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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B.M.S. College of Engineering,

Bull Temple Road, Bangalore 560019

(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled " Bio Inspired Systems (23CS5BSBIS)" carried out by **Shaikh Uzair Ahmed (1BM23CS307),** 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.

Rohith Vaidya K Assistant Professor Department of CSE, BMSCE	Dr. Kavitha Sooda Professor & HOD Department of CSE, BMSCE

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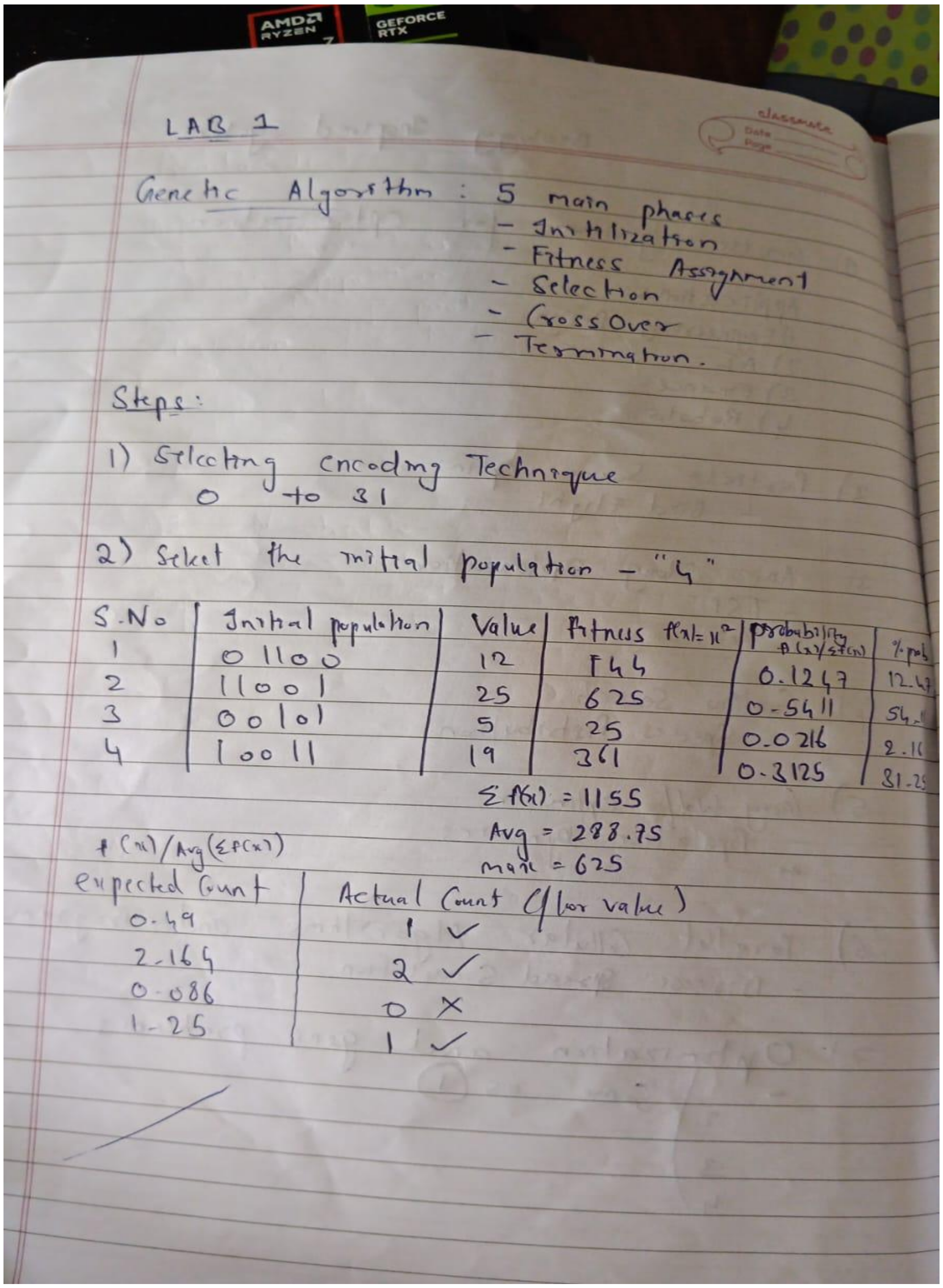
Github Link:
https://github.com/Shaikh-Uzair-Ahmed/BIS_LAB

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.

Algorithm:



LAB 1

Genetic Algorithm : 5 main phases
- Initialization
- Fitness Assignment
- Selection
- Cross Over
- Termination.

Steps:

1) Selecting encoding Technique
0 to 31

2) Select the initial population – "4"

S.No	Initial population	Value	Fitness $f(x) = x^2$	probability $f(x)/\Sigma f(x)$	% prob
1	01100	12	144	0.1247	12.47
2	11001	25	625	0.5411	54.
3	00101	5	25	0.0216	2.1
4	10011	19	361	0.3125	31.2

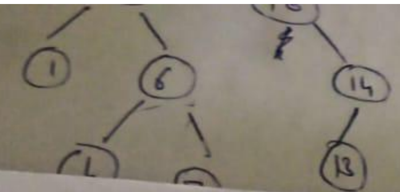
$\Sigma f(x) = 1155$

Avg = 288.75

max = 625

$f(x) / Avg(\Sigma f(x))$

expected Count	Actual Count (floor value)
0.49	1 ✓
2.164	2 ✓
0.086	0 ✗
1.25	1 ✓



3) Select Mating Pool

S.No	Mating Pool	Crossover point	offspring after Crossover	X Value	fitness $f(x)=x^2$
1	01100	4	01101	13	169
2	11001		11000	24	576
3	11001	3	11011	27	729
4	10011		10001	17	289
Sum					
Avg					
Max					

4) Crossover : Random 4 2 2

Max value = 729

5) Mutation

S.No	offspring after Crossover	Mutation chromose for flipping	offspring after mutation	X Value	fitness $f(x)=x^2$
1	01101	10000	11101	29	841
2	11000	00000	11000	24	576
3	11011	00000	11011	27	729
4	10001	00101	10100	20	400
Sum					2546
Avg					630.5
Max					841

6) Iteration until convergen criteria are met

Pseudo Code

Start
- Define Function
- Define Parameters
- Create population
- Select Mating pool
- Mutation after Mating
- Iterate
- Write best value.

