VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by

SUHAS B P (1BM23CS345)

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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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 **SUHAS B P (1BM23CS345),** 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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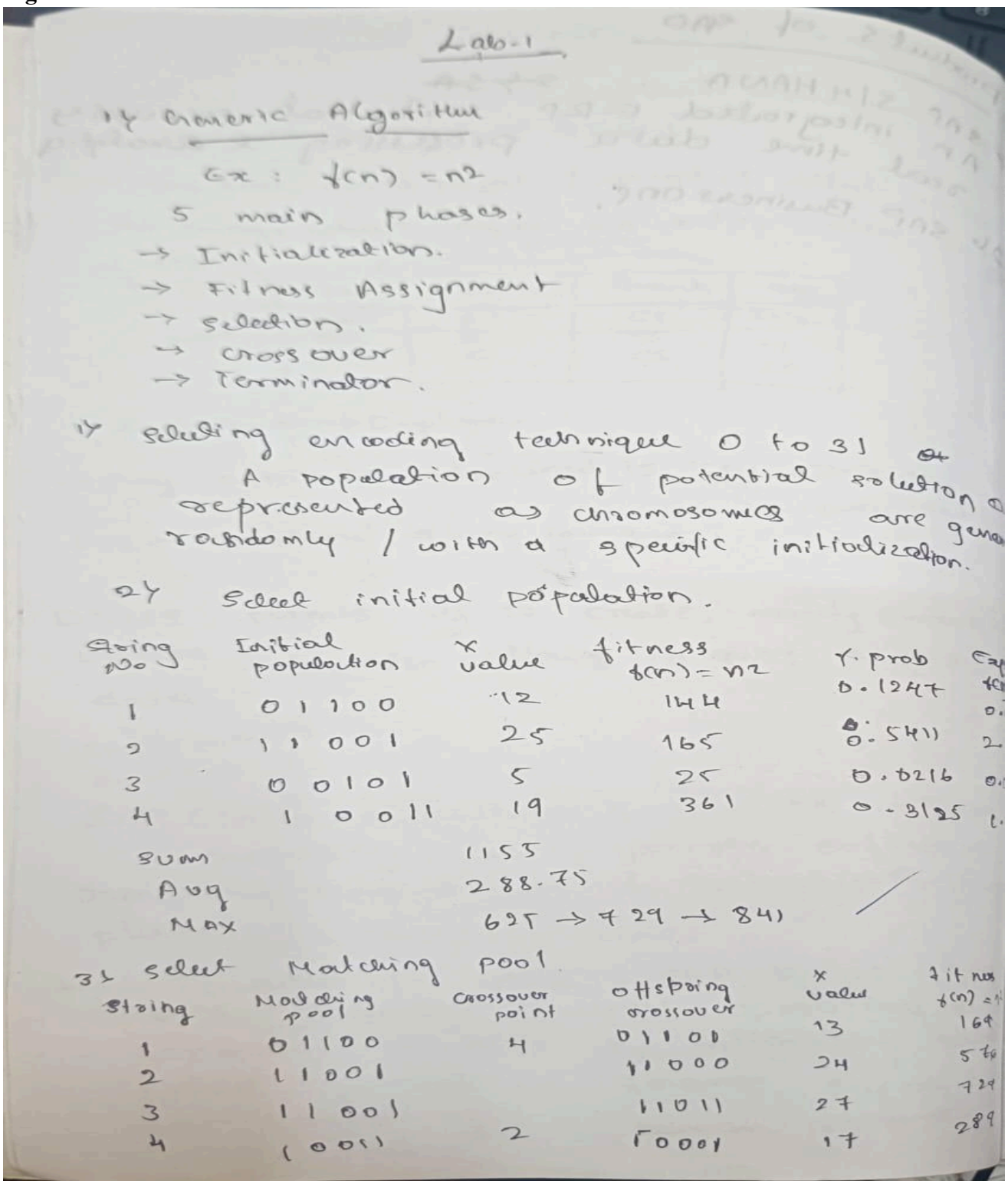
Github Link: https://github.com/1BM23CS345/BIS

Program 1 : Genetic Algorithm for Optimization Problems:

Algorithm:



Lab-1

1) Generic Algorithm

Ex : $f(n) = n^2$

5 main phases.

→ Initialization.
→ Fitness Assignment
→ Selection.
→ Crossover
→ Terminator.

1) Selecting encoding technique 0 to 31 or A population of potential solution are represented as chromosomes are generated randomly / with a specific initialization.

2) Select initial population.

String No	Initial population	x value	fitness $f(n) = n^2$	r. prob	Exp
1	0 1 1 0 0	12	144	0.1247	0.
2	1 1 0 0 1	25	165	0.5411	2.
3	0 0 1 0 1	5	25	0.0216	0.
4	1 0 0 1 1	19	361	0.3125	1.
Sum		1155			
Avg		288.75			
Max		625 → 729 → 841			

3) Select Matching pool

String	Matching pool	Crossover point	Offspring crossover	x value	fitness $f(n) = n^2$
1	0 1 1 0 0	4	0 1 1 0 1	13	169
2	1 1 0 0 1		1 1 0 0 0	24	576
3	1 1 0 0 1		1 1 0 1 1	27	729
4	1 0 0 1 1	2	1 0 0 0 1	17	289

4Y crossover: Random 442 0-1

Max value -729 '0-20

String No	Off string after crossover	Mutation chromosome	Offspring after mutation	x value	fitness $f(x)=x^2$
1	0 1 1 0 1	1 0 0 0 0	11101	29	841
2	1 1 0 0 0	0 0 0 0 0	11 000	24	576
3	11 0 1 1	0 0 0 0 0	11011	27	729
4	1 0 0 0 1	0 0 1 0 1	10100	20	400

~~procedure~~ output.

Generation : 1 String (a) (?) 7 Fitness : 6

Generation : 2 String ULS f[L] ? Fitness : 5

Generation : 3 String ULS [L] Fitness : 4.

Generation : 4 String BJS LAB Fitness : 1

Generation : 5 String : BJS LAB Fitness : 1

Generation : 6 String BIS LAB Fitness : 0.

Code:

```
import random
import math

def fitness_function(x):

    return x * math.sin(10 * math.pi * x) + 1

POPULATION_SIZE = 20
MUTATION_RATE = 0.1
CROSSOVER_RATE = 0.8
GENERATIONS = 100
X_BOUND = (-1, 2)  # Search space for x

def create_individual():
    return random.uniform(*X_BOUND)

def create_population(size):
    return [create_individual() for _ in range(size)]

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

def select(population, fitnesses):
    total_fitness = sum(fitnesses)
    probs = [f / total_fitness for f in fitnesses]
    return random.choices(population, weights=probs, k=2)

def crossover(parent1, parent2):
    if random.random() < CROSSOVER_RATE:
        alpha = random.random()
        child1 = alpha * parent1 + (1 - alpha) * parent2
        child2 = alpha * parent2 + (1 - alpha) * parent1
        return child1, child2
    else:
        return parent1, parent2


def mutate(individual):
    if random.random() < MUTATION_RATE:
        mutation = random.uniform(-0.1, 0.1)
        individual += mutation
        individual = max(min(individual, X_BOUND[1]), X_BOUND[0])  # Keep in bounds
    return individual

def genetic_algorithm():
    population = create_population(POPULATION_SIZE)
```

```
    best_individual = None
    best_fitness = float('-inf')

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

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

        new_population = []
        while len(new_population) < POPULATION_SIZE:
            parent1, parent2 = select(population, fitnesses)
            child1, child2 = crossover(parent1, parent2)
            child1 = mutate(child1)
            child2 = mutate(child2)
            new_population.extend([child1, child2])

        population = new_population[:POPULATION_SIZE]

        print(f"Generation {generation+1}: Best Fitness = {best_fitness:.5f}, Best X =
{best_individual:.5f}")

    print("\nOptimization complete!")
    print(f"Best solution: x = {best_individual:.5f}, f(x) = {best_fitness:.5f}")

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

Output:

```
= RESTART: C:/Users/student/AppData/Local/Prog
Best Fitness = 16
Best Fitness = 17
Best Fitness = 17
Best Fitness = 18
Best Fitness = 19
Best Fitness = 18
Best Fitness = 18
Best Fitness = 18
Best Fitness = 19
Best Fitness = 20
Best Fitness = 20
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Best Fitness = 20
Best Fitness = 20

