

VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“JnanaSangama”, Belgaum -590014, Karnataka.



LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by

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1BM23CS083

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING



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CERTIFICATE

This is to certify that the Lab work entitled “ Bio Inspired Systems (23CS5BSBIS)” carried out by **D A Chethan (1BM23CS083)**, 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/DACHethan2485/1BM23CS083-BIS>

Program 1

Genetic Algorithm for Optimization Problems:

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:

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Genetic Algorithm

1. Selecting initial population
2. calculate the fitness
3. Selecting the mating pool
4. Crossover
5. Mutation

$n \rightarrow 0 \text{ to } 3$

String no	Initial population	x value	fitness	prob	%E out	A out
1	01100	12	144	0.124	12.4	0.49 - 1
2	11001	25	625	0.541	54.1	2.16 - 2
3	00101	5	25	0.021	2.1	0.02 - 0
4	10011	19	361	0.312	31.2	1.25 - 1
total				1.155	0.25	25
av				= 988.75		

Accepted output = $f(n) = 144 \cdot 0.49$
Avg (Eff(n)) = 288.75

③

S.No	Mating pool	Crossover point	After	X	f(x)
1	01100	4	01101	13	169
2	11001		11000	24	576
3	11001	2	11011	27	729
4	10011		10001	17	289
					<u>1763</u>

440.75

729

④ Crossover chosen randomly

⑤ Mutation

String No	offspring th Crossover	Mutation Chromosome	offspring after mutation	x	f(x)
1	01101	10000	11101	29	841
2	11000	00000	11000	24	576
3	11011	00000	11011	27	729
4	10001	00101	10100	20	400
					<u>2546</u>

Code:

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

def fitness_function(x):
    return x * np.sin(10 * np.pi * x) + 1.0

POP_SIZE = 30
GENES = 16
MUTATION_RATE = 0.01
CROSSOVER_RATE = 0.7
GENERATIONS = 100

def generate_individual():
    return "".join(random.choice('01') for _ in range(GENES))

def decode(individual):
    return int(individual, 2) / (2**GENES - 1)

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

def select(population, fitnesses):
    total_fit = sum(fitnesses)
    if total_fit == 0:
        return random.choices(population, k=2)
    probabilities = [f / total_fit for f in fitnesses]
    return random.choices(population, weights=probabilities, k=2)

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

def mutate(individual):
    return "".join(
        bit if random.random() > MUTATION_RATE else random.choice('01')
        for bit in individual
    )
```

```

def genetic_algorithm():
    population = [generate_individual() for _ in range(POP_SIZE)]
    best_individual = population[0]    best_fitness =
    fitness_function(decode(best_individual))    fitness_history = []

    for generation in range(GENERATIONS):
        fitnesses = evaluate_population(population)
        max_fit = max(fitnesses)    max_idx =
        fitnesses.index(max_fit)    if max_fit >
        best_fitness:    best_fitness = max_fit
        best_individual = population[max_idx]
        fitness_history.append(best_fitness)
        new_population = []    while
        len(new_population) < POP_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[:POP_SIZE]

    best_x = decode(best_individual)
    return best_x, best_fitness, fitness_history

best_x, best_fitness, history = genetic_algorithm()

print(f"Best solution found: x = {best_x:.5f}, f(x) = {best_fitness:.5f}") plt.plot(history)
plt.title("Fitness over Generations") plt.xlabel("Generation") plt.ylabel("Best Fitness") plt.grid(True)
plt.show()

import random

POP_SIZE = 100
NUM_CITIES = 20
GENERATIONS = 5
MUTATION_RATE = 5 / 100
CROSSOVER_RATE = 80 / 100

def generate_distance_matrix(num_cities):
    distance_matrix = [[0 if i == j else random.randint(10, 100) for j in range(num_cities)] for i in
    range(num_cities)]    for i in range(num_cities):    for j in range(i + 1, num_cities):
        distance_matrix[j][i] = distance_matrix[i][j]
    return distance_matrix

```

```
DISTANCE_MATRIX = generate_distance_matrix(NUM_CITIES)
```

```
class Individual:
```

```
def __init__(self):
```

```
    self.genome = random.sample(range(NUM_CITIES), NUM_CITIES)
```

```
    self.fitness = self.calculate_fitness()
```

```
    def calculate_fitness(self):
```

```
        total_distance = 0        for i in
```

```
range(NUM_CITIES - 1):
```

```
    total_distance += DISTANCE_MATRIX[self.genome[i]][self.genome[i + 1]]
```

```
total_distance += DISTANCE_MATRIX[self.genome[NUM_CITIES - 1]][self.genome[0]]
```

```
self.fitness = 1 / total_distance    return self.fitness
```

```
    def mutate(self):        if random.random() <
```

```
MUTATION_RATE:
```

```
        i, j = random.sample(range(NUM_CITIES), 2)
```

```
self.genome[i], self.genome[j] = self.genome[j], self.genome[i]
```

```
self.fitness = self.calculate_fitness()
```

```
    @staticmethod    def
```

```
crossover(parent1, parent2):
```

```
start, end =
```

```
sorted(random.sample(range(NUM_CITIES), 2))
```

```
child1_genome = [-1] *
```

```
NUM_CITIES
```

```
child2_genome = [-1] *
```

```
NUM_CITIES
```

```
child1_genome[start:end] =
```

```
parent1.genome[start:end]
```

```
child2_genome[start:end] =
```

```
parent2.genome[start:end]
```

```
fill_parent1 = [city for city in
```

```
parent2.genome if city not in
```

```
child1_genome]    fill_parent2
```

```
= [city for city in parent1.genome
```

```
if city not in child2_genome]
```

```
for i in range(NUM_CITIES):
```

```
if child1_genome[i] == -1:
```

```
    child1_genome[i] = fill_parent1.pop(0)
```

```
if child2_genome[i] == -1:
```

```
    child2_genome[i] = fill_parent2.pop(0)
```

```
child1 = Individual()    child1.genome =
```



```

child1_genome    child1.fitness =
child1.calculate_fitness()    child2 =
Individual()    child2.genome =
child2_genome    child2.fitness =
child2.calculate_fitness()    return child1,
child2

def selection(population):
    total_fitness = sum(individual.fitness for individual in population)
    pick = random.uniform(0, total_fitness)
    current = 0    for individual in
population:    current +=
individual.fitness    if current
> pick:    return individual
    return population[-1]

def initialize_population():
    return [Individual() for _ in range(POP_SIZE)]

def best_individual(population):
    return min(population, key=lambda individual: 1 / individual.fitness)

def main():
    population = initialize_population()    for
generation in range(GENERATIONS):
        population.sort(key=lambda individual: individual.fitness, reverse=True)
    print(f'Generation {generation}: Best fitness = {population[0].fitness}, Distance =
{1/population[0].fitness}')    new_population =
[population[0], population[1]]    while
len(new_population) < POP_SIZE:
        parent1 = selection(population)
    parent2 = selection(population)    if
random.random() < CROSSOVER_RATE:
    child1, child2 = Individual.crossover(parent1,
parent2)    else:
        child1, child2 = parent1, parent2
    child1.mutate()    child2.mutate()
    new_population.append(child1)    if
len(new_population) < POP_SIZE:
    new_population.append(child2)
    population = new_population    best_solution
= best_individual(population)    print("\nBest
solution found:")    print(f'Tour:
{best_solution.genome}')

```