Output

Gen 1 : New best $x = 993$ $f(x) = 986049.000$
Gen 2 : New Best $x = 1004$, $f(x) = 1008016$
Gen 3 : New Best $x = 1022$, $f(x) = 1044484$.
Gen 4 : $x = 1023$, $f(x) = 1046529.000$
⋮
Gen 10 : ______

29/8/25

Code:

```
import numpy as np
import matplotlib.pyplot as plt

# 1. Define the function to optimize
def func(x):
    return x * x  # Adjusted for new range

# 2. Parameters
POP_SIZE = 50
MUTATION_RATE = 0.01
CROSSOVER_RATE = 0.8
GENERATIONS = 10
CHROMOSOME_LENGTH = 10  # Now allows x in [0, 1023]

# 3. Decode chromosome to integer
def decode(chromosome):
    return int("".join(str(bit) for bit in chromosome), 2)

# 4. Create initial population
def create_population():
    return np.random.randint(2, size=(POP_SIZE, CHROMOSOME_LENGTH))

# 5. Evaluate fitness
def evaluate_fitness(population):
    decoded = np.array([decode(chrom) for chrom in population])
    fitness = func(decoded)
    return fitness

# 6. Selection (Roulette Wheel)
def select(population, fitness):
    min_fitness = np.min(fitness)
    if min_fitness < 0:
        fitness = fitness - min_fitness + 1e-6
    total_fitness = np.sum(fitness)
    probabilities = fitness / total_fitness
    indices = np.random.choice(np.arange(POP_SIZE), size=POP_SIZE, p=probabilities)
    return population[indices]

# 7. Crossover (Single-point)
def crossover(population):
    new_population = []
    for i in range(0, POP_SIZE, 2):
        parent1 = population[i]
```

```
        parent2 = population[(i + 1) % POP_SIZE]
        if np.random.rand() < CROSSOVER_RATE:
            point = np.random.randint(1, CHROMOSOME_LENGTH - 1)
            child1 = np.concatenate([parent1[:point], parent2[point:]])
            child2 = np.concatenate([parent2[:point], parent1[point:]])
            new_population.extend([child1, child2])
        else:
            new_population.extend([parent1, parent2])
    return np.array(new_population)

# 8. Mutation
def mutate(population):
    for i in range(POP_SIZE):
        for j in range(CHROMOSOME_LENGTH):
            if np.random.rand() < MUTATION_RATE:
                population[i, j] = 1 - population[i, j]
    return population

# 9. Main GA loop
def genetic_algorithm():
    population = create_population()
    best_solution = None
    best_fitness = -np.inf
    best_fitness_list = []

    for generation in range(GENERATIONS):
        fitness = evaluate_fitness(population)
        max_idx = np.argmax(fitness)
        current_best_fitness = fitness[max_idx]
        current_best_solution = decode(population[max_idx])

        # Update global best
        print(f"Generation {generation + 1}:  x = {current_best_solution}, f(x) = 
{current_best_fitness:.4f}")

        best_fitness_list.append(current_best_fitness)

        # Elitism
        elite = population[max_idx].copy()

        # GA steps
        population = select(population, fitness)
        population = crossover(population)
        population = mutate(population)

        # Preserve elite
        population[np.random.randint(POP_SIZE)] = elite
```

```
    # Plot fitness over generations
    plt.figure(figsize=(10, 5))
    plt.plot(range(1, GENERATIONS + 1), best_fitness_list, label='Best Fitness')
    plt.xlabel('Generation')
    plt.ylabel('Fitness')
    plt.title('Best Fitness Over Generations')
    plt.grid(True)
    plt.legend()
    plt.tight_layout()
    plt.show()

    return current_best_solution, current_best_fitness

# Run the GA
best_x, best_val = genetic_algorithm()
print(f"\nFinal Best Solution: x = {best_x}, f(x) = {best_val:.4f}")
```

Output:

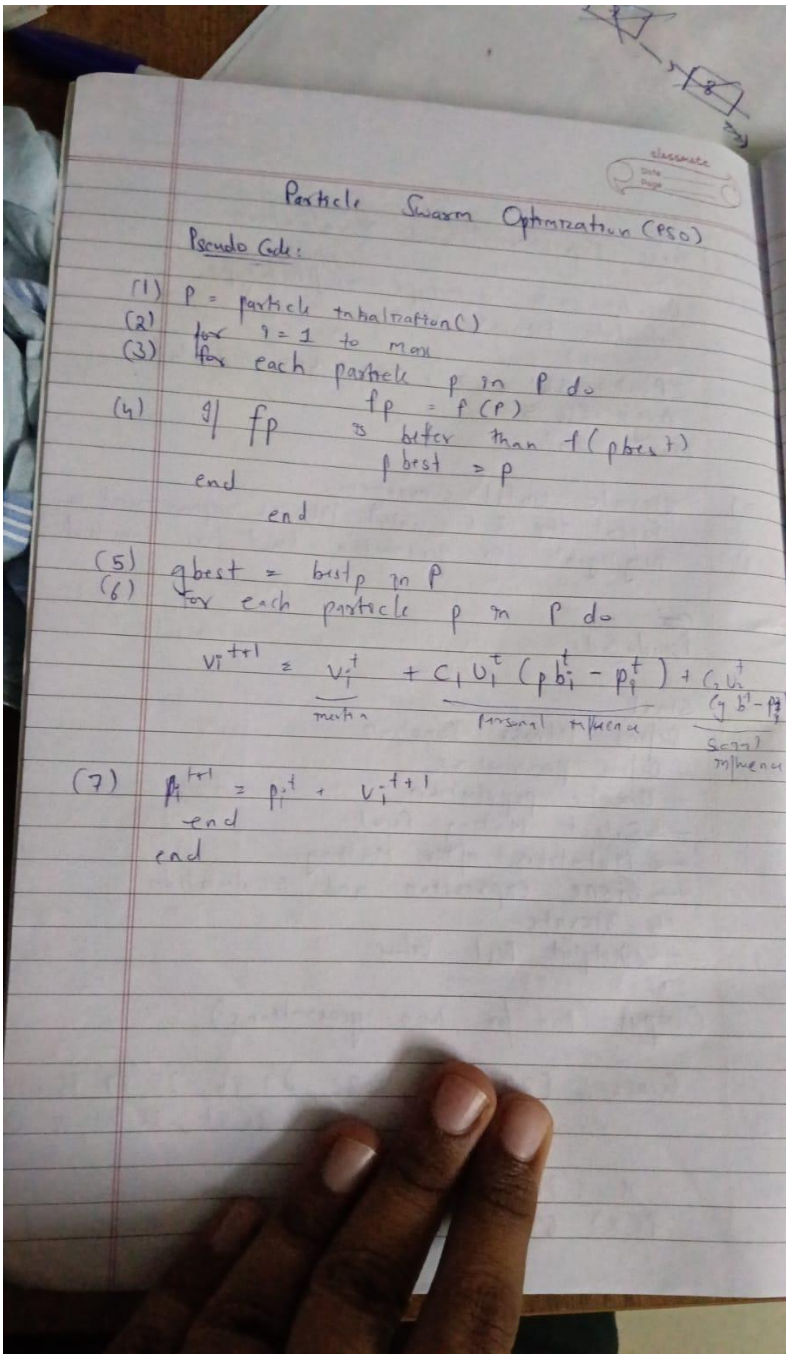
```
Generation 1:  x = 991, f(x) = 982081.0000
Generation 2:  x = 991, f(x) = 982081.0000
Generation 3:  x = 991, f(x) = 982081.0000
Generation 4:  x = 1008, f(x) = 1016064.0000
Generation 5:  x = 1008, f(x) = 1016064.0000
Generation 6:  x = 1008, f(x) = 1016064.0000
Generation 7:  x = 1008, f(x) = 1016064.0000
Generation 8:  x = 1012, f(x) = 1024144.0000
Generation 9:  x = 1012, f(x) = 1024144.0000
Generation 10:  x = 1014, f(x) = 1028196.0000

 Final Best Solution: x = 1014, f(x) = 1028196.0000
```

Program 2

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.