Best solution found:
Fitness (X value): 20
```
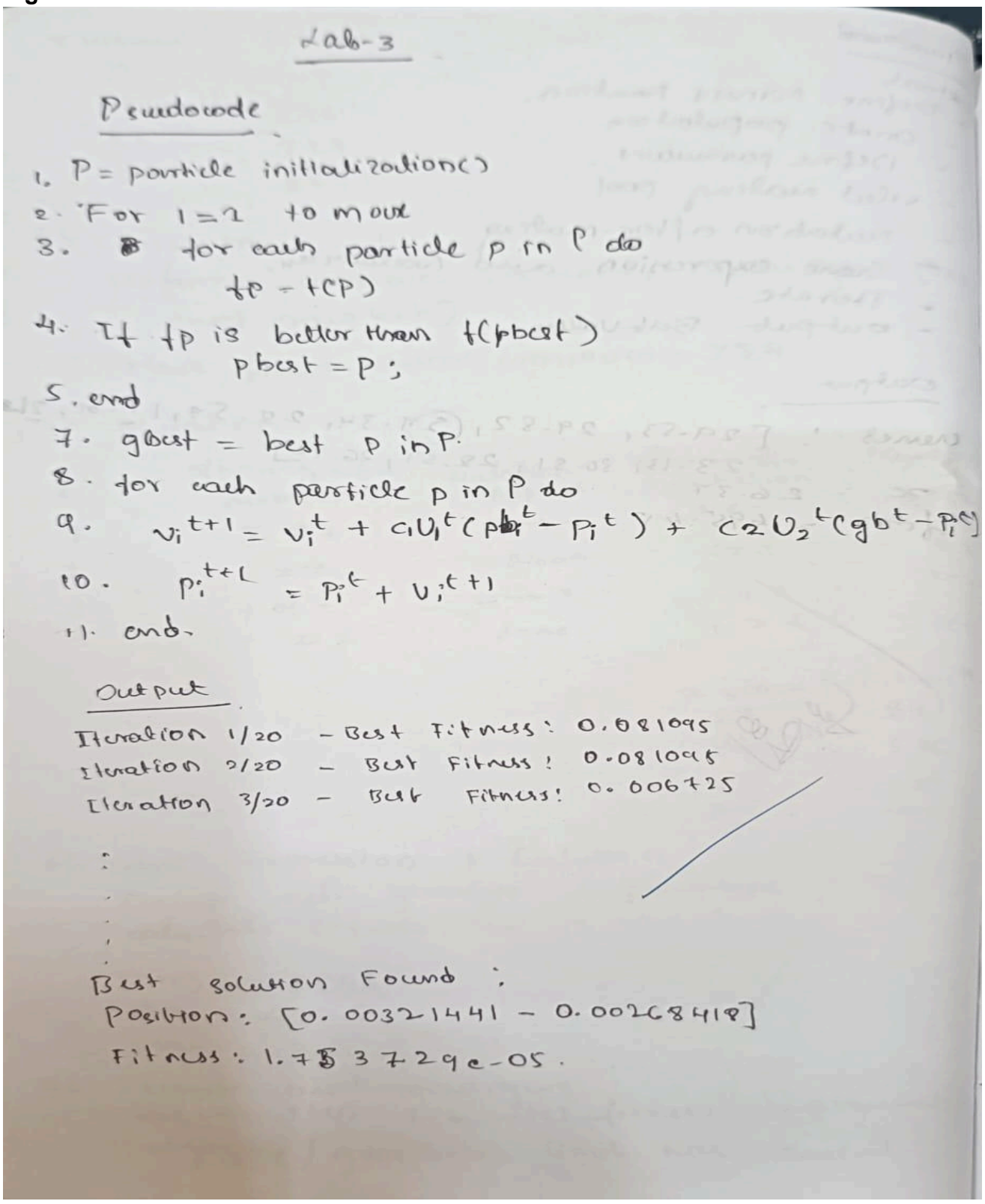

Program 02: Particle Swarm Optimization for Function Optimization:

Algorithm :



Lab-3

Pseudocode

1. P = particle initialization()
2. For i = 1 to max iter
3. for each particle p in P do
   fp = f(p)
4. If fp is better than f(pbest)
   pbest = p;
5. end
7. gBest = best p in P.
8. for each particle p in P do
9. $v_i^{t+1} = v_i^t + c_1 U_1^t (pb_i^t - p_i^t) + c_2 U_2^t (gb^t - p_i^t)$
10. $p_i^{t+1} = p_i^t + v_i^{t+1}$
11. end.

Output

Iteration 1/20 - Best Fitness: 0.081095
Iteration 2/20 - Best Fitness: 0.081095
Iteration 3/20 - Best Fitness: 0.006725

:

Best solution Found:
Position: [0.00321441 - 0.00268418]
Fitness: 1.753729e-05.

Example: $f(0,4) = x^2 + y^2$

initial = 0.3

value of cognitive & social constant

$c_1 = 2 + c_2 = 2$

initial solⁿ range to 1000

initial P_1 Fitness value $1^2 + 1^2 = 2$

Iteration 1

Particle No	Initial Pos x	Pos y	velocity x	velocity y	Best x	Best y	fitness value
P1	1	1	0	0	-	-	2
P2	-1	1	0	0	-	-	2
P3	0.5	-0.5	0	0	-	-	0.5
P4	1	-1	0	0	-	-	2
P5	0.25	-0.25	0	0	-	-	0.25

Iteration 2.

Pno	initial x	initial y	velocity x	velocity y	Best Pos x	Best Pos y	Best Sol	fitness
P1	1	1	-0.75	-0.75	1	-1	2	2
P2	-1	1	1.25	1.25	-1	1	2	2
P3	0.5	-0.5	-0.25	0.75	0.5	0.5	0.5	0.5
P4	1	-1	-0.75	1.25	1	-1	2	2
P5	0.25	0.25	0	0	0.25	0.25	0.125	0.125

Iteration - 3.

Pno	initial x	initial y	velocity x	velocity y	Best Sol	Best Pos x	Best Pos y	fitness
P1	0.25	0.25	-0.375	0.375	2	1	1	0.125
P2	0.25	0.25	-0.625	-0.375	2	-1	1	0.125
P3	0.25	0.25	-0.125	-0.375	0.5	0.5	0.5	0.125
P4	0.25	0.25	-0.37	-0.615	2	1	-1	0.125
P5	0.25	0.25	0	0	0.125	0.25	0.25	0.125

Code:

```
import random
import math
def fitness_function(x):
    return x * math.sin(10 * math.pi * x) + 1

# 2. Initialize parameters
NUM_PARTICLES = 30
MAX_ITER = 100
W = 0.7
C1 = 1.5
C2 = 1.5
X_BOUND = (-1, 2)
V_MAX = 0.1

class Particle:
    def __init__(self):
        self.position = random.uniform(*X_BOUND)
        self.velocity = random.uniform(-V_MAX, V_MAX)
        self.best_position = self.position
        self.best_fitness = fitness_function(self.position)

    def update_velocity(self, global_best_position):
        r1 = random.random()
        r2 = random.random()
        cognitive = C1 * r1 * (self.best_position - self.position)
        social = C2 * r2 * (global_best_position - self.position)
        self.velocity = W * self.velocity + cognitive + social
        # Clamp velocity within limits
        self.velocity = max(min(self.velocity, V_MAX), -V_MAX)

    def update_position(self):
        self.position += self.velocity
        # Keep particle within bounds
        self.position = max(min(self.position, X_BOUND[1]), X_BOUND[0])

def particle_swarm_optimization():

    swarm = [Particle() for _ in range(NUM_PARTICLES)]

    global_best_particle = max(swarm, key=lambda p: p.best_fitness)
    global_best_position = global_best_particle.position
    global_best_fitness = global_best_particle.best_fitness

    for iteration in range(MAX_ITER):
        for particle in swarm:

            current_fitness = fitness_function(particle.position)

            if current_fitness > particle.best_fitness:
                particle.best_fitness = current_fitness
```

```
            particle.best_position = particle.position

        # Update global best
        if current_fitness > global_best_fitness:
            global_best_fitness = current_fitness
            global_best_position = particle.position

    for particle in swarm:
        particle.update_velocity(global_best_position)
        particle.update_position()


        print(f"Iteration {iteration+1:03d} | Best Fitness = {global_best_fitness:.5f} | Best X = {global_best_position:.5f}")

    print("\nOptimization complete!")
    print(f"Best solution: x = {global_best_position:.5f}, f(x) = {global_best_fitness:.5f}")

