = float("inf"), float("inf"), float("inf")

    convergence_curve = []

    for t in range(max_iter):
        for i in range(n_wolves):
            fitness = obj_func(wolves[i])
            # Update alpha, beta, delta
            if fitness < alpha_score:
                alpha_score, alpha = fitness, wolves[i].copy()
            elif fitness < beta_score:
                beta_score, beta = fitness, wolves[i].copy()
            elif fitness < delta_score:
                delta_score, delta = fitness, wolves[i].copy()

        # Linearly decreasing 'a' from 2 to 0
        a = 2 - t * (2 / max_iter)

        # Update positions of wolves
        for i in range(n_wolves):
            for j in range(dim):
                r1, r2 = np.random.rand(), np.random.rand()
                A1, C1 = 2 * a * r1 - a, 2 * r2
                D_alpha = abs(C1 * alpha[j] - wolves[i][j])
                X1 = alpha[j] - A1 * D_alpha

                r1, r2 = np.random.rand(), np.random.rand()
                A2, C2 = 2 * a * r1 - a, 2 * r2
                D_beta = abs(C2 * beta[j] - wolves[i][j])
                X2 = beta[j] - A2 * D_beta

```

```

r1, r2 = np.random.rand(), np.random.rand()
A3, C3 = 2 * a * r1 - a, 2 * r2
D_delta = abs(C3 * delta[j] - wolves[i][j])
X3 = delta[j] - A3 * D_delta

wolves[i][j] = (X1 + X2 + X3) / 3

# Boundary handling
wolves[i] = np.clip(wolves[i], lb, ub)

convergence_curve.append(alpha_score)

return alpha, alpha_score, convergence_curve

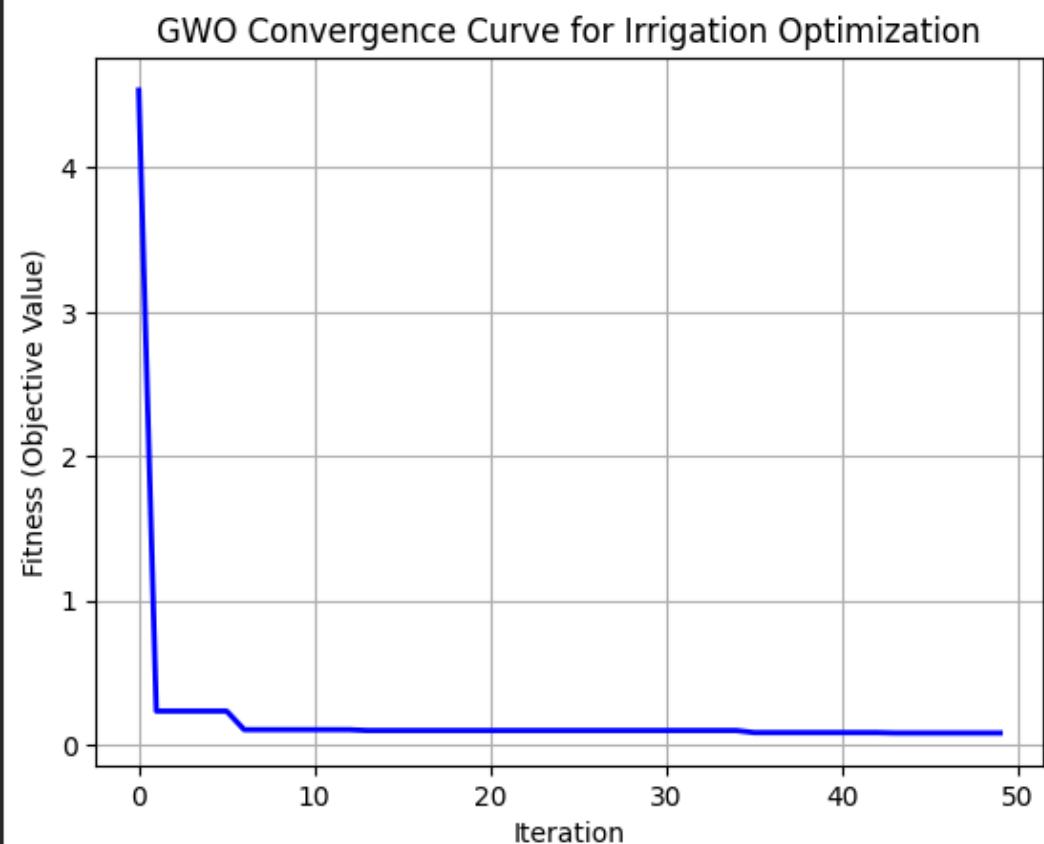
dim = 1
lb, ub = 10, 100 # irrigation limits (mm/day)
n_wolves = 20
max_iter = 50