Algorithm:



Particle Swarm Optimization (PSO)

Pseudo Code:

(1) P = particle initialization()
(2) for i = 1 to max
(3) for each particle p in P do
fp = f(p)
(4) if fp is better than f(pbest)
pbest = p
end
end

(5) gbest = best p in P
(6) for each particle p in P do

$$v_i^{t+1} = \underbrace{v_i^t}_{\text{inertia}} + \underbrace{c_1 U_1^t (pb_i^t - p_i^t)}_{\text{personal influence}} + \underbrace{c_2 U_2^t (gb^t - p_i^t)}_{\text{social influence}}$$

(7) $p_i^{t+1} = p_i^t + v_i^{t+1}$
end
end

eg: Iteration 1

$F(x, y) = x^2 + y^2$

Inertia $(\omega) = 0.4$

value of Cognitive + Social Constants

$c_1 = 2 + c_2 = 2$

Initial Sol^n are set to 1000

" P1 fitness value $= 1^2 + 1^2 = 2$

Particle no	Initial Pos x	y	Velocity x	y	Best Sol^n	Best Pos x	y	fitness value
P_1	1	1	0	0	1000	~~1~~ -	~~1~~ -	2
P_2	-1	1	0	0	1000	~~1~~ -	~~1~~ -	2
P_3	0.5	-0.5	0	0	1000	-	-	0.5
P_4	1	-1	0	0	1000	-	-	2
P_5	0.25	0.25	0	0	1000	-	-	0.125

Iteration 2

P No	Initial pos x	y	Velocity x	y	Best Sol	Best Pos x	y	Fitness value
P_1	1	1	-0.75	-0.75	2	1	1	2
P_2	-1	1	1.25	-0.75	2	-1	1	2
P_3	0.5	-0.5	-0.25	0.75	0.5	0.5	-0.5	0.5
P_4	1	-1	-0.75	1.25	2	1	-1	2
P_5	0.25	0.25	0	0	0.125	0.25	0.25	0.125

Iteration 3

P.No	Initial Pos x	y	Velocity x	y	Best Sol	Best Pos x	y	Fitness value
P_1	0.25	0.25	-0.375	-0.375	2	1	1	0.125
P_2	0.25	0.25	0.6210	-0.375	2	-1	1	0.125
P_3	0.25	0.25	-0.125	0.375	0.5	0.5	0.5	0.125
P_4	0.25	0.25	-0.375	0.625	2	1	-1	0.125
P_5	0.25	0.25	0	0	0.125	0.25	0.25	0.125

<u>Output</u>

Best position : 2.5 , Best = 26.2500

Code:

```
import random
from math import sqrt

c1, c2 = 1, 1


def fitness(x):
    return -x**2 + 5*x + 20


def init():
    n = int(input("Enter no. of particles: "))
    v = [0 for i in range(n)]
    x = list(map(float, input("Enter positions of particles:").split()))
    p = x.copy()
    fp = [fitness(xi) for xi in x]
    return n, v, fp, p, x


def find(n, fp, p):
    max_fitness = float('-inf')
    pos = -1
    for i in range(n):
        if fp[i] > max_fitness:
            max_fitness = fp[i]
            pos = i
    return pos


def update(n, v, fp, p, x, max_pos):
    r1, r2 = sqrt(random.random()), sqrt(random.random())

    for i in range(n):
        v[i] = v[i] + c1 * r1 * (p[i] - x[i]) + c2 * r2 * (p[max_pos] - x[i])
        x[i] = x[i] + v[i]

    for i in range(n):
        fp[i] = fitness(x[i])
        if fp[i] > fitness(p[i]):
            p[i] = x[i]


def print_state(v, fp, p, x):
    print(f'''
    {x}
```

```
    {p}
    {v}
    {fp}
    ''')


n, v, fp, p, x = init()
print_state(v, fp, p, x)
max_pos = find(n, fp, p)
gbest = p[max_pos]

while True:
    update(n, v, fp, p, x, max_pos)
    max_pos = find(n, fp, p)
    if fitness(gbest) == fitness(p[max_pos]):
        break
    print_state(v, fp, p, x)
    gbest = p[max_pos]

print(f"Global Best Solution: {gbest} with fitness: {fitness(gbest)}")
```

Output:

```
Enter no. of particles: 5
Enter positions of particles:1 -1 0.5 1 0.25

    [1.0, -1.0, 0.5, 1.0, 0.25]
    [1.0, -1.0, 0.5, 1.0, 0.25]
    [0, 0, 0, 0, 0]
    [24.0, 14.0, 22.25, 24.0, 21.1875]

Global Best Solution: 1.0 with fitness: 24.0
```

Program 3

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 route that visits a list of cities and returns to the origin city.

Algorithm:

LAB - AOP

Pseudo Code:

```
initialize phermone levels on all edges to a
small positive value

For iteration = 1 to max_iterations:
    for each ant:
        place ant on starting city
        initialize empty path with starting city

    while path not complete:
        Calculate probability to move to each unvisited city
          based on:
          - alpha (phermone level)
          - beta) (heuristic information)
        Select next city probabilistically based on
        these probabilities
        Add chosen city to path.

    Calculate total length of the constructed path

    Update phermone levels on all edges:
      - evaporate phermone by reducing existing phermone
      - Add phermone based on quality of ants

Return best path found.
```

Input Matrix =
$$\begin{bmatrix} \infty & 2 & 2 & 5 & 7 \\ 2 & \infty & 4 & 8 & 2 \\ 2 & 4 & \infty & 1 & 3 \\ 5 & 8 & 1 & \infty & 2 \\ 7 & 2 & 3 & 2 & \infty \end{bmatrix}$$

Output:

Best path: [0, 2, 3, 4, 1] with path length 9.