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

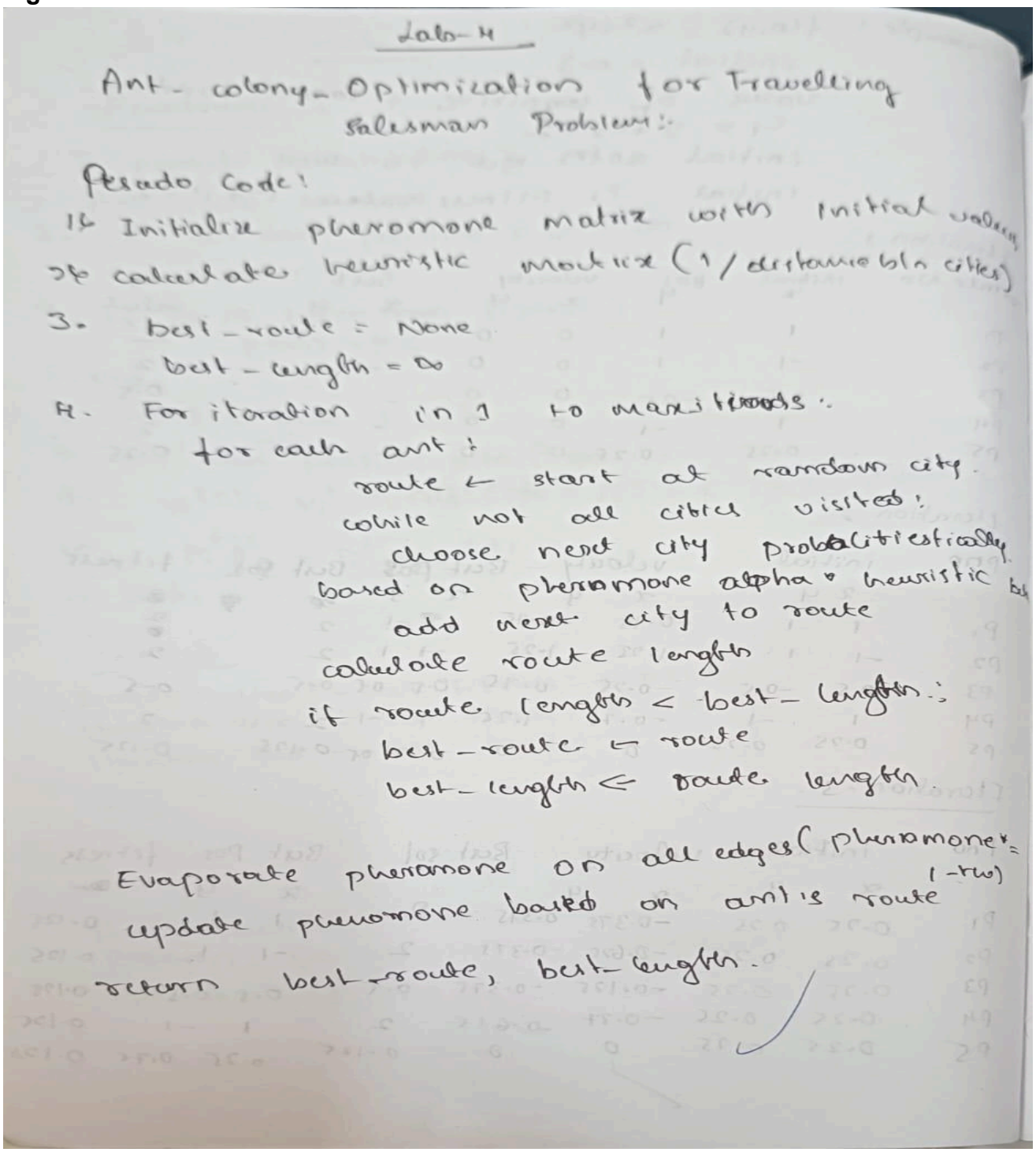
Output:

OUTPUT:

```
Iteration 1/20 - Best Fitness: 0.081095
Iteration 2/20 - Best Fitness: 0.081095
Iteration 3/20 - Best Fitness: 0.006725
Iteration 4/20 - Best Fitness: 0.003298
Iteration 5/20 - Best Fitness: 0.003298
Iteration 6/20 - Best Fitness: 0.003298
Iteration 7/20 - Best Fitness: 0.002956
Iteration 8/20 - Best Fitness: 0.002956
Iteration 9/20 - Best Fitness: 0.002956
Iteration 10/20 - Best Fitness: 0.002956
Iteration 11/20 - Best Fitness: 0.002956
Iteration 12/20 - Best Fitness: 0.001661
Iteration 13/20 - Best Fitness: 0.001066
Iteration 14/20 - Best Fitness: 0.001066
Iteration 15/20 - Best Fitness: 0.001066
Iteration 16/20 - Best Fitness: 0.000587
Iteration 17/20 - Best Fitness: 0.000587
Iteration 18/20 - Best Fitness: 0.000165
Iteration 19/20 - Best Fitness: 0.000095
Iteration 20/20 - Best Fitness: 0.000018

Best solution found:
Position: [ 0.00321441 -0.00268418]
Fitness: 1.753729128139239e-05
```

Program 03: Ant Colony Optimization for the Traveling Salesman Problem:

Algorithm:



Lab-4

Ant - colony - Optimization for Travelling Salesman Problem:

Pseudo Code:

1. Initialize pheromone matrix with initial values
2. calculate heuristic matrix (1/distance b/n cities)
3. best_route = None
   best_length = ∞
4. For iteration in 1 to max iterations:
   for each ant:
   route ← start at random city
   while not all cities visited:
   choose next city probabilistically based on pheromone alpha * heuristic beta
   add next city to route
   calculate route length
   if route length < best_length:
   best_route ← route
   best_length ← route length

Evaporate pheromone on all edges (pheromone *= (1-rho))
update pheromone based on ant's route

return best_route, best_length.

output

Iteration 1/20 - Best length: 31.6147

Iteration 2/20 - Best length: 24.7691

.

.

.

Iteration 20/20 - Best length: 24.7691

Best route found:

Route length: 24.769131.

Seen RP 10/10

Code:

```
import numpy as np

def distance(city1, city2):
    return np.linalg.norm(city1 - city2)

def route_length(route, cities):
    dist = 0.0
    for i in range(len(route) - 1):
        dist += distance(cities[route[i]], cities[route[i+1]])
    dist += distance(cities[route[-1]], cities[route[0]])
    return dist

def select_next_city(current_city, unvisited, pheromone, heuristic, alpha, beta):
    pheromone_vals = pheromone[current_city, unvisited] ** alpha
    heuristic_vals = heuristic[current_city, unvisited] ** beta
    probs = pheromone_vals * heuristic_vals
    probs /= probs.sum()
    return np.random.choice(unvisited, p=probs)


def aco_tsp(cities, num_ants=20, num_iterations=20, alpha=1.0, beta=5.0, rho=0.5,
initial_pheromone=1.0):
    num_cities = len(cities)


    pheromone = np.full((num_cities, num_cities), initial_pheromone)


    heuristic = np.zeros((num_cities, num_cities))
    for i in range(num_cities):
        for j in range(num_cities):
            if i != j:
                heuristic[i, j] = 1.0 / (distance(cities[i], cities[j]) + 1e-10)

    best_route = None
    best_length = float('inf')

    for iteration in range(num_iterations):
        all_routes = []
        all_lengths = []

        for ant in range(num_ants):
            route = []
            unvisited = list(range(num_cities))


            current_city = np.random.choice(unvisited)
            route.append(current_city)
            unvisited.remove(current_city)


            while unvisited:
                next_city = select_next_city(current_city, unvisited, pheromone,
heuristic, alpha, beta)
                route.append(next_city)
```