best_pos, best_score, curve = GWO(irrigation_objective, lb, ub, dim, n_wolves, max_iter)
print(f"Optimal Irrigation Level: {best_pos[0]:.3f} mm/day")
print(f"Minimum Cost Function Value: {float(best_score):.4f}")

plt.plot(curve, 'b-', linewidth=2)
plt.title('GWO Convergence Curve for Irrigation Optimization')
plt.xlabel('Iteration')
plt.ylabel('Fitness (Objective Value)')
plt.grid(True)
plt.show()
OUTPUT:

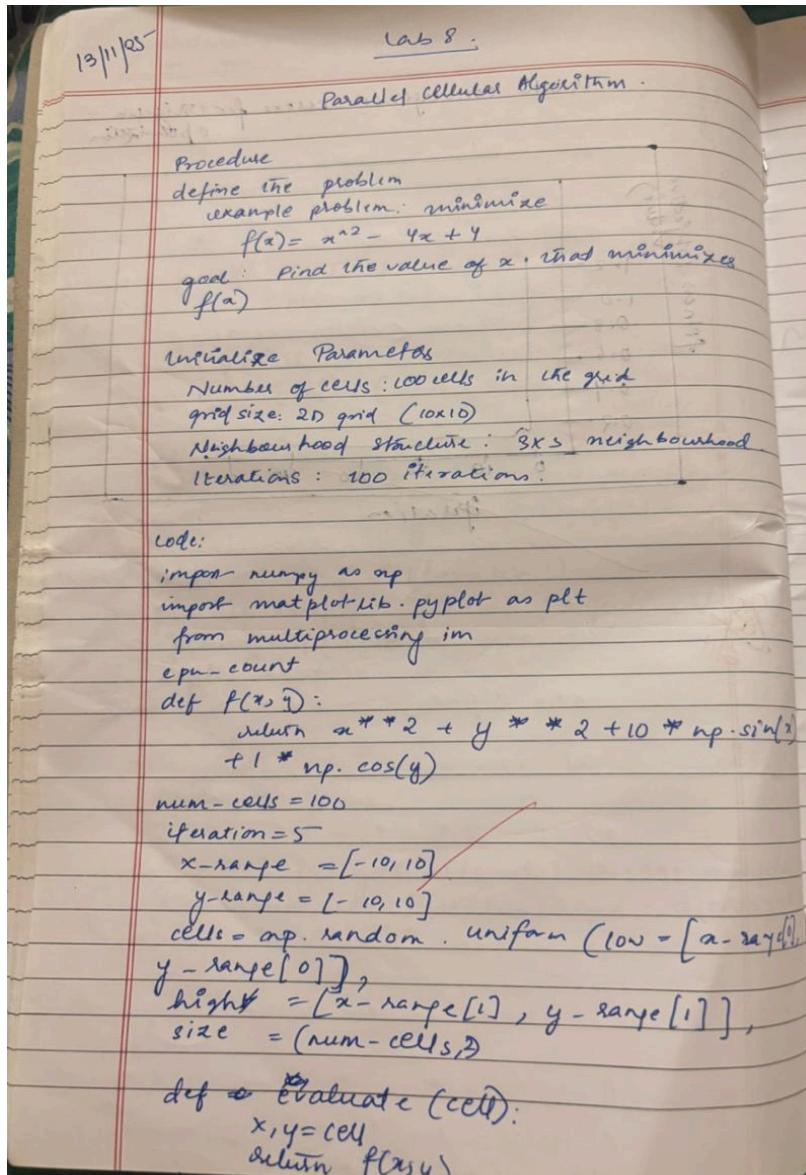
```

```
... Optimal Irrigation Level: 59.990 mm/day
Minimum Cost Function Value: 0.0834
/tmp/ipython-input-2606069732.py:76: DeprecationWarning: Conversion of an array w
    print(f"Minimum Cost Function Value: {float(best_score):.4f}")
```



Program 7

Parallel Cellular Algorithms are inspired by the functioning of biological cells that operate in a highly parallel and distributed manner. These algorithms leverage the principles of cellular automata and parallel computing to solve complex optimization problems efficiently. Each cell represents a potential solution and interacts with its neighbors to update its state based on predefined rules. This interaction models the diffusion of information across the cellular grid, enabling the algorithm to explore the search space effectively. Parallel Cellular Algorithms are particularly suitable for large scale optimization problems and can be implemented on parallel computing architectures for enhanced performance.