Code:

```
import numpy as np
import random

def initialize_pheromone(num_cities, initial_pheromone=1.0):
    return np.ones((num_cities, num_cities)) * initial_pheromone

def calculate_probabilities(pheromone, distances, visited, alpha=1, beta=2):
    pheromone = np.copy(pheromone)
    pheromone[list(visited)] = 0  # zero out visited cities

    heuristic = 1 / (distances + 1e-10)  # inverse of distance
    heuristic[list(visited)] = 0

    prob = (pheromone ** alpha) * (heuristic ** beta)
    total = np.sum(prob)
    if total == 0:
        # If no options (all visited), choose randomly among unvisited
        choices = [i for i in range(len(distances)) if i not in visited]
        return choices, None
    prob = prob / total
    return range(len(distances)), prob

def select_next_city(probabilities, cities):
    if probabilities is None:
        return random.choice(cities)
    return np.random.choice(cities, p=probabilities)

def path_length(path, distances):
    length = 0
    for i in range(len(path)):
        length += distances[path[i-1]][path[i]]
    return length

def ant_colony_optimization(distances, n_ants=5, n_iterations=50, decay=0.5, alpha=1, beta=2):
    num_cities = len(distances)
    pheromone = initialize_pheromone(num_cities)
    best_path = None
    best_length = float('inf')

    for iteration in range(n_iterations):
        all_paths = []
        for _ in range(n_ants):
            path = [0]  # start at city 0
            visited = set(path)
```

```
            for _ in range(num_cities - 1):
                current_city = path[-1]
                cities, probabilities = calculate_probabilities(pheromone[current_city], distances[current_city], visited, alpha, beta)
                next_city = select_next_city(probabilities, cities)
                path.append(next_city)
                visited.add(next_city)

            length = path_length(path, distances)
            all_paths.append((path, length))

            if length < best_length:
                best_length = length
                best_path = path

        # Evaporate pheromone
        pheromone *= (1 - decay)

        # Deposit pheromone proportional to path quality
        for path, length in all_paths:
            deposit = 1 / length
            for i in range(len(path)):
                pheromone[path[i-1]][path[i]] += deposit

    return best_path, best_length

# Example usage
if __name__ == "__main__":
    distances = np.array([
        [np.inf, 2, 2, 5, 7],
        [2, np.inf, 4, 8, 2],
        [2, 4, np.inf, 1, 3],
        [5, 8, 1, np.inf, 2],
        [7, 2, 3, 2, np.inf]
    ])

    best_path, best_length = ant_colony_optimization(distances)
    print(f"Best path: {[int(city) for city in best_path]} with length: {best_length:.2f}")
```

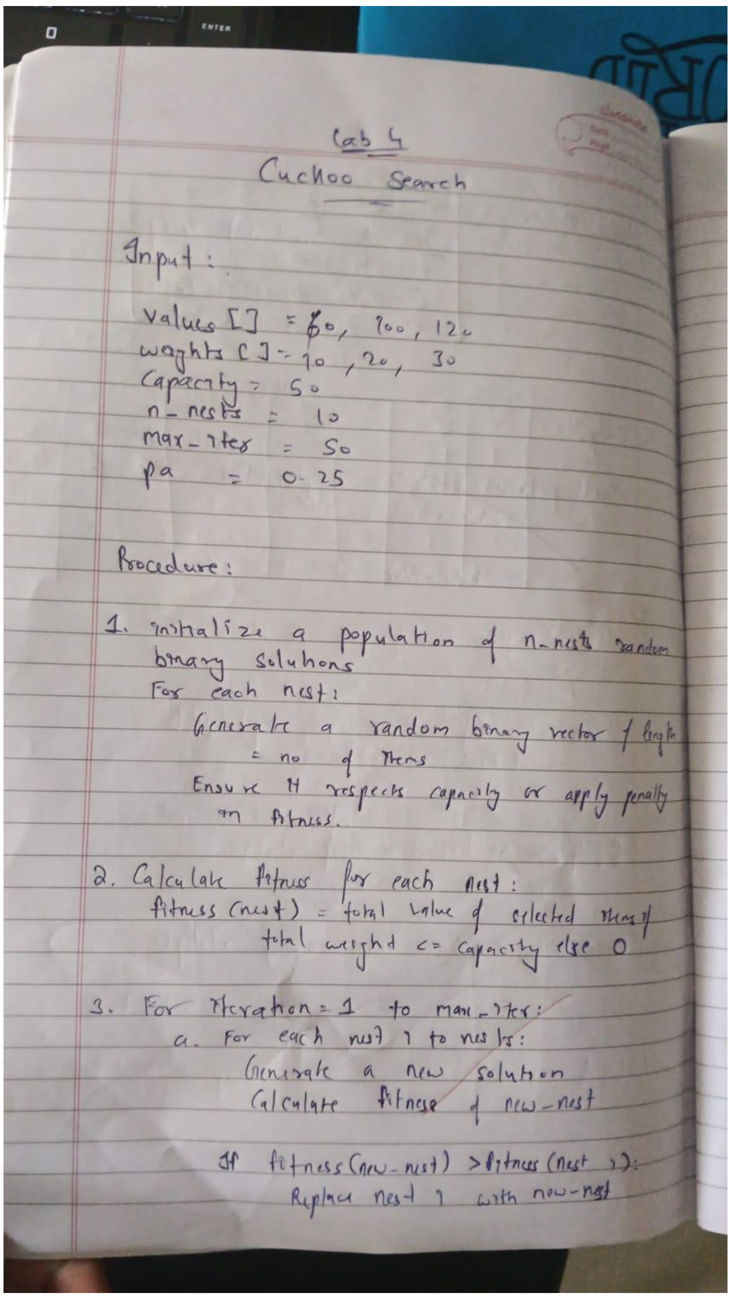
Output:

Best path: [0, 2, 3, 4, 1] with length: 9.00

Program 4

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.

Algoithm:



Lab 4

Cuckoo Search

Input:

values [] = 60, 100, 120
weights [] = 10, 20, 30
capacity = 50
n_nests = 10
max_iter = 50
pa = 0.25

Procedure:

1. initialize a population of n_nests random binary solutions
   For each nest:
      Generate a random binary vector of length = no of items
      Ensure it respects capacity or apply penalty in fitness.