```
print(f'Distance: {1 / best_solution.fitness}')
```

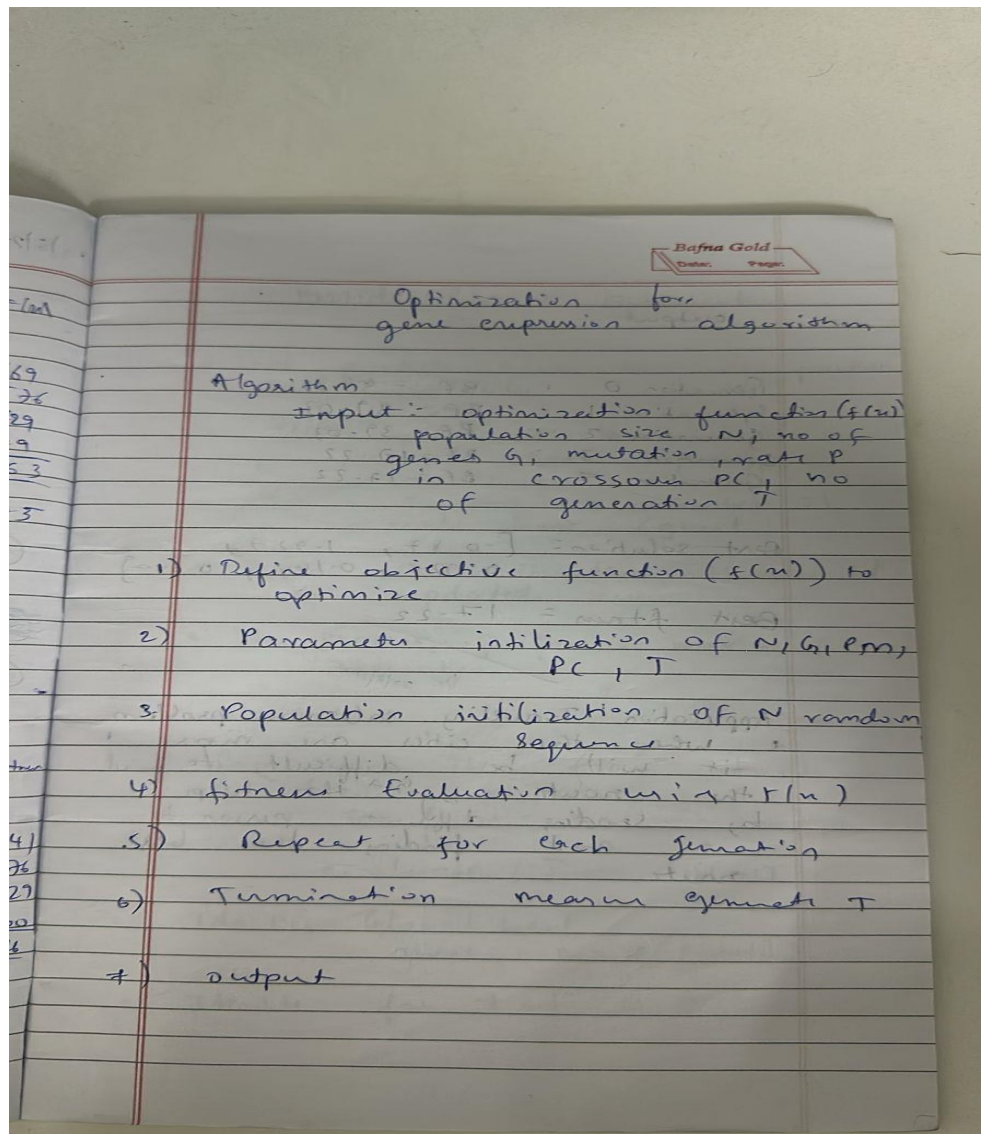
```
if __name__ == "__main__":  
    main()
```

Program 2

Optimization via Gene Expression Algorithms:

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:



output

Generation 0 : BF = 59.73
Generation 1 : BF = 39.03
Generation 2 : BF = 39.03
Generation 3 : BF = 17.22
Generation 4 : BF = 17.22

Best solution = $[-0.87, 1.927, 0.026, 0.144, 0.847]$

Best fitness = 17.22

~~Application~~ ~~Traveling salesman problem~~
* when the cities are more
it will be difficult to find
the route by G.A. this helps
by sending different person to
it and finding the best
route.

Code:

```
import random

POP_SIZE = 20
GENES = 5
GENERATIONS = 5
MUTATION_RATE = 0.1
CROSSOVER_RATE = 0.7

def fitness_function(treatment_plan):
    survival_rate = sum(treatment_plan) / len(treatment_plan)
    return survival_rate

class Individual:
    def __init__(self):
        self.genome = [random.randint(0, 10) for _ in range(GENES)]
        self.fitness = self.calculate_fitness()

    def calculate_fitness(self):
        return fitness_function(self.genome)

    def mutate(self):
        if random.random() <
MUTATION_RATE:
            gene_idx =
random.randint(0, GENES - 1)
            self.genome[gene_idx] = random.randint(0, 10)
            self.fitness = self.calculate_fitness()

    @staticmethod
    def crossover(parent1, parent2):
        crossover_point = random.randint(1, GENES - 1)
        child1_genome =
parent1.genome[:crossover_point] + parent2.genome[crossover_point:]
        child2_genome =
parent2.genome[:crossover_point] + parent1.genome[crossover_point:]
        child1 =
Individual()
        child1.genome = child1_genome
        child1.fitness =
child1.calculate_fitness()
        child2 = Individual()
        child2.genome = child2_genome
        child2.fitness = child2.calculate_fitness()
        return child1, child2