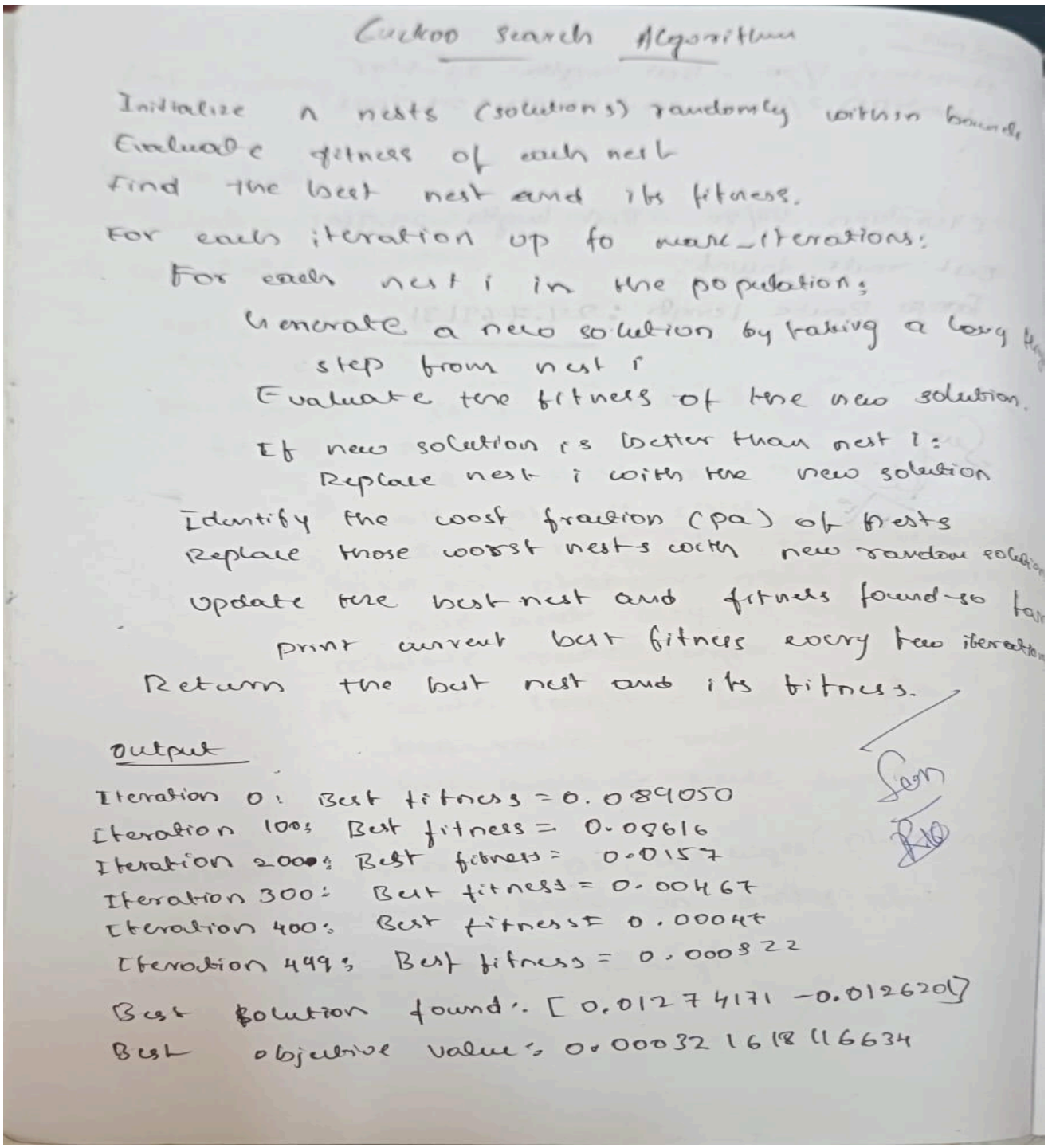
```
                unvisited.remove(next_city)
                current_city = next_city

            length = route_length(route, cities)
            all_routes.append(route)
            all_lengths.append(length)


            if length < best_length:
                best_length = length
                best_route = route

        pheromone *= (1 - rho)


        for route, length in zip(all_routes, all_lengths):
            for i in range(num_cities - 1):
                pheromone[route[i], route[i+1]] += 1.0 / length
                pheromone[route[i+1], route[i]] += 1.0 / length

            pheromone[route[-1], route[0]] += 1.0 / length
            pheromone[route[0], route[-1]] += 1.0 / length

        print(f"Iteration {iteration+1}/{num_iterations} - Best Length:
{best_length:.4f}")

    return best_route, best_length


if __name__ == "__main__":

    cities = np.array([
        [0, 0],
        [1, 5],
        [5, 2],
        [6, 6],
        [8, 3],
        [7, 9],
        [2, 8],
        [3, 3]
    ])

    best_route, best_length = aco_tsp(cities)

    print("\nBest route found:")
    print(best_route)
    print("Route length:", best_length)
```

Output:

```
Iteration 1/20 - Best Length: 31.6195
Iteration 2/20 - Best Length: 29.7691
Iteration 3/20 - Best Length: 29.7691
Iteration 4/20 - Best Length: 29.7691
Iteration 5/20 - Best Length: 29.7691
Iteration 6/20 - Best Length: 29.7691
Iteration 7/20 - Best Length: 29.7691
Iteration 8/20 - Best Length: 29.7691
Iteration 9/20 - Best Length: 29.7691
Iteration 10/20 - Best Length: 29.7691
Iteration 11/20 - Best Length: 29.7691
Iteration 12/20 - Best Length: 29.7691
Iteration 13/20 - Best Length: 29.7691
Iteration 14/20 - Best Length: 29.7691
Iteration 15/20 - Best Length: 29.7691
Iteration 16/20 - Best Length: 29.7691
Iteration 17/20 - Best Length: 29.7691
Iteration 18/20 - Best Length: 29.7691
Iteration 19/20 - Best Length: 29.7691
Iteration 20/20 - Best Length: 29.7691

Best route found:
[np.int64(3), np.int64(5), np.int64(6), np.int64(1), np.int64(0), np.int64(7), np.int64(2), np.int64(4)]
Route length: 29.76913194777377
```

Program 04: Cuckoo Search (CS):

Algorithm;



Cuckoo search Algorithm

Initialize n nests (solutions) randomly within bounds
Evaluate fitness of each nest
Find the best nest and its fitness.
For each iteration up to max_iterations:
  For each nest i in the population:
    Generate a new solution by taking a Levy flight step from nest i
    Evaluate the fitness of the new solution.
    If new solution is better than nest i:
      Replace nest i with the new solution
  Identify the worst fraction (pa) of nests
  Replace those worst nests with new random solutions
  Update the best nest and fitness found so far
  print current best fitness every two iterations
Return the best nest and its fitness.

Output

Iteration 0: Best fitness = 0.089050
Iteration 100: Best fitness = 0.08616
Iteration 200: Best fitness = 0.0157
Iteration 300: Best fitness = 0.00467
Iteration 400: Best fitness = 0.00047
Iteration 499: Best fitness = 0.000322

Best solution found: [0.01274171 -0.01262207]
Best objective value: 0.00032161811663 4

Code:

```
import numpy as np
import math


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

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)
    sigma_v = 1
    u = np.random.normal(0, sigma_u)
    v = np.random.normal(0, sigma_v)
    step = u / (abs(v) ** (1 / Lambda))
    return step

def cuckoo_search_nest_location(n=10, iterations=200, pa=0.25, lower_bound=0,
upper_bound=10):
    nests = np.random.uniform(lower_bound, upper_bound, n)
    fitness = np.array([food_availability(x) for x in nests])

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

    Lambda = 1.5

    for t in range(iterations):
        for i in range(n):
            step_size = 0.1 * levy_flight(Lambda)
            new_nest = nests[i] + step_size * (nests[i] - best_nest)
            new_nest = np.clip(new_nest, lower_bound, upper_bound)

            new_fitness = food_availability(new_nest)
            if new_fitness > fitness[i]:
                nests[i] = new_nest
                fitness[i] = new_fitness

                if new_fitness > best_fitness:
                    best_fitness = new_fitness
                    best_nest = new_nest

        num_abandon = int(pa * n)
        worst_indices = np.argsort(fitness)[:num_abandon]
        nests[worst_indices] = np.random.uniform(lower_bound, upper_bound,
num_abandon)
        fitness[worst_indices] = [food_availability(x) for x in
nests[worst_indices]]

        current_best_idx = np.argmax(fitness)
        if fitness[current_best_idx] > best_fitness:
            best_fitness = fitness[current_best_idx]
            best_nest = nests[current_best_idx]
```