2. Calculate fitness for each nest:
   fitness (nest) = total value of selected items if total weight <= capacity else 0

3. For iteration = 1 to max_iter:
   a. For each nest i to nests:
      Generate a new solution
      Calculate fitness of new_nest

      If fitness (new_nest) > fitness (nest i):
         Replace nest i with new_nest

b. Abandon a fraction pa of worst nests and replace them with new random solutions

c. Update fitness of all nests

d. Find the current best nest with max fitness

4. Return the best solution and best fitness found

~~Inputs~~ Values = [60, 100, 120] capacity = 50

Output: weights = [10, 20, 30]

~~Best~~ Iteration 1 : Best fitness = 220

⋮

10 : ——— = 160

⋮

Iteration 50 : ——— = 220

Best Solution : [0 1 1]

Best Value : 220

Code:

```
import numpy as np
import math

def knapsack_fitness(solution, values, weights, capacity):
    """Calculate fitness: total value if weight within capacity, else zero."""
    total_weight = np.sum(solution * weights)
    if total_weight > capacity:
        return 0  # Penalize overweight solutions
    return np.sum(solution * values)

def levy_flight(Lambda, size):
    """Generate Levy flight steps."""
    sigma = (math.gamma(1 + Lambda) * math.sin(math.pi * Lambda / 2) /
             (math.gamma((1 + Lambda) / 2) * Lambda * 2 ** ((Lambda - 1) / 2))) ** (1 / Lambda)
    u = np.random.normal(0, sigma, size)
    v = np.random.normal(0, 1, size)
    step = u / (np.abs(v) ** (1 / Lambda))
    return step

def sigmoid(x):
    """Sigmoid function for mapping continuous to probability."""
    return 1 / (1 + np.exp(-x))

def cuckoo_search_knapsack(values, weights, capacity, n_nests=25, max_iter=100, pa=0.25):
    """
    Cuckoo Search for 0/1 Knapsack Problem.

    Args:
        values: numpy array of item values
        weights: numpy array of item weights
        capacity: max capacity of knapsack
        n_nests: number of nests (population size)
        max_iter: max iterations
        pa: probability of abandoning nests

    Returns:
        best_solution: binary numpy array with item selection
        best_fitness: total value of best_solution
    """
```

```
n_items = len(values)
nests = np.random.randint(0, 2, size=(n_nests, n_items))
fitness = np.array([knapsack_fitness(n, values, weights, capacity) for n in nests])

best_idx = np.argmax(fitness)
best_solution = nests[best_idx].copy()
best_fitness = fitness[best_idx]

Lambda = 1.5  # Levy flight exponent

for iteration in range(max_iter):
    for i in range(n_nests):
        step = levy_flight(Lambda, n_items)
        current = nests[i].astype(float)
        new_solution_cont = current + step
        probs = sigmoid(new_solution_cont)
        new_solution_bin = (probs > 0.5).astype(int)

        new_fitness = knapsack_fitness(new_solution_bin, values, weights, capacity)

        # Greedy selection
        if new_fitness > fitness[i]:
            nests[i] = new_solution_bin
            fitness[i] = new_fitness

            if new_fitness > best_fitness:
                best_fitness = new_fitness
                best_solution = new_solution_bin.copy()

    # Abandon worst nests with probability pa
    n_abandon = int(pa * n_nests)
    if n_abandon > 0:
        abandon_indices = np.random.choice(n_nests, n_abandon, replace=False)
        for idx in abandon_indices:
            nests[idx] = np.random.randint(0, 2, n_items)
            fitness[idx] = knapsack_fitness(nests[idx], values, weights, capacity)

    # Update global best after abandonment
    current_best_idx = np.argmax(fitness)
    if fitness[current_best_idx] > best_fitness:
        best_fitness = fitness[current_best_idx]
```

```
            best_solution = nests[current_best_idx].copy()

        # Print progress: every 10 iterations and first iteration
        if iteration == 0 or (iteration + 1) % 10 == 0:
            print(f"Iteration {iteration + 1}/{max_iter}, Best Fitness: {best_fitness}")

    return best_solution, best_fitness

if __name__ == "__main__":
    # Example knapsack problem
    values = np.array([60, 100, 120, 80, 30])
    weights = np.array([10, 20, 30, 40, 50])
    capacity = 100

    best_sol, best_val = cuckoo_search_knapsack(values, weights, capacity, n_nests=30,
max_iter=100, pa=0.25)

    print("\nBest solution found:")
    print(best_sol)
    print("Total value:", best_val)
    print("Total weight:", np.sum(best_sol * weights))
```

Output:

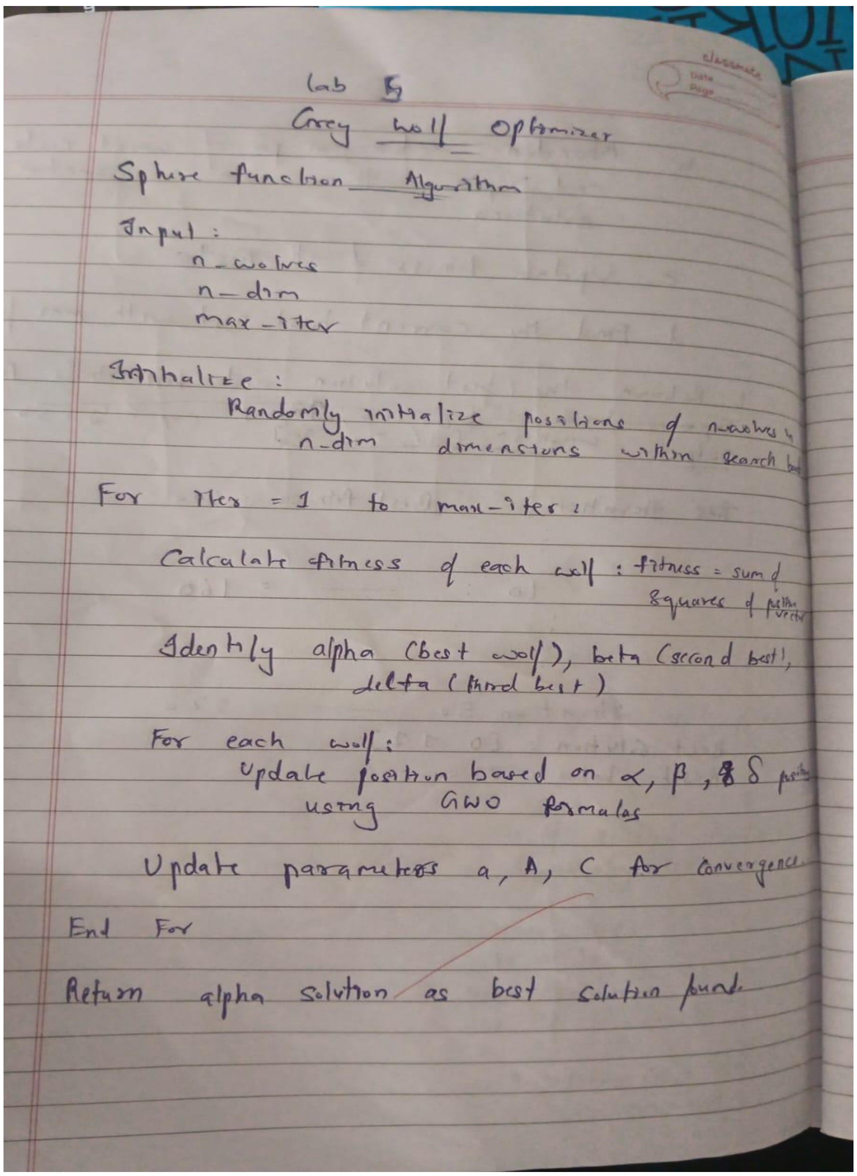
```
Iteration 1/100, Best Fitness: 360
Iteration 10/100, Best Fitness: 360
Iteration 20/100, Best Fitness: 360
Iteration 30/100, Best Fitness: 360
Iteration 40/100, Best Fitness: 360
Iteration 50/100, Best Fitness: 360
Iteration 60/100, Best Fitness: 360
Iteration 70/100, Best Fitness: 360
Iteration 80/100, Best Fitness: 360
Iteration 90/100, Best Fitness: 360
Iteration 100/100, Best Fitness: 360

Best solution found:
[1 1 1 1 0]
Total value: 360
Total weight: 100
```

Program 5

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.