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

```

    return population[-1]

def initialize_population():
    return [Individual() for _ in range(POP_SIZE)]

def best_individual(population):
    return max(population, key=lambda individual: individual.fitness)

def main():
    population = initialize_population()
    for generation in range(GENERATIONS):
        population.sort(key=lambda individual: individual.fitness, reverse=True)
        print(f"Generation {generation}: Best fitness = {population[0].fitness}, Genome = {population[0].genome}")
        new_population = [population[0], population[1]]
        while len(new_population) < POP_SIZE:
            parent1 = selection(population)
            parent2 = selection(population)
            if random.random() < CROSSOVER_RATE:
                child1, child2 = Individual.crossover(parent1, parent2)
            else:
                child1, child2 = parent1, parent2
            child1.mutate()
            child2.mutate()
            new_population.append(child1)
            if len(new_population) < POP_SIZE:
                new_population.append(child2)
        population = new_population
        best = best_individual(population)
        print("\nBest treatment plan found:")
        print(f"Genome: {best.genome}, Fitness (Survival Rate): {best.fitness}")

if __name__ == "__main__":
    main()

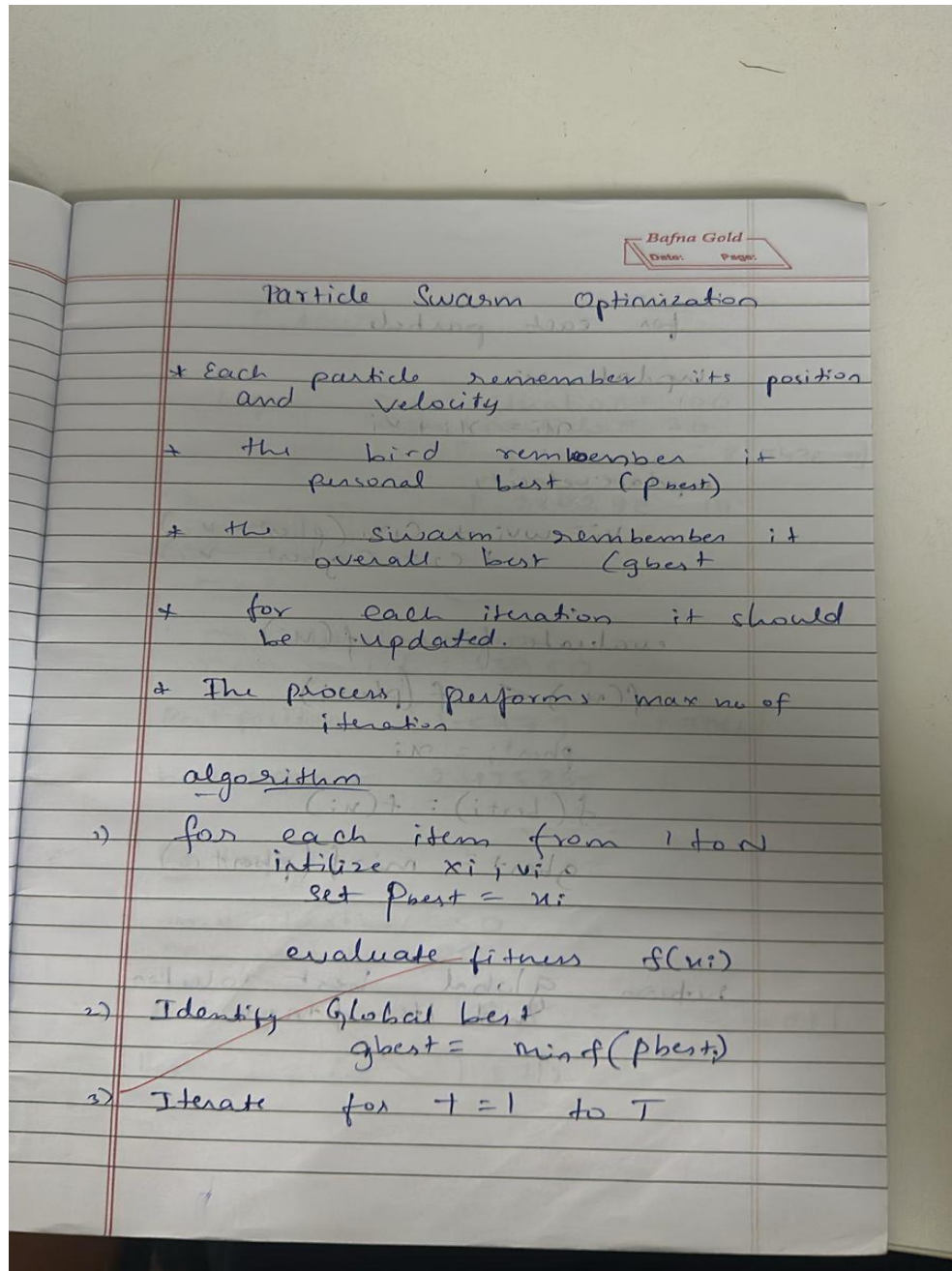
```

Program 3

Particle Swarm Optimization for Function Optimization:

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.

Algorithm:



for each particle

update x_i

$$x_i = x_i + v_i$$

update velocity

$$v_i = wv_i + C_1r_1(pbest_i - x_i) + C_2r_2(gbest - x_i)$$

evaluate fitness $f(x_i)$

$$f(x_i) < f(pbest_i)$$

$$pbest_i = x_i$$

$$f(best_i) = f(x_i)$$

$$gbest = \min f(pbest_i)$$

return global best solution
and its fitness

Output

try 1 max. iteration = 100
num. particle = 30

Best position = $[-7.172e-06 \quad 8.747e-07]$

Best score = $1.28027e-14$

try 2

max. iteration = 100
num. particle = 50

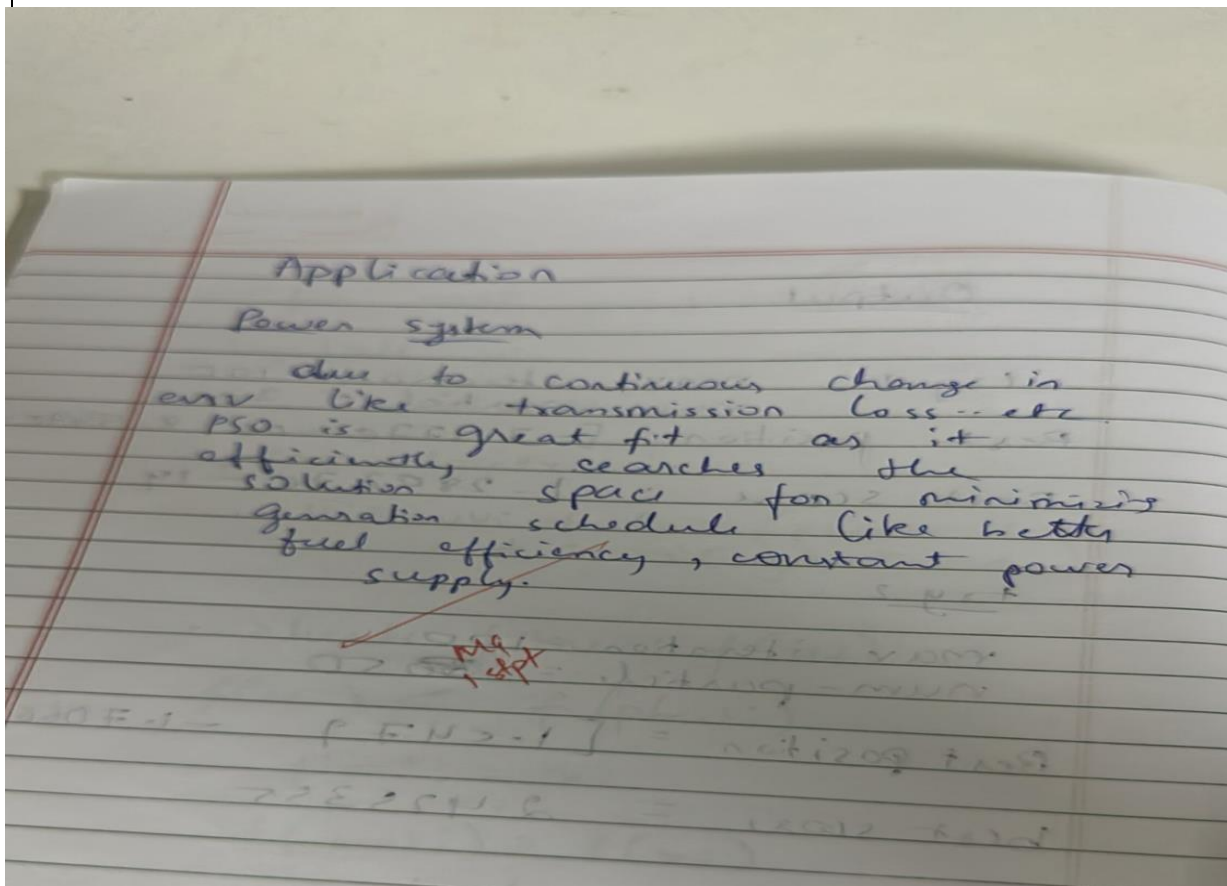
Best position = $[1.5479 \quad -1.7066]$