```

def parallel_fitness(cells):
    with Pool(cpu_count()) as p:
        fitness = p.starmap(f[(x,y) for x,y
                           in cells], in cells)
    return np.array(fitness)

```

best solutions = []

for it in range(Iterations):

fitness = parallel_fitness(cells)

best_idx = np.argmax(fitness)

best_cell = cells[best_idx]

best_solutions.append(fitness[best_idx])

cells = np.clip(cells, [x_range[0], y_range[0]], [x_range[1], y_range[1]])

best_x, best_y = cells[best_idx]

print(f"Best solution found x={best_x:4f},
y={best_y:4f}, f(x,y)={f(best_x,
best_y):4f y}")

~~plt.plot(best_solutions)~~

~~plt.title("Parallel cellular algorithm -
function optimization")~~

~~plt.xlabel("Iteration")~~

~~plt.ylabel("Best Fitness Value")~~

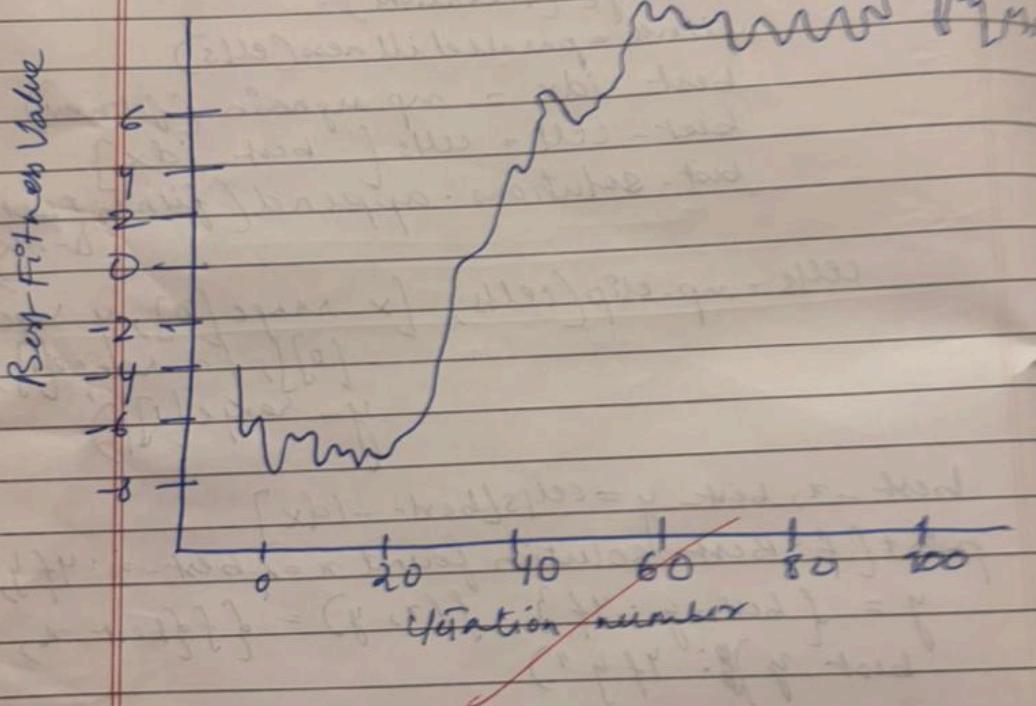
~~plt.grid(True)~~

~~plt.show()~~

output

Best solution found. $x = 0.0632$,
 $y = 0.6227$, $f(x,y) = 6.7094$

Parallel cellular Algorithm - Function optimization