Algorithm:



Lab 5

Grey Wolf Optimizer

Sphere function Algorithm

Input:

n_wolves

n_dim

max_iter

Initialize:

Randomly initialize positions of n_wolves in n_dim dimensions within search bounds

For iter = 1 to max_iter:

Calculate fitness of each wolf : fitness = sum of squares of position vector

Identify alpha (best wolf), beta (second best), delta (third best)

For each wolf:

Update position based on α, β, & δ positions using GWO formulas

Update parameters a, A, C for convergence

End For

Return alpha solution as best solution found.

Output:

Enter no of wolves : 5
Enter no of dimensions : 4
" max iterations : 10

Best Position : [2.1675797, 2.364, -1.00125, 0.49522]

Best Score : 11.4438

MG
17/10/25

Code:

```
import numpy as np

def sphere(x):
    return np.sum(x**2)

class GreyWolfOptimizer:
    def __init__(self, obj_func, n_wolves, dim, max_iter, lb=-10, ub=10):
        self.obj_func = obj_func
        self.n_wolves = n_wolves
        self.dim = dim
        self.max_iter = max_iter
        self.lb = lb
        self.ub = ub

        self.positions = np.random.uniform(self.lb, self.ub, (self.n_wolves, self.dim))

        self.alpha_pos = np.zeros(self.dim)
        self.alpha_score = float('inf')

        self.beta_pos = np.zeros(self.dim)
        self.beta_score = float('inf')

        self.delta_pos = np.zeros(self.dim)
        self.delta_score = float('inf')

    def optimize(self):
        for iter in range(self.max_iter):
            for i in range(self.n_wolves):
                self.positions[i] = np.clip(self.positions[i], self.lb, self.ub)

                fitness = self.obj_func(self.positions[i])

                if fitness < self.alpha_score:
                    self.alpha_score = fitness
                    self.alpha_pos = self.positions[i].copy()
                elif fitness < self.beta_score:
                    self.beta_score = fitness
                    self.beta_pos = self.positions[i].copy()
                elif fitness < self.delta_score:
```

```
                self.delta_score = fitness
                self.delta_pos = self.positions[i].copy()

        a = 2 - iter * (2 / self.max_iter)

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

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

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

                self.positions[i, j] = (X1 + X2 + X3) / 3

    return self.alpha_pos, self.alpha_score


if __name__ == "__main__":
    # Take inputs from user
    n_wolves = int(input("Enter number of wolves: "))
    dim = int(input("Enter number of dimensions: "))
    max_iter = int(input("Enter max iterations: "))

    gwo = GreyWolfOptimizer(obj_func=sphere, n_wolves=n_wolves, dim=dim, max_iter=max_iter)
    best_pos, best_score = gwo.optimize()
```

```
    print(f"Best Position: {best_pos}")
    print(f"Best Score: {best_score}")
```

Output:

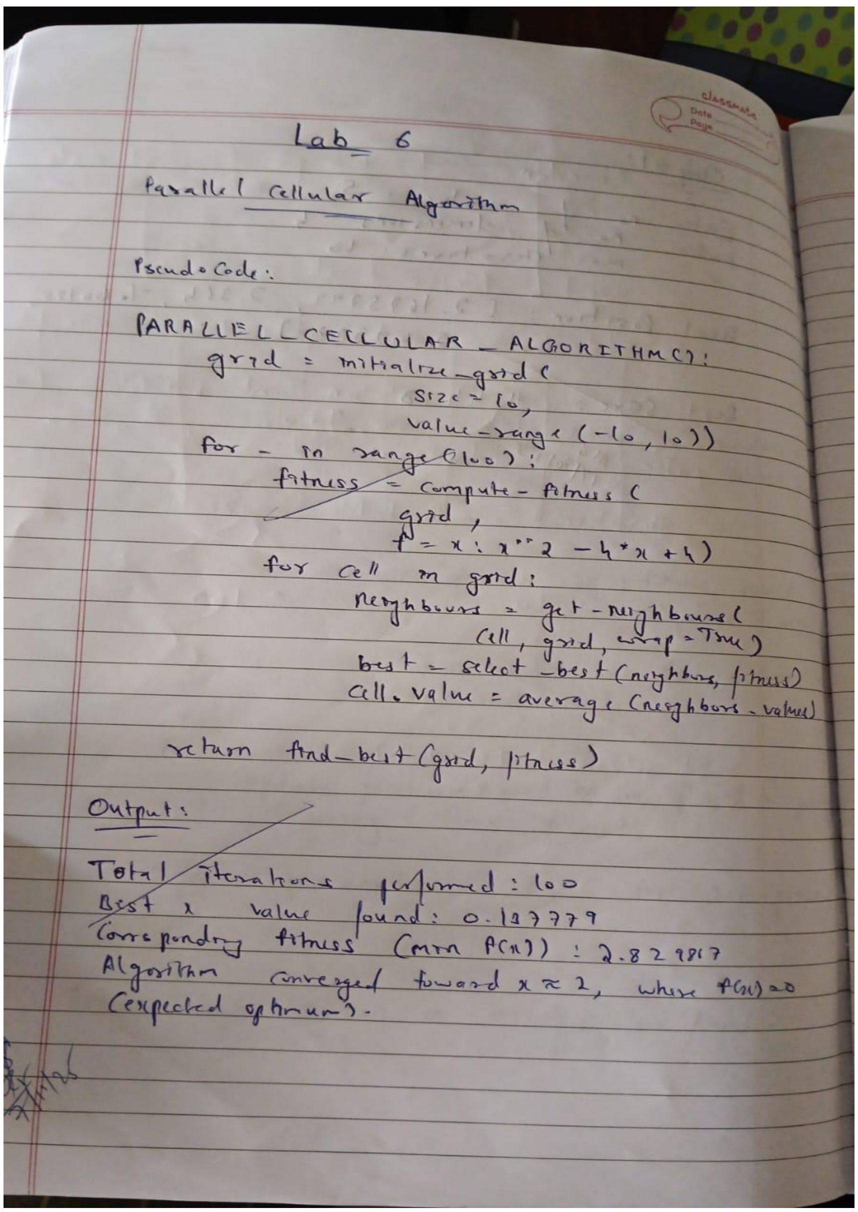
```
Enter number of wolves: 5
Enter number of dimensions: 4
Enter max iterations: 10

Best Position: [ 2.16579979  2.34635848 -1.00125355  0.49522175]
Best Score: 11.443840087181393
```

Program 6

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.