best score = 2.425355

try-3

max. iteration = 50
no. particle = 20

Best position = $[0.0002 \quad -0.0003]$



Code:

```
import random
import math
start = (0, 0)
goal = (10, 10)
obstacles = [(3, 3), (5, 5), (6, 7), (8, 9)]

def is_collision(p1, p2):
    for (bl, tr) in obstacles:
        x1, y1 = bl
        x2, y2 = tr
        if (min(p1[0], p2[0]) < x2 and max(p1[0], p2[0]) > x1 and
            min(p1[1], p2[1]) < y2 and max(p1[1], p2[1]) > y1):
            return True
    return False

def path_length(path):
    length = 0
    for i in range(len(path)-1):
        p1, p2 = path[i], path[i+1]
        if is_collision(p1, p2):
            return 10**6
        length += math.dist(p1, p2)
    return length
```

```

class Particle:
    def __init__(self, num_waypoints, bounds):
        self.position = [(random.uniform(bounds[0][0], bounds[0][1]),
random.uniform(bounds[1][0], bounds[1][1])) for _
in range(num_waypoints)]
        self.velocity = [(0, 0) for _ in
range(num_waypoints)]
        self.best_position = list(self.position)
        self.best_value = float("inf")
        def evaluate(self, func):
            path = [start] +
self.position + [goal]
            value =
func(path)
            if value < self.best_value:
self.best_value = value
        self.best_position = list(self.position)
        return value

    def update_velocity(self, global_best, w, c1, c2):
        new_velocity = []
        for i in
range(len(self.position)):
            r1, r2 =
random.random(), random.random()
            vx = (w * self.velocity[i][0] +
c1 * r1 *
(self.best_position[i][0] - self.position[i][0]) +
c2 * r2 *
(global_best[i][0] - self.position[i][0]))
            vy = (w * self.velocity[i][1] +
c1 * r1 *
(self.best_position[i][1] - self.position[i][1]) +
c2 * r2 *
(global_best[i][1] - self.position[i][1]))
            new_velocity.append((vx, vy))
        self.velocity = new_velocity

    def update_position(self, bounds):
        new_position = []
        for i in
range(len(self.position)):
            x = self.position[i][0] + self.velocity[i][0]
            y = self.position[i][1] + self.velocity[i][1]
            x
            y
            = max(bounds[0][0], min(x, bounds[0][1]))
            = max(bounds[1][0], min(y, bounds[1][1]))
        new_position.append((x, y))
        self.position = new_position

class PSO:
    def __init__(self, func, num_waypoints=3, bounds=[(0, 10), (0, 10)],
num_particles=20, max_iter=100, w=0.5, c1=1.5, c2=1.5):
        self.func = func
        self.num_waypoints = num_waypoints

```

```

        self.bounds = bounds        self.swarm = [Particle(num_waypoints, bounds) for
_ in range(num_particles)]
        self.global_best_position = list(self.swarm[0].position)
self.global_best_value = float("inf")        self.max_iter =
max_iter        self.w, self.c1, self.c2 = w, c1, c2

    def run(self):        for _ in
range(self.max_iter):        for
particle in self.swarm:
            value = particle.evaluate(self.func)        if value <
self.global_best_value:        self.global_best_value =
value        self.global_best_position =
list(particle.best_position)        for particle in self.swarm:
            particle.update_velocity(self.global_best_position, self.w, self.c1, self.c2)
particle.update_position(self.bounds)        return self.global_best_position,
self.global_best_value if __name__ == "__main__":
    pso = PSO(func=path_length, num_waypoints=3, max_iter=100)
    best_path, best_value = pso.run()
full_path = [start] + best_path + [goal]
print("Best Path Found:")    for p in
full_path:
    print(p)
    print("Total Path Length:", best_value)

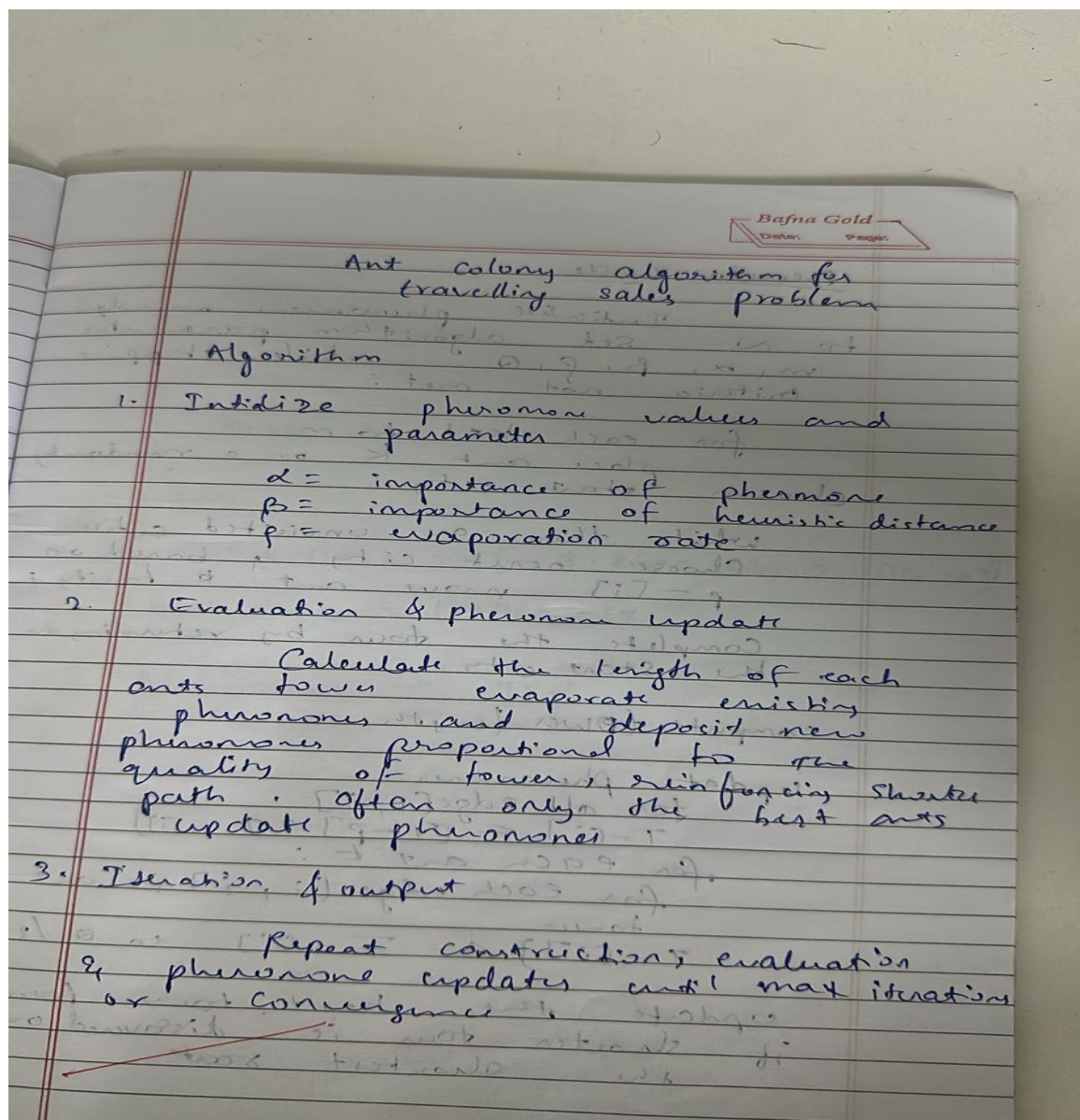
```