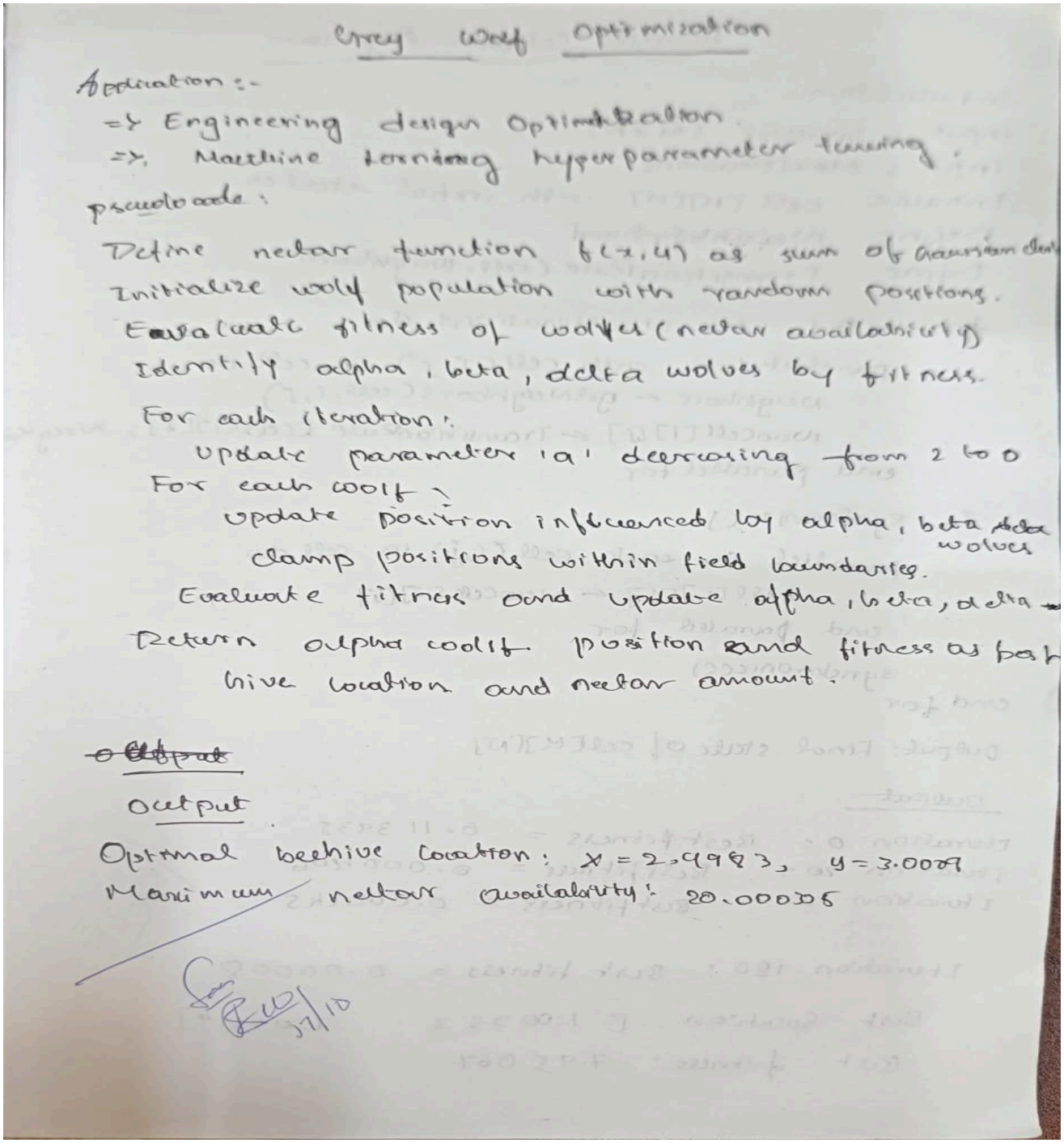
```
        if (t+1) % 20 == 0 or t == 0:
            print(f"Iteration {t+1}: Best nest location = {best_nest:.4f}, Max food
= {best_fitness:.6f}")

    return best_nest, best_fitness

if __name__ == "__main__":
    best_location, max_food = cuckoo_search_nest_location()
    print("\nFinal Results:")
    print(f"Best nest location: {best_location:.4f}")
    print(f"Maximum food collected: {max_food:.6f}")
```

Output:

```
Iteration 1: Best nest location = 5.3102, Max food = 19.903783
Iteration 20: Best nest location = 4.9646, Max food = 19.998744
Iteration 40: Best nest location = 4.9646, Max food = 19.998744
Iteration 60: Best nest location = 5.0038, Max food = 19.999985
Iteration 80: Best nest location = 4.9992, Max food = 19.999999
Iteration 100: Best nest location = 5.0000, Max food = 20.000000
Iteration 120: Best nest location = 5.0000, Max food = 20.000000
Iteration 140: Best nest location = 5.0000, Max food = 20.000000
Iteration 160: Best nest location = 5.0000, Max food = 20.000000
Iteration 180: Best nest location = 5.0000, Max food = 20.000000
Iteration 200: Best nest location = 5.0000, Max food = 20.000000

Final Results:
Best nest location: 5.0000
Maximum food collected: 20.000000
```

Program 05: Grey Wolf Optimizer (GWO):

Algorithm:



Grey Wolf Optimization

Application :-
=> Engineering design Optimization
=> Machine learning hyperparameter tuning.

pseudocode :

Define nectar function f(x,y) as sum of Gaussian dens
Initialize wolf population with random positions.
Evaluate fitness of wolves (nectar availability)
Identify alpha, beta, delta wolves by fitness.
For each iteration:
Update parameter 'a' decreasing from 2 to 0
For each wolf:
Update position influenced by alpha, beta & delta wolves
clamp positions within field boundaries.
Evaluate fitness and update alpha, beta, delta
Return alpha wolf position and fitness as best hive location and nectar amount.

~~Output~~

Output

Optimal beehive location: x = 2.9983, y = 3.0009
Maximum nectar availability: 20.000005

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Code:

```
import numpy as np

def nectar_availability(position):
    x, y = position
    term1 = 20 * np.exp(-((x - 3) ** 2 + (y - 3) ** 2) / 4)
    term2 = 15 * np.exp(-((x - 7) ** 2 + (y - 7) ** 2) / 3)
    term3 = 10 * np.exp(-((x - 5) ** 2 + (y - 8) ** 2) / 2)
    return term1 + term2 + term3

def gwo_beehive(n_wolves=30, iterations=20, lower_bound=0, upper_bound=10):
    dim = 2

    wolves = np.random.uniform(lower_bound, upper_bound, (n_wolves, dim))

    alpha_pos = np.zeros(dim)
    alpha_score = -np.inf
    beta_pos = np.zeros(dim)
    beta_score = -np.inf
    delta_pos = np.zeros(dim)
    delta_score = -np.inf

    for t in range(iterations):
        for i in range(n_wolves):
            fitness = nectar_availability(wolves[i])

            if fitness > alpha_score:
                alpha_score = fitness
                alpha_pos = wolves[i].copy()
            elif fitness > beta_score:
                beta_score = fitness
                beta_pos = wolves[i].copy()
            elif fitness > delta_score:
                delta_score = fitness
                delta_pos = wolves[i].copy()

        a = 2 - t * (2 / iterations)

        for i in range(n_wolves):
            for j in range(dim):
                r1 = np.random.rand()
                r2 = np.random.rand()
                A1 = 2 * a * r1 - a
                C1 = 2 * r2
                D_alpha = abs(C1 * alpha_pos[j] - wolves[i][j])
                X1 = 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 * beta_pos[j] - wolves[i][j])
                X2 = 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 * delta_pos[j] - wolves[i][j])
                X3 = delta_pos[j] - A3 * D_delta

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

            wolves[i] = np.clip(wolves[i], lower_bound, upper_bound)

        print(f"Iteration {t+1:2d}: Best nectar = {alpha_score:.6f} at location
x={alpha_pos[0]:.4f}, y={alpha_pos[1]:.4f}")

    return alpha_pos, alpha_score

if __name__ == "__main__":
    best_hive_location, max_nectar = gwo_beehive()
    print("\nFinal optimal beehive location:")
    print(f"x = {best_hive_location[0]:.4f}, y = {best_hive_location[1]:.4f}")
    print(f"Maximum nectar availability: {max_nectar:.6f}")
```