Algorithm:



Lab 6

Parallel Cellular Algorithm

Pseudo Code:

```
PARALLEL_CELLULAR_ALGORITHM():
    grid = initialize_grid(
                size = 10,
                value_range(-10, 10))
    for _ in range(100):
        fitness = compute_fitness(
                grid,
                f = x: x**2 - 4*x + 4)
        for cell in grid:
            neighbours = get_neighbours(
                    cell, grid, wrap = True)
            best = select_best(neighbours, fitness)
            cell.value = average(neighbors_values)

    return find_best(grid, fitness)
```

Output:

Total iterations performed: 100
Best x value found: 0.137779
Corresponding fitness (min f(x)): 2.822817
Algorithm converged toward x ≈ 2, where f(x) = 0 (expected optimum).

Code:

```
import numpy as np

# Initialize
grid = np.random.uniform(low=-10, high=10, size=(10, 10))
num_iterations = 100

# Define fitness function
def fitness_function(x):
    return x**2 - 4*x + 4

# Iterate
for iteration in range(num_iterations):
    new_grid = np.zeros_like(grid)
    for r in range(grid.shape[0]):
        for c in range(grid.shape[1]):
            neighbor_values = []
            for dr in [-1, 0, 1]:
                for dc in [-1, 0, 1]:
                    nr = (r + dr) % grid.shape[0]
                    nc = (c + dc) % grid.shape[1]
                    neighbor_values.append(grid[nr, nc])
            # Update to average of neighbor values (per algorithm spec)
            new_grid[r, c] = np.mean(neighbor_values)
    grid = new_grid.copy()

# Find best solution
fitness_values = fitness_function(grid)
best_fitness_overall = np.min(fitness_values)
best_x_overall = grid[np.unravel_index(np.argmin(fitness_values), grid.shape)]

# Verbose Output
print("=== Parallel Cellular Algorithm Results ===")
print(f"Total iterations performed: {num_iterations}")
print(f"Best x value found: {best_x_overall:.6f}")
print(f"Corresponding fitness (minimum f(x)): {best_fitness_overall:.6f}")
print("Algorithm converged toward x ≈ 2, where f(x) = 0 (expected optimum).")
```

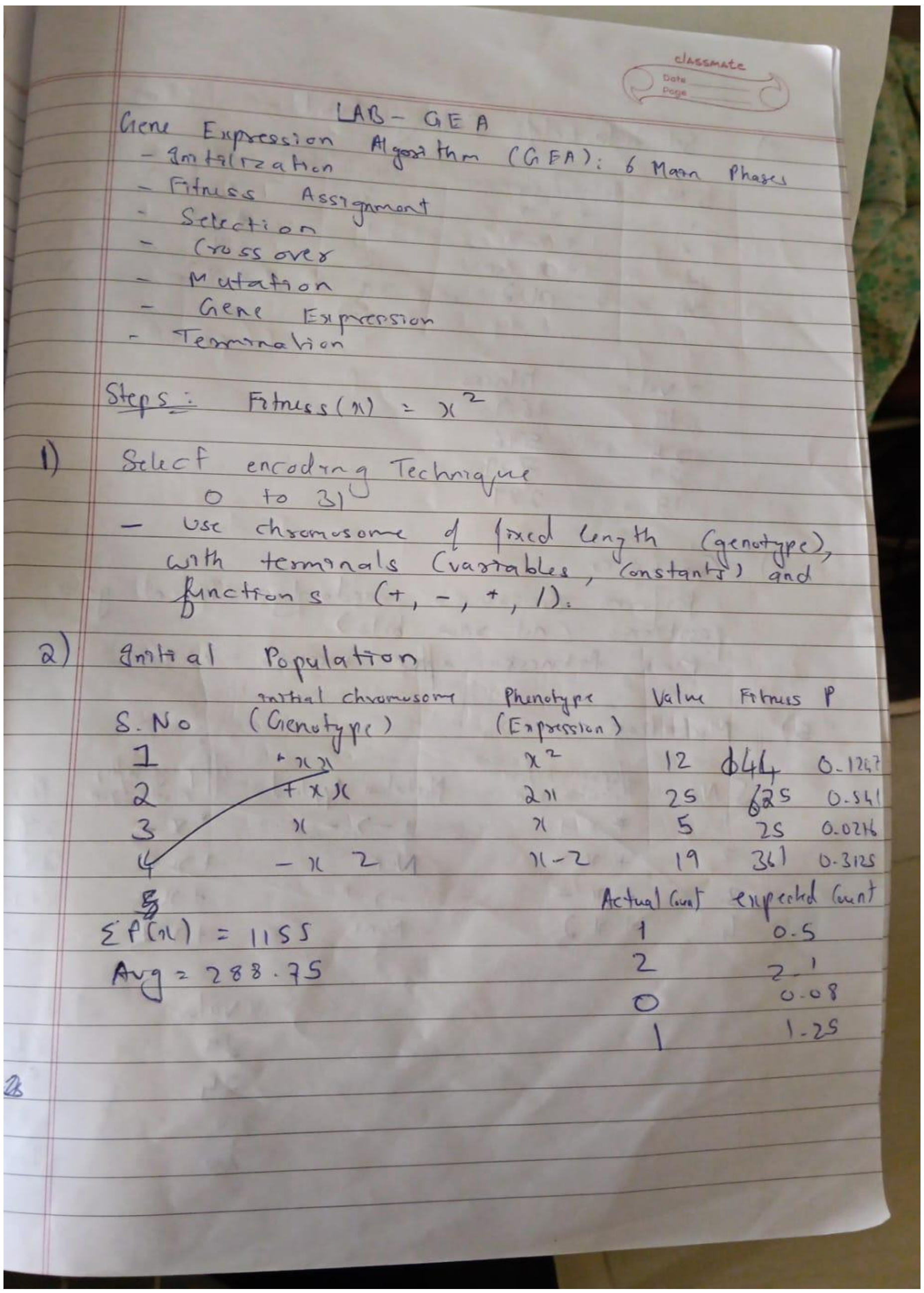
Output:

=== Parallel Cellular Algorithm Results ===
Total iterations performed: 100
Best x value found: 0.317779
Corresponding fitness (minimum f(x)): 2.829867
Algorithm converged toward x ≈ 2, where f(x) = 0 (expected optimum).

Program 7

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

Algorithm:



LAB - GEA

Gene Expression Algorithm (GEA): 6 Main Phases

- Initialization
- Fitness Assignment
- Selection
- Crossover
- Mutation
- Gene Expression
- Termination

Steps: Fitness$(x) = x^2$

1) Select encoding Technique
   0 to 31
   - Use chromosome of fixed length (genotype), with terminals (variables, constants) and functions (+, −, *, /).