Program 4

Ant Colony Optimization for the Traveling Salesman Problem:

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:



Pseudo code

Initialize pheromone on edges
to α Set algorithm parameters
 $m, \alpha, \beta, \rho, Q$ while stopping
criteria not met:

for each $k=1$ to m :
place ant k on a randomly
chosen start city

while there are unvisited cities
choose next city j based on
 P_{ij} move ant k to city j

Complete the tour by returning to
the start city

compute fitness length

update pheromones:

for all edge $[i, j]$:
 $T_{ij} \leftarrow (1-\rho) \cdot T_{ij} + \rho \cdot Q$

for each ant k :

for each edge $[i, j]$ in ant
tour

$T_{ij} \leftarrow T_{ij} \cdot \alpha / L_k$

Input

$n_ants = 10$

$n_iteration = 100$

$\alpha = 1$

$\beta = 5$

$\rho = 0.5$

Output

best position = $[-3.860e-09, -2.464e-09]$

best score = $1.476e-17$

Application \rightarrow TSP

Code:

```
import random
```

```
import numpy as np
```

```
def calculate_distance(city1, city2):
```

```
    return np.sqrt((city1[0] - city2[0])**2 + (city1[1] - city2[1])**2)
```

```
def ant_colony_optimization(cities, n_ants, n_best, n_iterations, decay, alpha=1, beta=5, Q=100):
```

```
    n_cities = len(cities)
```

```
    dist = np.zeros((n_cities, n_cities))
```

```
    for i in range(n_cities):
```

```
        for j in
```

```
range(n_cities):
```

```
    dist[i][j] = calculate_distance(cities[i], cities[j])
```

```
    pheromone = np.ones((n_cities, n_cities)) * 0.1
```

```

best_path = None    best_path_length = float('inf')
for _ in range(n_iterations):
    all_paths = []
    all_lengths = []    for ant
in range(n_ants):
    path = []
    visited = [False] * n_cities    current_city = random.randint(0, n_cities - 1)
path.append(current_city)    visited[current_city] = True    for _ in
range(n_cities - 1):    next_city = choose_next_city(current_city, visited,
pheromone, dist, alpha, beta)    path.append(next_city)
visited[next_city] = True    current_city = next_city    path.append(path[0])
path_length = calculate_path_length(path, dist)    all_paths.append(path)
all_lengths.append(path_length)    if path_length < best_path_length:
best_path_length = path_length
    best_path = path    pheromone *= (1 - decay)    for
path, length in zip(all_paths[:n_best], all_lengths[:n_best]):
    for i in range(len(path) - 1):
        pheromone[path[i]][path[i+1]] += Q / length
print(f'Best path length so far: {best_path_length}')    return
best_path, best_path_length

```

```

def choose_next_city(current_city, visited, pheromone, dist, alpha, beta):
    n_cities = len(pheromone)
    probabilities = []    for i in
range(n_cities):    if not
visited[i]:
        pheromone_level = pheromone[current_city][i] ** alpha
distance_factor = (1.0 / dist[current_city][i]) ** beta
probabilities.append(pheromone_level * distance_factor)    else:
    probabilities.append(0)
total_prob = sum(probabilities)
probabilities = [p / total_prob for p in probabilities]
next_city = random.choices(range(n_cities), weights=probabilities)[0]
return next_city

```

```

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

```

```

if __name__ == "__main__":
    cities = [
(0, 0),

```

```
(1, 2),
(2, 4),
(3, 1),
(5, 0),
(6, 3)
]
n_ants = 10    n_best = 5    n_iterations = 100    decay = 0.95    best_path, best_path_length =
ant_colony_optimization(cities, n_ants, n_best, n_iterations, decay)    print("Best path found:",
best_path)
print("Length of best path:", best_path_length)
```


Program 5

Cuckoo Search (CS):

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.

Algorithm:

Cuckoo search optimization

1. Initialization

- + Randomly generate population of cuckoo soln
- + set parameter

2. fitness evaluation

- + evaluate the fitness of solution

3. Generate new soln

$$n_i^{new} = n_i + \alpha \cdot Levy(t)$$

4. Solution Replacement

If the new soln is better than current one, replace it.

5. Host nest abandonment

if new nest doesn't perform well, it's abandoned and replaced by a new nest.

6. Stopping Condition

the algorithm stops when a predefined stopping criterion is met.

Input

$n_{init} = 5$
 $w_{max} = 10$
 $n_{ests} = 50$
 $max_iteration = 100$
 $items = np.array([[-20, 2], [5, 3], [10, 5], [40, 10], [30, 6]])$

output

Best soln: $[1.15 \quad 0.51 \quad 0.36 \quad 0.17 \quad 1.5]$

Best value: 57.08166

Pseudocode

Initialize population of cuckoos randomly (each cuckoo represents a soln).