```

#PCA
import numpy as np
import random

num_customers = int(input("Enter number of customers (excluding depot): "))
num_vehicles = int(input("Enter number of vehicles: "))

print("\nEnter the distance matrix (including depot 0):")
print(f"Matrix should be {num_customers + 1} x {num_customers + 1}")
distance_matrix = []

for i in range(num_customers + 1):
    row = list(map(int, input(f"Row {i+1}: ").split()))
    distance_matrix.append(row)

distance_matrix = np.array(distance_matrix)

rows = int(input("\nEnter number of grid rows: "))
cols = int(input("Enter number of grid columns: "))
grid_dim = (rows, cols)
population_size = rows * cols

num_generations = int(input("\nEnter number of generations: "))

def generate_individual():
    perm = list(range(1, num_customers + 1))
    random.shuffle(perm)
    return perm

population = [generate_individual() for _ in range(population_size)]

def fitness(individual):
    split_points = np.linspace(0, num_customers, num_vehicles + 1, dtype=int)
    total_distance = 0
    for i in range(num_vehicles):
        route = [0] + individual[split_points[i]:split_points[i+1]] + [0]
        for j in range(len(route) - 1):
            total_distance += distance_matrix[route[j], route[j+1]]
    return total_distance

def get_neighbors(idx):
    r, c = divmod(idx, grid_dim[1])
    neighbors = []
    for dr in [-1, 0, 1]:
        for dc in [-1, 0, 1]:
            if dr == 0 and dc == 0:
                continue
            nr = r + dr
            nc = c + dc
            if nr < 0 or nr >= rows or nc < 0 or nc >= cols:
                continue
            neighbors.append(nr * grid_dim[1] + nc)
    return neighbors

```

```

for dc in [-1, 0, 1]:
    nr, nc = r + dr, c + dc
    if 0 <= nr < grid_dim[0] and 0 <= nc < grid_dim[1]:
        n_idx = nr * grid_dim[1] + nc
        if n_idx != idx:
            neighbors.append(n_idx)
return neighbors

def crossover(parent1, parent2):
    size = len(parent1)
    a, b = sorted(random.sample(range(size), 2))
    child = [None] * size
    child[a:b] = parent1[a:b]

    pointer = b
    for gene in parent2[b:] + parent2[:b]:
        if gene not in child:
            if pointer == size:
                pointer = 0
            child[pointer] = gene
            pointer += 1
    return child

def mutate(individual):
    a, b = random.sample(range(len(individual)), 2)
    individual[a], individual[b] = individual[b], individual[a]
    return individual

def pca_iteration(pop):
    new_pop = pop.copy()
    for idx in range(len(pop)):
        neighbors = get_neighbors(idx)
        partner_idx = random.choice(neighbors)
        parent1 = pop[idx]
        parent2 = pop[partner_idx]

        child = crossover(parent1, parent2)
        if random.random() < 0.2:
            child = mutate(child)

        if fitness(child) < fitness(pop[idx]):
            new_pop[idx] = child
    return new_pop

```

```

for gen in range(num_generations):
    population = pca_iteration(population)
    best_fitness = min(fitness(ind) for ind in population)
    print(f"Generation {gen+1}: Best total distance = {best_fitness}")

best_individual = min(population, key=fitness)
print("\nBest route assignment (split evenly):")
split_points = np.linspace(0, num_customers, num_vehicles + 1, dtype=int)
for i in range(num_vehicles):
    route = [0] + best_individual[split_points[i]:split_points[i+1]] + [0]
    print(f"Vehicle {i+1} route: {route}")
print(f"Total distance: {fitness(best_individual)})")

```

OUTPUT:

```

Enter number of customers (excluding depot): 3
Enter number of vehicles: 2

Enter the distance matrix (including depot 0):
Matrix should be 4 x 4
Row 1: 0 2 9 10
Row 2: 2 0 6 4
Row 3: 9 6 0 8
Row 4: 10 4 8 0

Enter number of grid rows: 3
Enter number of grid columns: 3

Enter number of generations: 10
Generation 1: Best total distance = 31
Generation 2: Best total distance = 31
Generation 3: Best total distance = 31
Generation 4: Best total distance = 31
Generation 5: Best total distance = 31
Generation 6: Best total distance = 31
Generation 7: Best total distance = 31
Generation 8: Best total distance = 31
Generation 9: Best total distance = 31
Generation 10: Best total distance = 31

Best route assignment (split evenly):
Vehicle 1 route: [0, 1, 0]
Vehicle 2 route: [0, 2, 3, 0]
Total distance: 31

```