2) Initial Population

S. No	Initial chromosome (Genotype)	Phenotype (Expression)	Value	Fitness	P
1	* x x	x^2	12	144	0.1247
2	+ x x	$2x$	25	625	0.541
3	x	x	5	25	0.0216
4	− x 2	$x-2$	19	361	0.3125

Actual Count	expected Count
1	0.5
2	2.1
0	0.08
1	1.25

$\Sigma f(x) = 1155$

Avg = 288.75

3) Selection of Mating Pool

S. No	Selected Chromosome	Cross Over Point	Offspring	Phenotype
1	* x x	2	* x +	$x^2(x+$ [illegible]
2	+ x x	1	+ x x	2x
3	+ x x	3	+ x −	x + x [illegible]
4	− x 2	1	+ x 2	x + 2

x Value	Fitness
13	169
24	576
27	729
17	289

4) Crossover

perform crossover randomly chosen gene positions (not raw bits).

Max fitness after crossover = 729

5) Mutation

S. No	Offspring before mutation	Mutation Applied	Offspring after mutation	Phenotype
1	* x +	+ → −	* x −	$x^2(x-$ [illegible]
2	+ x x	None	+ x x	2x
3	+ x −	− → *	+ x *	$x + x^2 x$
4	+ x 2	None	+ x 2	x + 2

x value	Fitness f(x)
29	841
24	576
27	729
20	400

6) Gene Expression and Evaluation

Decode each genotype → phenotype.
Calculate Fitness

$\Sigma f(x) = 841 + 576 + 729 + 400 = 2546$
Avg = 636.5
Max = 841

7) Iterate until convergence
Repeat step 3-6 until fitness improvement is negligible or generation limit has reached.

Pseudo Code

Start
- Define Fitness Function
- Define parameters
- Create population
- Select Mating Pool
- Mutation after Mating
- Gene expression and Evaluation
- Iterate
- Output Best Value.

Output: (Ran for 1000 generations)

Genes : [29.53, 29.82, 29.84, 28.57, 15.07, 21.83, 23.13, 30.81, 28.51, 26.22]

x : 26.37
f(x) : 695.45 # Generation limit reached.

Code:

```
import random
import math

# Example: f(x) = x * sin(10*pi*x) + 2
def fitness_function(x):
    return x * math.sin(10 * math.pi * x) + 2

POPULATION_SIZE = 6
GENE_LENGTH = 10
MUTATION_RATE = 0.05
CROSSOVER_RATE = 0.8
GENERATIONS = 20
DOMAIN = (-1, 2)

def random_gene():
    return random.uniform(DOMAIN[0], DOMAIN[1])

def create_chromosome():
    return [random_gene() for _ in range(GENE_LENGTH)]

def initialize_population(size):
    return [create_chromosome() for _ in range(size)]

def evaluate_population(population):
    return [fitness_function(express_gene(chrom)) for chrom in population]

def express_gene(chromosome):
    return sum(chromosome) / len(chromosome)

def select(population, fitnesses):
    total_fitness = sum(fitnesses)
    pick = random.uniform(0, total_fitness)
    current = 0
    for individual, fitness in zip(population, fitnesses):
        current += fitness
        if current > pick:
            return individual
    return random.choice(population)
```

```
def crossover(parent1, parent2):
    if random.random() < CROSSOVER_RATE:
        point = random.randint(1, GENE_LENGTH - 1)
        child1 = parent1[:point] + parent2[point:]
        child2 = parent2[:point] + parent1[point:]
        return child1, child2
    return parent1[:], parent2[:]

def mutate(chromosome):
    new_chromosome = []
    for gene in chromosome:
        if random.random() < MUTATION_RATE:
            new_chromosome.append(random_gene())
        else:
            new_chromosome.append(gene)
    return new_chromosome

def gene_expression_algorithm():
    population = initialize_population(POPULATION_SIZE)
    best_solution = None
    best_fitness = float("-inf")

    for generation in range(GENERATIONS):
        fitnesses = evaluate_population(population)

        for i, chrom in enumerate(population):
            if fitnesses[i] > best_fitness:
                best_fitness = fitnesses[i]
                best_solution = chrom[:]

        print(f"Generation {generation+1}: Best Fitness = {best_fitness:.4f}, Best x =
{express_gene(best_solution):.4f}")

        new_population = []
        while len(new_population) < POPULATION_SIZE:
            parent1 = select(population, fitnesses)
            parent2 = select(population, fitnesses)
            offspring1, offspring2 = crossover(parent1, parent2)
            offspring1 = mutate(offspring1)
            offspring2 = mutate(offspring2)
            new_population.extend([offspring1, offspring2])
```

```
        population = new_population[:POPULATION_SIZE]

    print("\nBest solution found:")
    print(f"Genes: {best_solution}")
    x_value = express_gene(best_solution)
    print(f"x = {x_value:.4f}")
    print(f"f(x) = {fitness_function(x_value):.4f}")

if __name__ == "__main__":
    gene_expression_algorithm()
```

output:

```
Generation 1: Best Fitness = 2.4347, Best x = 0.6245
Generation 2: Best Fitness = 2.4827, Best x = 0.6746
Generation 3: Best Fitness = 2.4827, Best x = 0.6746
Generation 4: Best Fitness = 2.4827, Best x = 0.6746
Generation 5: Best Fitness = 2.4827, Best x = 0.6746
Generation 6: Best Fitness = 2.4827, Best x = 0.6746
Generation 7: Best Fitness = 2.4827, Best x = 0.6746
Generation 8: Best Fitness = 2.4827, Best x = 0.6746
Generation 9: Best Fitness = 2.4827, Best x = 0.6746
Generation 10: Best Fitness = 2.4827, Best x = 0.6746
Generation 11: Best Fitness = 2.4827, Best x = 0.6746
Generation 12: Best Fitness = 2.4827, Best x = 0.6746
Generation 13: Best Fitness = 2.4827, Best x = 0.6746
Generation 14: Best Fitness = 2.4827, Best x = 0.6746
Generation 15: Best Fitness = 2.5073, Best x = 0.6728
Generation 16: Best Fitness = 2.5073, Best x = 0.6728
Generation 17: Best Fitness = 2.5073, Best x = 0.6728
Generation 18: Best Fitness = 2.5315, Best x = 0.6318
Generation 19: Best Fitness = 2.5315, Best x = 0.6318
Generation 20: Best Fitness = 2.5315, Best x = 0.6318

Best solution found:
Genes: [-0.9341914889787352, 1.582236333230926, 0.5195878130862375, 1.8961703080811958, 1.9026923622619076, -0.42906418830093207, -0.5325680984167858, 1.8332299106440781, -0.369575018958584, 0.8496492245933607]
x = 0.6318
f(x) = 2.5315
```