Evaluate fitness of each cuckoo (fitness checks if the total weight exceeds the capacity)

Set best solution = the best cuckoo (solution) found so far

while stopping condition ~~not~~ not met (max iteration):

for each cuckoo i in population:
generate a new soln using
 Levy flight (mutation)

Evaluate fitness of new soln:

If new soln is better than current
Replace current Cuckoo soln
with new one.

If new soln is better than
best soln found
Update best soln

randomly replace some cuckoos
in the population with new
random soln

return the best soln found after
all iterations.

Application \rightarrow Job scheduling

Sen
RCA
10/4

Code:

```
import random
import math

def distance(a, b):
    return math.sqrt((a[0] - b[0]) ** 2 + (a[1] - b[1]) ** 2)

def tour_length(tour, cities):
    total = 0.0
    n = len(tour)
    for i in range(n - 1):
        total += distance(cities[tour[i]], cities[tour[i + 1]])
    total += distance(cities[tour[-1]], cities[tour[0]])
    return total

def levy_step_length(beta=1.5):
    u = random.random()
    step = int(1 / (u ** (1 / beta)))
    return max(1, step)

def discrete_levy_flight(tour):
    new_tour = tour[:]
    L = len(new_tour)
    n = levy_step_length()
    for _ in range(L):
        i, j = random.sample(range(n), 2)
        new_tour[i], new_tour[j] = new_tour[j], new_tour[i]
    return new_tour

def random_permutation(n):
    perm = list(range(n))
    random.shuffle(perm)
    return perm

def cuckoo_search_tsp(cities, n_nests=15, pa=0.25, max_iter=500, verbose=True):
    n_cities = len(cities)
    nests = [random_permutation(n_cities) for _ in range(n_nests)]
    fitness = [tour_length(tour, cities) for tour in nests]
    best_index = min(range(n_nests), key=lambda i: fitness[i])
    best_tour = nests[best_index][:]
    best_distance = fitness[best_index]
    for t in range(max_iter):
        j = random.randrange(n_nests)
        cuckoo = discrete_levy_flight(nests[j])
```

```

cuckoo_fit = tour_length(cuckoo, cities)
k = random.randrange(n_nests)
    if cuckoo_fit < fitness[k]:
nests[k] = cuckoo
fitness[k] = cuckoo_fit    for i
in range(n_nests):        if
random.random() < pa:
    nests[i] = random_permutation(n_cities)
fitness[i] = tour_length(nests[i], cities)    best_index =
min(range(n_nests), key=lambda i: fitness[i])    if
fitness[best_index] < best_distance:    best_tour =
nests[best_index][:]    best_distance = fitness[best_index]
if verbose and (t % (max_iter // 10 + 1) == 0):
    print(f"Iteration {t}: Best distance so far = {best_distance:.3f}")
return best_tour, best_distance

if __name__ == "__main__":
    print("=== Cuckoo Search Algorithm for TSP ===")
    n_cities = int(input("Enter number of cities: "))
    cities = []    for i in range(n_cities):
        x = float(input(f"Enter x-coordinate of city {i}: "))    y =
float(input(f"Enter y-coordinate of city {i}: "))    cities.append((x,
y))    n_nests = int(input("Enter number of nests (population size): "))
pa = float(input("Enter discovery probability (0.0-1.0): "))    max_iter
= int(input("Enter maximum number of iterations: "))
    print("\nRunning Cuckoo Search...")    best_tour, best_dist =
cuckoo_search_tsp(cities, n_nests=n_nests, pa=pa,
max_iter=max_iter, verbose=True
)
    print("\n=== Result ===")    print("Best
tour (city indices):", best_tour)
    print(f"Best distance: {best_dist:.3f}")

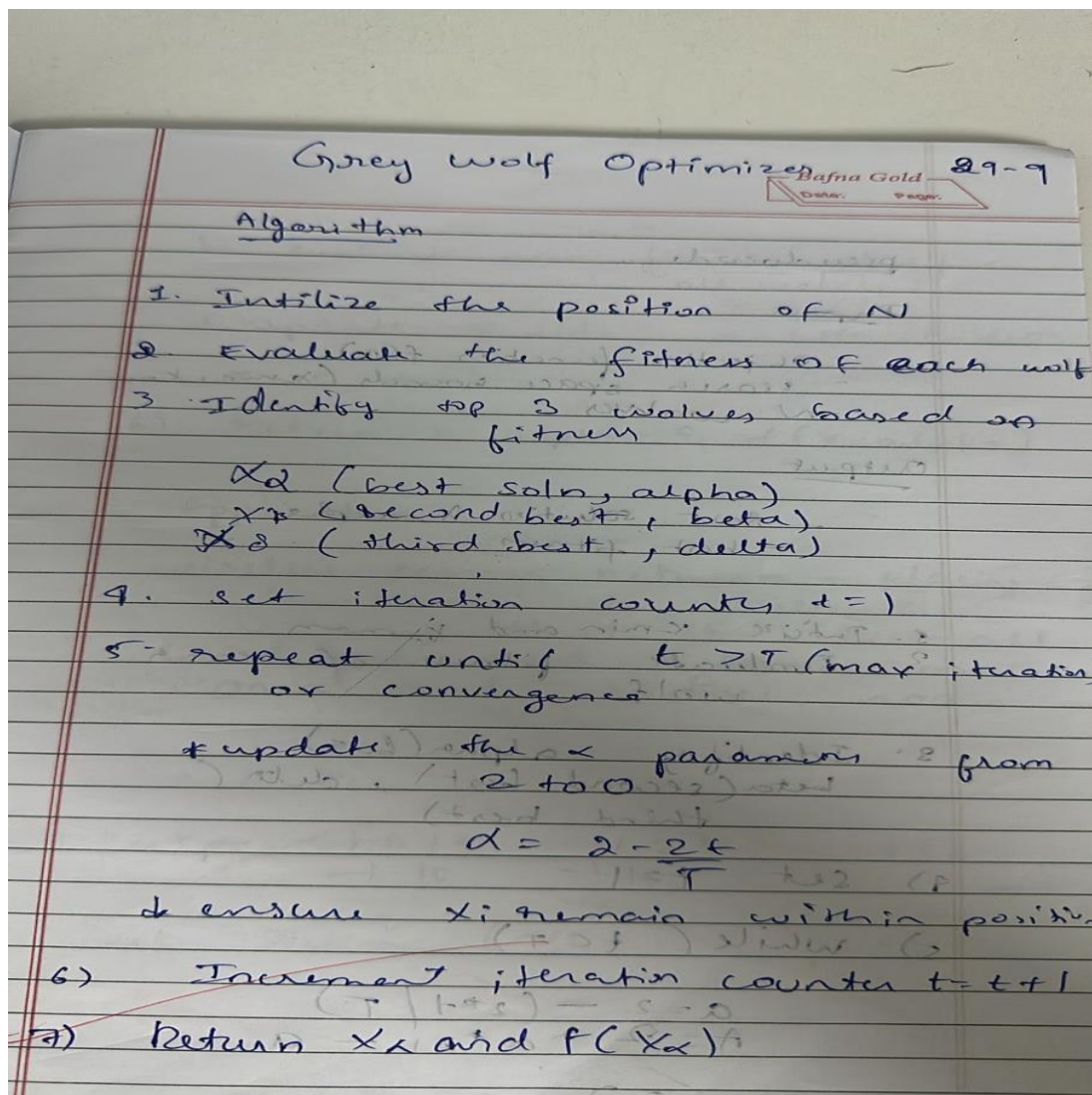
```