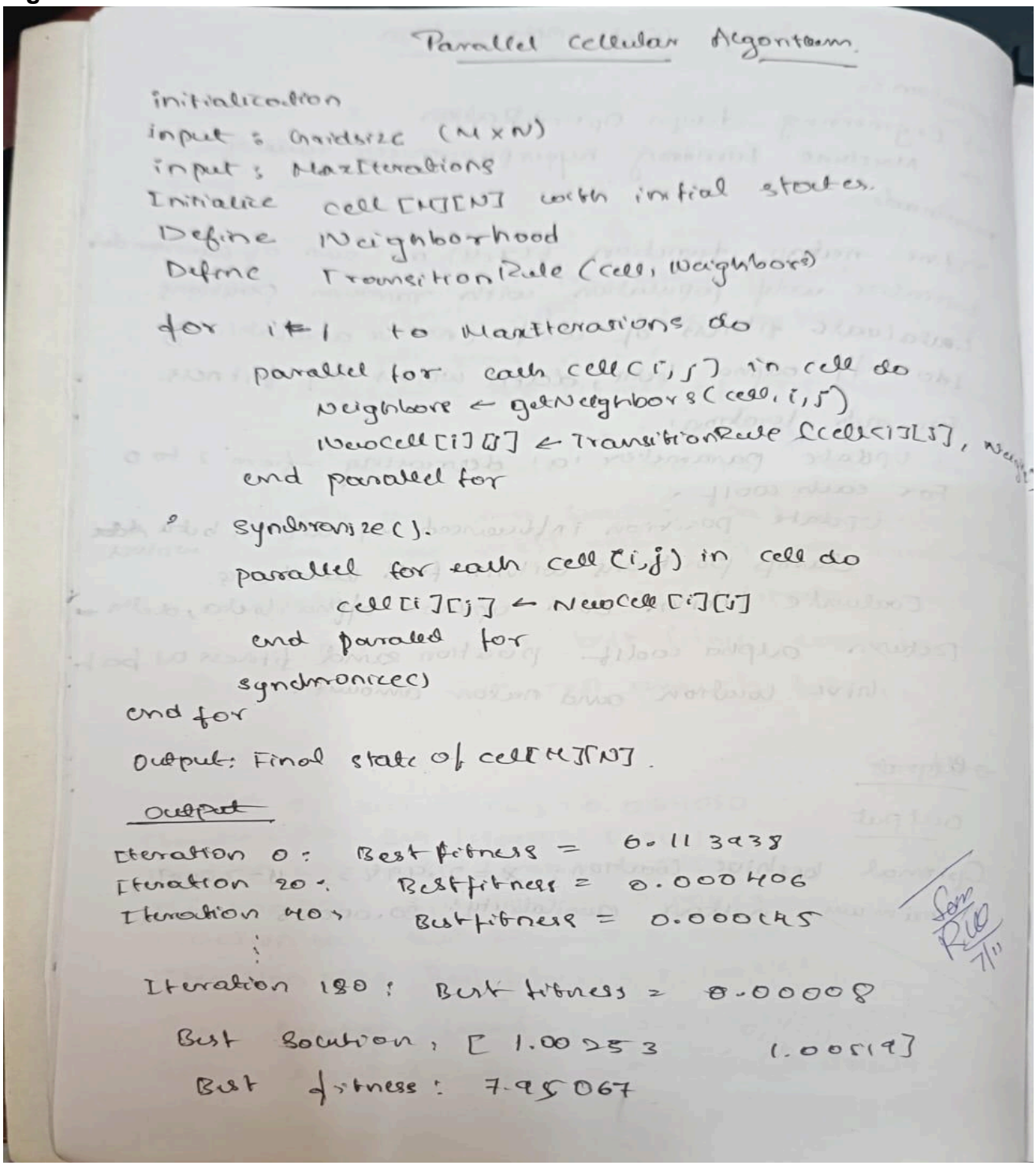
Output:

```
Iteration  1: Best nectar = 14.314430 at location x=5.9729, y=6.9847
Iteration  2: Best nectar = 14.314430 at location x=5.9729, y=6.9847
Iteration  3: Best nectar = 18.833972 at location x=3.4183, y=2.7443
Iteration  4: Best nectar = 18.833972 at location x=3.4183, y=2.7443
Iteration  5: Best nectar = 19.918544 at location x=2.8770, y=3.0355
Iteration  6: Best nectar = 19.918544 at location x=2.8770, y=3.0355
Iteration  7: Best nectar = 19.918544 at location x=2.8770, y=3.0355
Iteration  8: Best nectar = 19.918544 at location x=2.8770, y=3.0355
Iteration  9: Best nectar = 19.926097 at location x=3.1064, y=2.9403
Iteration 10: Best nectar = 19.976975 at location x=3.0522, y=3.0444
Iteration 11: Best nectar = 19.976975 at location x=3.0522, y=3.0444
Iteration 12: Best nectar = 19.976975 at location x=3.0522, y=3.0444
Iteration 13: Best nectar = 19.976975 at location x=3.0522, y=3.0444
Iteration 14: Best nectar = 19.976975 at location x=3.0522, y=3.0444
Iteration 15: Best nectar = 19.976975 at location x=3.0522, y=3.0444
Iteration 16: Best nectar = 19.976975 at location x=3.0522, y=3.0444
Iteration 17: Best nectar = 19.976975 at location x=3.0522, y=3.0444
Iteration 18: Best nectar = 19.976975 at location x=3.0522, y=3.0444
Iteration 19: Best nectar = 19.990873 at location x=2.9582, y=3.0120
Iteration 20: Best nectar = 19.999439 at location x=3.0134, y=2.9978

Final optimal beehive location:
x = 3.0134, y = 2.9978
Maximum nectar availability: 19.999439
```

Program 6: Parallel Cellular Algorithms and Programs:

Algorithm:



Parallel cellular Algorithm

```
initialization
input : GridSize (N x N)
input : MaxIterations
Initialize cell[N][N] with initial states.
Define Neighborhood
Define TransitionRule (cell, Neighbors)

for i=1 to MaxIterations do
    parallel for each cell[i,j] in cell do
        Neighbors ← getNeighbors(cell, i, j)
        NewCell[i][j] ← TransitionRule [cell[i][j], Neighbors]
    end parallel for
    synchronize().
    parallel for each cell[i,j] in cell do
        cell[i][j] ← NewCell[i][j]
    end parallel for
    synchronize()
end for
Output: Final state of cell[N][N].
```

Output

```
Iteration 0 :   Best fitness = 0.113938
Iteration 20 :  Best fitness = 0.000406
Iteration 40 :  Best fitness = 0.000145
      :
Iteration 180 : Best fitness = 0.00008

Best Solution : [ 1.00253      1.00519]
Best fitness : 7.95067
```

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Code:

```
import numpy as np

def rosenbrock(x):
    return (1 - x[0])**2 + 100 * (x[1] - x[0]**2)**2

grid_size = (10, 10)
num_dimensions = 2
num_iterations = 200
beta0 = 1.0        # Base attractiveness
gamma = 1.0        # Light absorption coefficient
alpha = 0.2        # Randomness factor
radius = 1
search_bounds = (-2, 2)

cells = np.random.uniform(search_bounds[0], search_bounds[1],
                          size=(grid_size[0], grid_size[1], num_dimensions))

get neighbors (Moore neighborhood)
def get_neighbors(cells, i, j):
    neighbors = []
    for di in range(-radius, radius + 1):
        for dj in range(-radius, radius + 1):
            if di == 0 and dj == 0:
                continue
            ni, nj = (i + di) % grid_size[0], (j + dj) % grid_size[1]
            neighbors.append(cells[ni, nj])
    return np.array(neighbors)

best_solution = None
best_fitness = float('inf')

for t in range(num_iterations):
    new_cells = np.copy(cells)

    for i in range(grid_size[0]):
        for j in range(grid_size[1]):
            firefly = cells[i, j]
            fit_i = rosenbrock(firefly)
            neighbors = get_neighbors(cells, i, j)

            for n in neighbors:
                fit_n = rosenbrock(n)
                if fit_n < fit_i:  # brighter (better)
                    distance = np.linalg.norm(firefly - n)
                    beta = beta0 * np.exp(-gamma * distance**2)
                    step = beta * (n - firefly) + alpha * np.random.uniform(-1, 1,
num_dimensions)
                    firefly = firefly + step
                    fit_i = rosenbrock(firefly)

            new_cells[i, j] = firefly

            if fit_i < best_fitness:
                best_fitness = fit_i
                best_solution = firefly
```