Program 6

Grey Wolf Optimizer (GWO):

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:



pseudocode

Input

- objective function $f(x)$
- search space bounds (x_{min}, x_{max})
- N wolves

Output

- best solution x_{alpha}
- best fitness

1. Define x_{min} and x_{max}
2. Evaluate fitness of each wolf
3. Identify $alpha$ (best), $beta$ (second best), $delta$ (third best)

4) set $t=1$

5) while ($t < T$)

$$a = 2 - (2 \times t / T)$$

$$A = 2 \times a \times r_1 - a$$

$$x_i[d] = (x1_d + x2_d + x3_d) / 3$$

6) evaluate new fitness value for all wolves

* update x_{alpha} , x_{beta} , x_{delta}

* $t = t + 1$

6) return x_{alpha} & $f(x_{alpha})$

Application

wireless sensor networks - placing in sensor in such a way that it covers all blindspot and covers max area and reduce nodes

output

$$\text{Best pos} = \begin{bmatrix} 1.19 & 1.27 & -9.57 \\ -1.10 & -1.18 & \end{bmatrix}$$

$$\text{Best soln} = 6.44$$

MG
20/11/20

Code:

```
import random
import math
```

```
def kapur_entropy(thresholds, image):
    thresholds = sorted([int(round(t)) for t in thresholds])
    thresholds = [0] + thresholds + [256]
    hist = [0]*256
    total_pixels = 0
    for row in image:
        for pixel in row:
            hist[pixel] += 1
        total_pixels += 1
    prob = [h/total_pixels for h in hist]
    total_entropy = 0
    for i in range(len(thresholds)-1):
```

```

        start = thresholds[i]
    end = thresholds[i+1]
    P = [p for p in prob[start:end] if p>0]
    total_entropy += -sum([p*math.log(p) for p in P])
    return -total_entropy

def GWO_image(image, D, N=10, MaxIter=50, lb=0, ub=255):
    wolves = [[random.uniform(lb, ub) for _ in range(D)] for _ in range(N)]
    alpha_pos = [0]*D    beta_pos = [0]*D    delta_pos = [0]*D
    alpha_score = float("inf")    beta_score = float("inf")    delta_score =
float("inf")    for t in range(MaxIter):        a = 2 - 2*t/MaxIter        for i
in range(N):
        fitness = kapur_entropy(wolves[i], image)
    if fitness < alpha_score:
        delta_score, delta_pos = beta_score, beta_pos[:]
    beta_score, beta_pos = alpha_score, alpha_pos[:]
    alpha_score, alpha_pos = fitness, wolves[i][:]        elif
    fitness < beta_score:
        delta_score, delta_pos = beta_score, beta_pos[:]
    beta_score, beta_pos = fitness, wolves[i][:]        elif
    fitness < delta_score:
        delta_score, delta_pos = fitness, wolves[i][:]
    for i in range(N):        for d in range(D):
        r1, r2 = random.random(), random.random()
        A1 = 2*a*r1 - a; C1 = 2*r2
        r1, r2 = random.random(), random.random()
    A2 = 2*a*r1 - a; C2 = 2*r2
        r1, r2 = random.random(), random.random()
        A3 = 2*a*r1 - a; C3 = 2*r2
        D_alpha = abs(C1*alpha_pos[d] - wolves[i][d])
        D_beta = abs(C2*beta_pos[d] - wolves[i][d])
        D_delta = abs(C3*delta_pos[d] - wolves[i][d])
        X1 = alpha_pos[d] - A1*D_alpha
        X2 = beta_pos[d] - A2*D_beta        X3 =
delta_pos[d] - A3*D_delta        wolves[i][d] = (X1 + X2
+ X3)/3        if wolves[i][d] < lb: wolves[i][d] = lb
    if wolves[i][d] > ub: wolves[i][d] = ub    return [int(round(x))
for x in alpha_pos]
def main():    filename = input("Enter PGM
image filename (grayscale): ")    image = []    with
open(filename, 'r') as f:
    lines = f.readlines()    lines = [l for l in
lines if not l.startswith('#')]    if
lines[0].strip() != 'P2':
    print("Only ASCII PGM (P2) supported.")

```

```

        return idx = 2 while len(image) <
int(lines[1].split()[1]): row =
list(map(int, lines[idx].split()))
    image.append(row)
idx += 1
    D = int(input("Enter number of thresholds: "))
    N = int(input("Enter number of wolves: ")) MaxIter =
int(input("Enter maximum iterations: "))
best_thresholds = GWO_image(image, D, N, MaxIter)
print("Best thresholds found:", best_thresholds)
thresholds = sorted(best_thresholds) thresholds = [0] +
thresholds + [256] segmented = [[0 for _ in row] for
row in image] for i in range(len(thresholds)-1): for
r in range(len(image)): for c in
range(len(image[0])): if thresholds[i] <=
image[r][c] < thresholds[i+1]:
    segmented[r][c] = int((i+1)*(255/(len(thresholds)-1)))
    out_file = "segmented.pgm"
with open(out_file, 'w') as f:
f.write("P2\n")
    f.write(f'{len(segmented[0])} {len(segmented)}\n')
    f.write("255\n")
    for row in segmented:
        f.write(' '.join(map(str,row)) + '\n')
    print(f'Segmented image saved as {out_file}')

if __name__ == "__main__":
    main()

```

Program 7

Parallel Cellular Algorithms and Programs:

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 largescale optimization problems and can be implemented on parallel computing architectures for enhanced performance.

Algorithm:

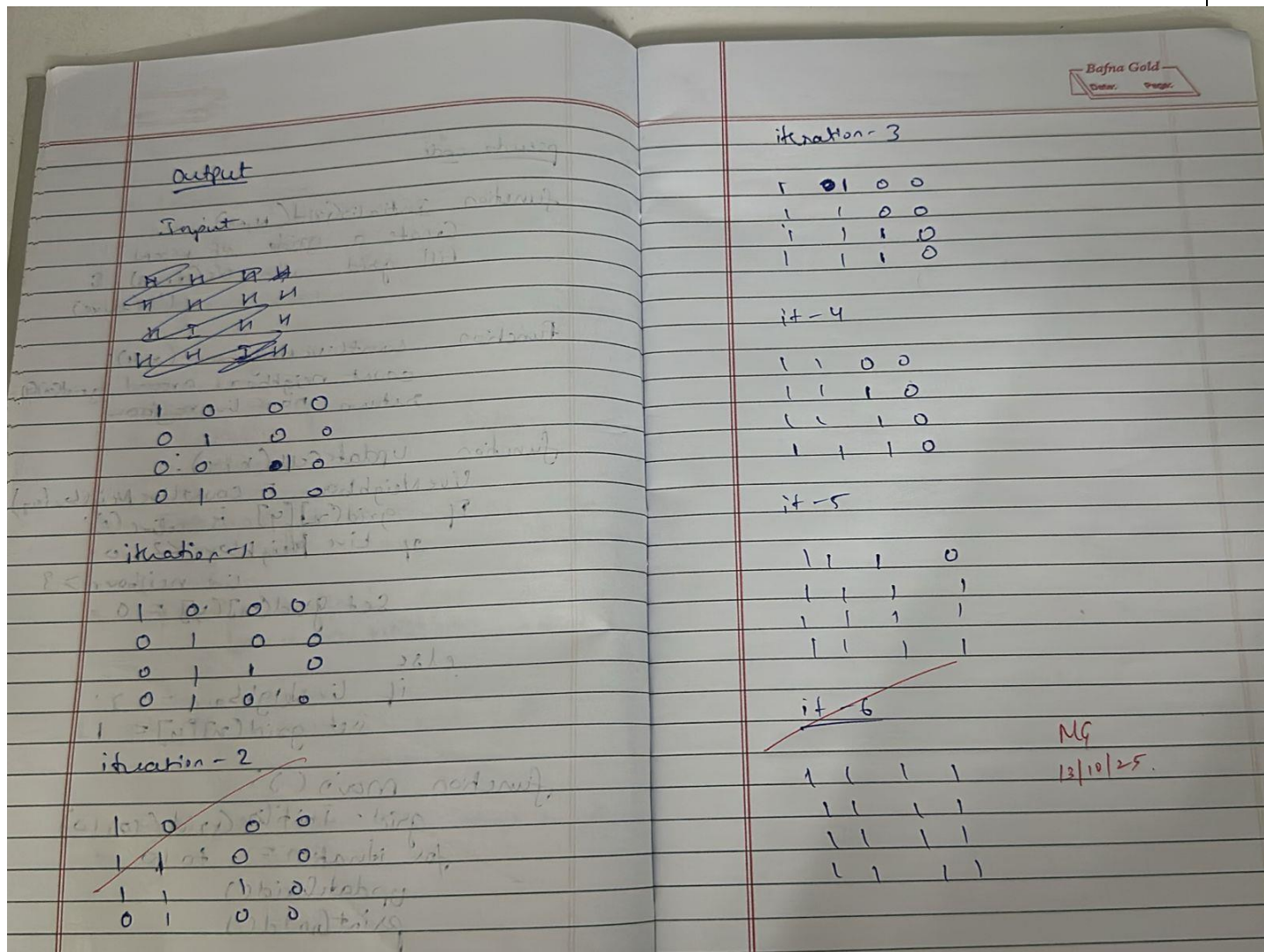
The image shows a handwritten document on a notebook, divided into two pages. The left page is titled "Parallel cellular Algorithm" and lists seven steps. The right page is titled "pseudo code" and contains the implementation of the algorithm in a functional style.

Parallel cellular Algorithm

1. Initialize grid
 - setup a 2D grid ($M \times N$) with initial states for each cell
2. Define Neighborhood
 - Decide which neighbours influence a cell's next state
3. Create a Temporary grid
 - Initialize the population randomly
4. Evaluate fitness \rightarrow Assess how well each cell performs
5. update states: Cells update based on neighbour attention
6. Iterate: repeat until the convergence
7. Output best solution: Track and report best

pseudo code

```
function InitializeGrid(N,M):  
    Create a grids of  $M \times N$   
    fill grid with 0's (dead) &  
    1's (alive)  
  
function CountLiveNeighbour(x,y):  
    count neighbors around grid(x,y)  
    return no of live neighbour  
  
function UpdateCell(x,y):  
    liveNeighbour = CountLiveNeighbour(x,y)  
    if grid[x][y] is alive (1):  
        if liveNeighbour < 2 or  
           liveNeighbour > 3  
            Set grid[x][y] = 0  
    else  
        if liveNeighbour == 3:  
            set grid[x][y] = 1  
  
function main():  
    grid = InitializeGrid(10,10)  
    for iteration = 1 to 10  
        updateGrid()  
        printGrid()  
  
Main()
```

Code:

```
import random
```

```
EMPTY = " "
```

```
TREE = "T"
```

```
BURNING = "F"
```

```
def get_neighbors(grid, i, j, neighborhood_type=8):
```

```
    rows = len(grid)    cols =
```

```
    len(grid[0])    neighbors = []
```

```
    if neighborhood_type == 4:
```

```

        directions = [(-1, 0), (1, 0), (0, -1), (0, 1)]
    else:
        directions = [
            (-1, -1), (-1, 0), (-1, 1),
            (0, -1),      (0, 1),
            (1, -1), (1, 0), (1, 1)
        ]
        for dx, dy in directions:
            x, y = i
            + dx, j + dy
            if 0 <= x < rows and 0
            <= y < cols:
                neighbors.append((x, y))
    return neighbors

def ForestFireModel(grid, num_ iterations, probab_lightning, probab_tree_growth):
    for _ in range(num_ iterations):
        new_grid = [row[:] for row in grid]
        for i in range(len(grid)):
            for j in
            range(len(grid[0])):
                state = grid[i][j]
                neighbors =
                get_neighbors(grid, i, j, 8)
                if state ==
                BURNING:
                    new_grid[i][j] = EMPTY
                    elif state ==
                TREE:
                    if any(grid[x][y] == BURNING for x, y in
                    neighbors):
                        new_grid[i][j] = BURNING
                elif random.random() < probab_lightning:
                    new_grid[i][j] = BURNING
                elif state == EMPTY:
                    if
                    random.random() < probab_tree_growth:
                        new_grid[i][j] = TREE
                grid = new_grid
            print_grid(grid)
        return grid

def print_grid(grid):
    for row in grid:
        print(" ".join(row))
        print("-" * (2 * len(grid[0]) - 1))

if __name__ == "__main__":
    rows = int(input("Enter number of rows: "))
    cols = int(input("Enter
    number of columns: "))
    num_ iterations = int(input("Enter number of
    iterations: "))
    probab_lightning = float(input("Enter probability of lightning

```

```

(0-1): "))    prob_tree_growth = float(input("Enter probability of tree growth
(0-1): "))    grid = []    for i in range(rows):
    row = []    for j
in range(cols):
    r = random.random()
if r < 0.6:
row.append(TREE)
elif r < 0.8:
    row.append(EMPTY)
else:
    row.append(BURNING)
grid.append(row)
print("\nInitial Forest:")
print_grid(grid)
print("Simulating fire spread...\n")    final_grid = ForestFireModel(grid,
num_iterations, prob_lightning, prob_tree_growth)    print("Final Forest State:")
print_grid(final_grid)

```