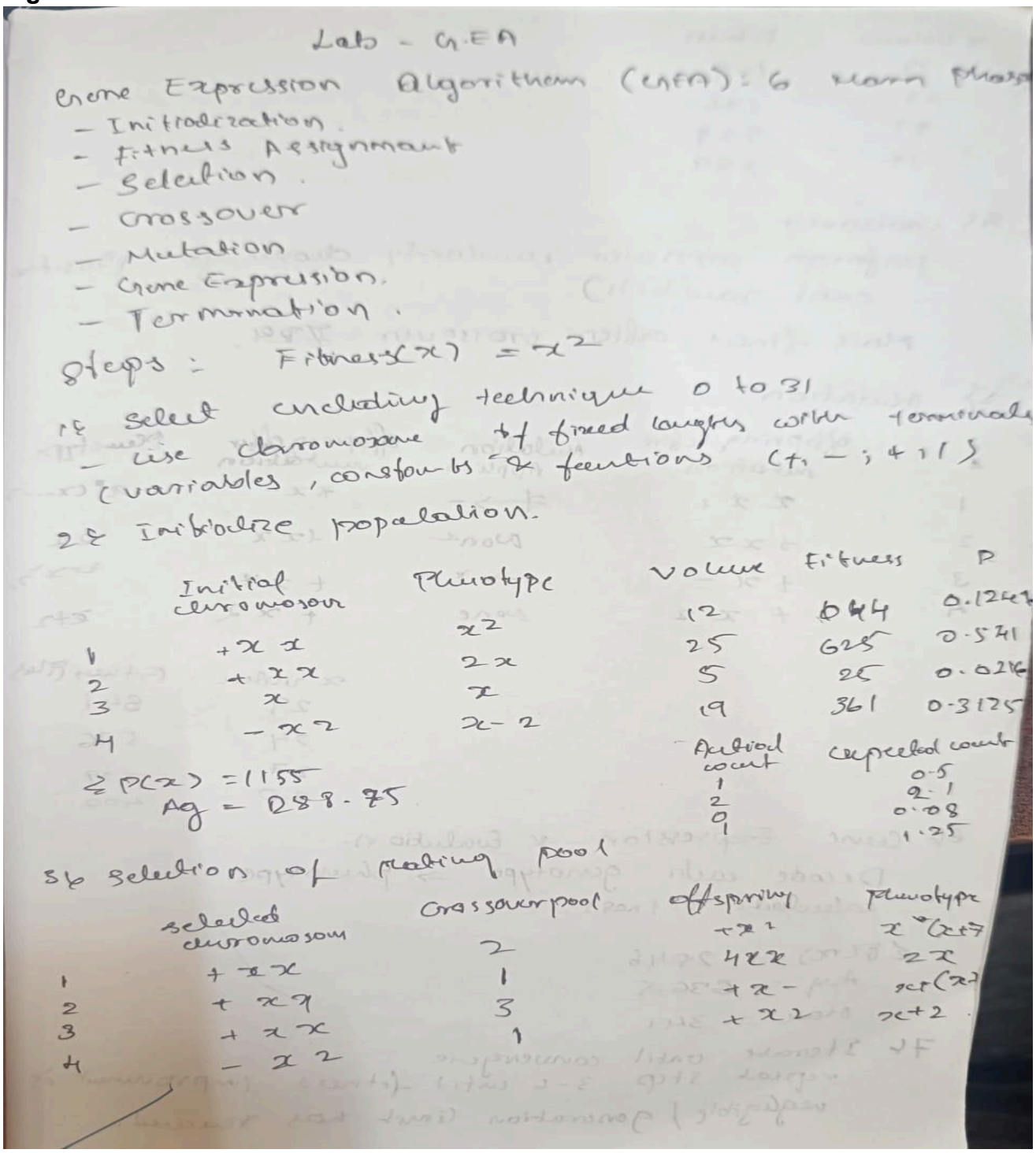
```
    cells = new_cells

    if t % 20 == 0:
        print(f"Iteration {t}: Best Fitness = {best_fitness:.6f}")

print("\n============================")
print(" Parallel Cellular Firefly Algorithm Results")
print("============================")
print("Best Solution:", best_solution)
print("Best Fitness:", best_fitness)
```

Output:

```
Iteration 0: Best Fitness = 0.120322
Iteration 20: Best Fitness = 0.000162
Iteration 40: Best Fitness = 0.000114
Iteration 60: Best Fitness = 0.000049
Iteration 80: Best Fitness = 0.000049
Iteration 100: Best Fitness = 0.000049
Iteration 120: Best Fitness = 0.000049
Iteration 140: Best Fitness = 0.000049
Iteration 160: Best Fitness = 0.000009
Iteration 180: Best Fitness = 0.000009

============================
🔥 Parallel Cellular Firefly Algorithm Results
============================
Best Solution: [0.99738409 0.99491349]
Best Fitness: 8.760504339778715e-06
```

Program 7: Optimization via Gene Expression Algorithms:

Algorithm:



Lab - G.E.A

Gene Expression Algorithem (GEA): 6 main phase
- 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 with terminals (variables, constants & functions (+, -, *, /)

2& Initialize population.

	Initial chromosom	Phenotype	Value	Fitness	P
1	+ x x	x^2	12	144	0.12
2	+ x x	2x	25	625	0.541
3	x	x	5	25	0.021
4	- x 2	x - 2	19	361	0.3125

Actual count: 1, 2, 0, 1

Expected count: 0.5, 2.1, 0.08, 1.25

$\sum P(x) = 1155$

Ag = 288.75

3& selection of mating pool

	selected chromosom	Crossover pool	offspring	Phenotype
1	+ x x	2	$+x^2$	$x * (x+7$
2	+ x 7	1	4 x x	2x
3	+ x x	3	+ x -	$x * (x$
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 (Parent not row wise)

Have fitness after crossover = 7729.

5) Mutation

#	offspring before mutation	Mutation Applied	offspring after mutation	Phenotype
1	x * +	* → -	*x-	x*(x-
2	+ x x	None	+x x	2x
3	+ x =	= → *	+ x *	x+x
4	+ x 2	None	+ x 2	x+2

x value	Fitness
29	841
24	576
27	729
20	400

6) Gene Expression & Evaluation.

Decode each genotype → phenotype.

calculate Fitness.

$\Sigma F(x) = 2546$

Avg = 636.5

max = 841

7) If stuck until convergence repeat step 3-6 until fitness improvement is negligible / generation limit has reached.

Pseudocod

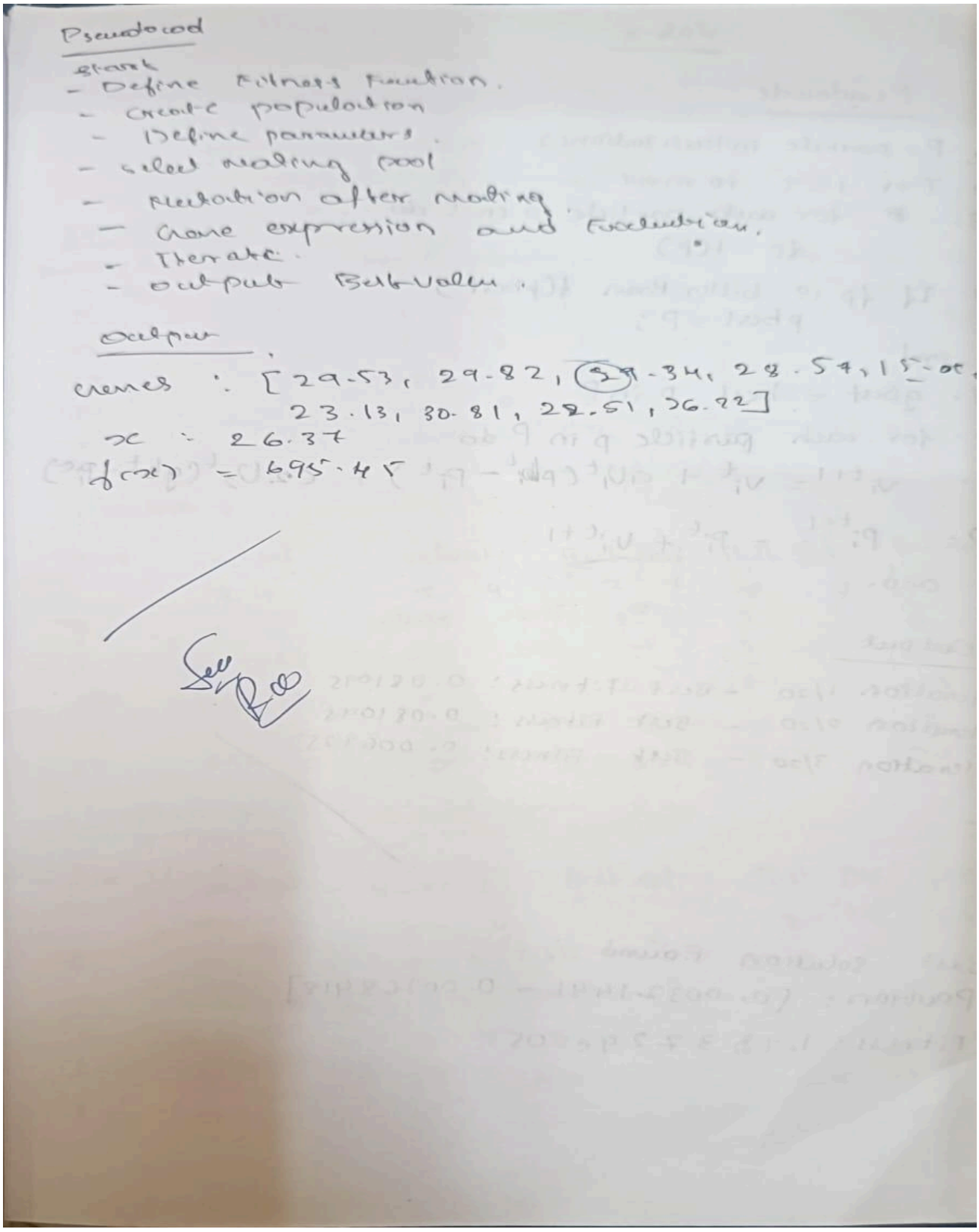
start
- Define Fitness function.
- Create population
- Define parameters.
- select mating pool
- Recombination after mating
- Clone expression and Excecution.
- Iterate.
- output Best Value.

Output

Genes : [29.53, 29.82, 29.34, 28.54, 15.00, 23.13, 30.81, 28.51, 26.92]

x : 26.37

f(x) = 695.45

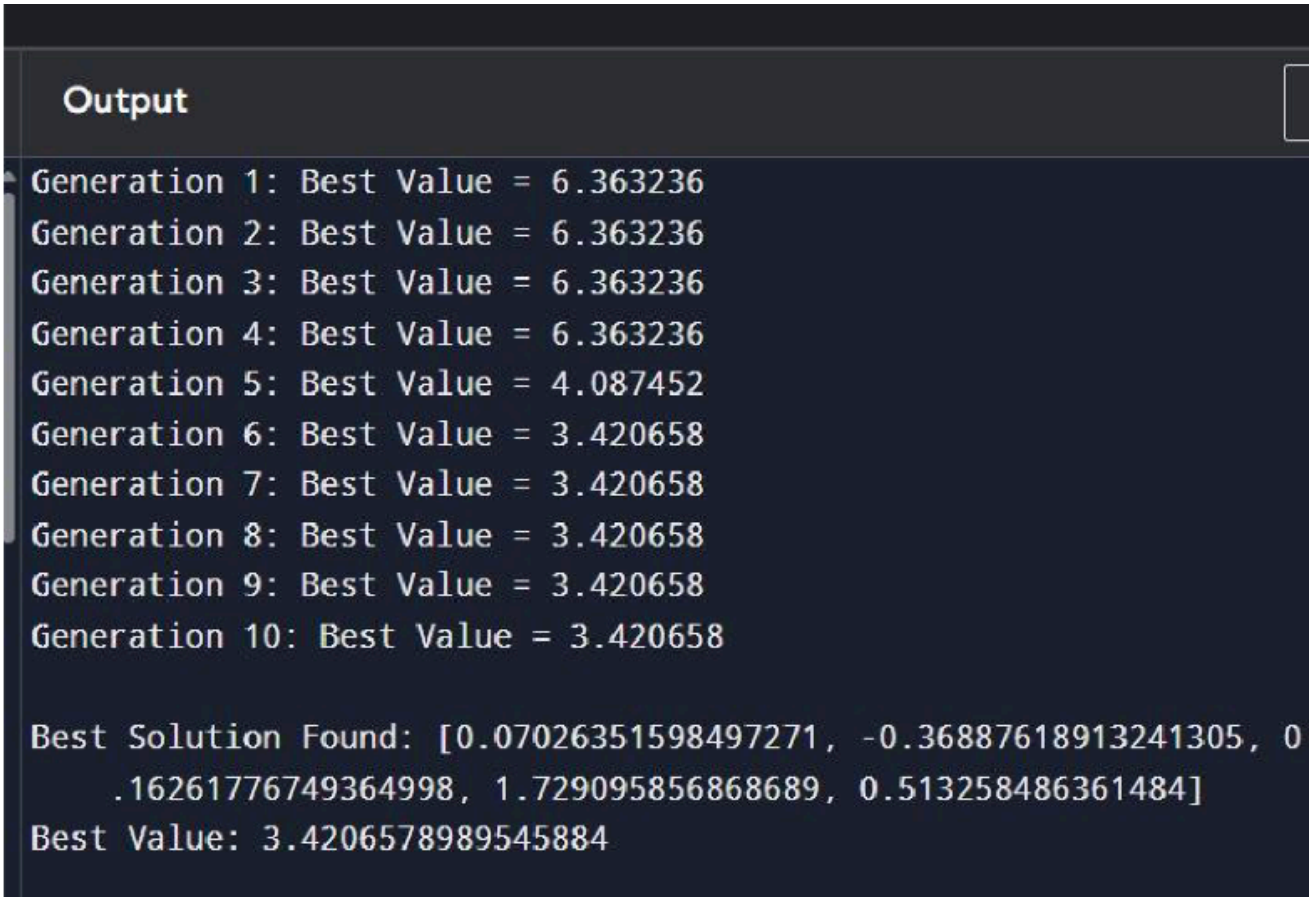


Code:

```
import random
import math

def fitness_function(x):
    return x * math.sin(10 * math.pi * x) + 1  # Objective: maximize this

POPULATION_SIZE = 30
NUM_GENES = 10          # Number of genes per chromosome
MUTATION_RATE = 0.1
CROSSOVER_RATE = 0.8
GENERATIONS = 100
X_BOUND = (-1, 2)

def create_individual():
    return [random.uniform(X_BOUND[0], X_BOUND[1]) for _ in range(NUM_GENES)]

def create_population(size):
    return [create_individual() for _ in range(size)]

def express_genes(individual):
    # Expression step: translate gene sequence into a single functional value (x)
    expressed_x = sum(individual) / len(individual)
    return expressed_x

def evaluate_fitness(individual):
    x = express_genes(individual)
    return fitness_function(x)

def tournament_selection(population, k=3):
    selected = random.sample(population, k)
    selected.sort(key=lambda ind: evaluate_fitness(ind), reverse=True)
    return selected[0]

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

def mutate(individual):
    for i in range(NUM_GENES):
        if random.random() < MUTATION_RATE:
            individual[i] += random.uniform(-0.1, 0.1)
            individual[i] = max(min(individual[i], X_BOUND[1]), X_BOUND[0])
    return individual
def gene_expression_algorithm():
    population = create_population(POPULATION_SIZE)
    best_individual = None
    best_fitness = float('-inf')
```

```
    for generation in range(GENERATIONS):
        new_population = []


        for ind in population:
            fit = evaluate_fitness(ind)
            if fit > best_fitness:
                best_fitness = fit
                best_individual = ind

        while len(new_population) < POPULATION_SIZE:
            parent1 = tournament_selection(population)
            parent2 = tournament_selection(population)
            child1, child2 = crossover(parent1, parent2)
            child1 = mutate(child1)
            child2 = mutate(child2)
            new_population.extend([child1, child2])

        population = new_population[:POPULATION_SIZE]

        expressed_x = express_genes(best_individual)
        print(f"Generation {generation+1:03d} | Best Fitness = {best_fitness:.5f} | Best X = {expressed_x:.5f}")

    final_x = express_genes(best_individual)
    print("\nOptimization complete!")
    print(f"Best solution: x = {final_x:.5f}, f(x) = {best_fitness:.5f}")

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

Output:


Output
Generation 1: Best Value = 6.363236
Generation 2: Best Value = 6.363236
Generation 3: Best Value = 6.363236
Generation 4: Best Value = 6.363236
Generation 5: Best Value = 4.087452
Generation 6: Best Value = 3.420658
Generation 7: Best Value = 3.420658
Generation 8: Best Value = 3.420658
Generation 9: Best Value = 3.420658
Generation 10: Best Value = 3.420658
Best Solution Found: [0.07026351598497271, -0.36887618913241305, 0
.16261776749364998, 1.729095856868689, 0.513258486361484]
Best Value: 3.4206578989545884