VISVESVARAYA TECHNOLOGICAL UNIVERSITY

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LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by

Shashank C (1BM22CS254)

in partial fulfillment for the award of the degree of

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in
COMPUTER SCIENCE AND 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 **Shashank C (1BM22CS254),** 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.

Sneha S Bagalkot Assistant Professor Department of CSE, BMSCE	Dr. Kavitha Sooda Professor & HOD Department of CSE, BMSCE

Index

Sl. No.	Date	Experiment Title	Page No.
1		Genetic Algorithm for Optimization Problems	1-4
2		Particle Swarm Optimization for Function Optimization	5-8
3		Ant Colony Optimization for the Traveling Salesman Problem	9-16
4		Cuckoo Search (CS)	17-23
5		Grey Wolf Optimizer (GWO)	24-30
6		Parallel Cellular Algorithms and Programs	31-36
7		Optimization via Gene Expression Algorithms	36-42

Github Link:
https://github.com/ShashankCS254/BIS-LAB.git

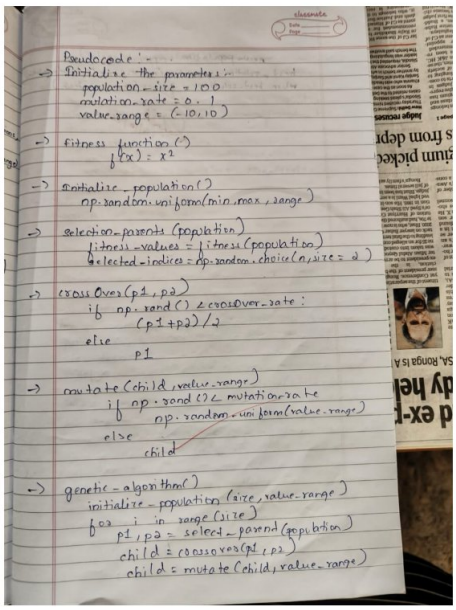
<u>Program 1:</u> Genetic Algorithm for Optimization Problems:

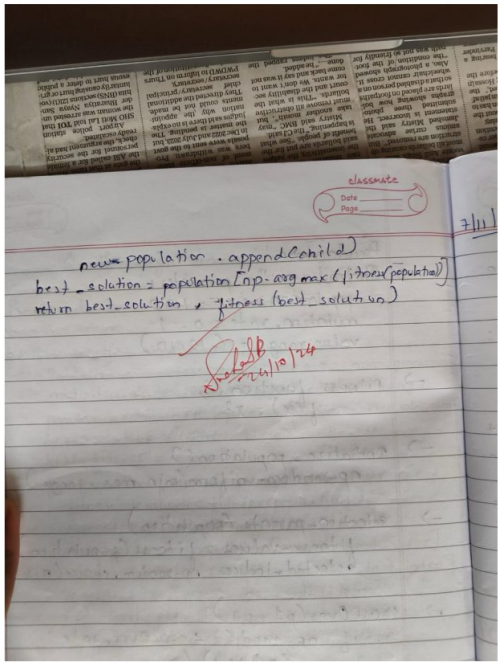
Genetic Algorithms (GA) are inspired by the process of natural selection and genetics, where
the fittest individuals are selected for reproduction to produce the next generation. GAs are
widely used for solving optimization and search problems. Implement a Genetic Algorithm
using Python to solve a basic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

Implementation Steps:

1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the population size, mutation rate, crossover rate, and number of generations.
3. Create Initial Population: Generate an initial population of potential solutions.
4. Evaluate Fitness: Evaluate the fitness of each individual in the population.
5. Selection: Select individuals based on their fitness to reproduce.
6. Crossover: Perform crossover between selected individuals to produce offspring.
7. Mutation: Apply mutation to the offspring to maintain genetic diversity.
8. Iteration: Repeat the evaluation, selection, crossover, and mutation processes for a fixed
number of generations or until convergence criteria are met.
9. Output the Best Solution: Track and output the best solution found during the generations.

Algorithm:





Code:

```
#lab-2: genetic
import numpy as np
import random

# Objective function to maximize
def objective_function(x):
    return x ** 2

# Initialize parameters
population_size = 100
num_generations = 50
mutation_rate = 0.1
crossover_rate = 0.7
range_min = -10
range_max = 10

# Create initial population
def initialize_population(size, min_val, max_val):
    return np.random.uniform(min_val, max_val, size)

# Evaluate fitness of the population
def evaluate_fitness(population):
    return np.array([objective_function(x) for x in population])
```

```
# Selection using roulette-wheel method
def selection(population, fitness):
    total_fitness = np.sum(fitness)
    probabilities = fitness / total_fitness
    return population[np.random.choice(range(len(population)), size=2, p=probabilities)]

# Crossover between two parents
def crossover(parent1, parent2):
    if random.random() < crossover_rate:
        return (parent1 + parent2) / 2  # Simple averaging for crossover
    return parent1  # No crossover

# Mutation of an individual
def mutate(individual):
    if random.random() < mutation_rate:
        return np.random.uniform(range_min, range_max)
    return individual

# Genetic Algorithm function
def genetic_algorithm():
    # Step 1: Initialize population
    population = initialize_population(population_size, range_min, range_max)

    for generation in range(num_generations):
        # Step 2: Evaluate fitness
        fitness = evaluate_fitness(population)

        # Track the best solution
        best_index = np.argmax(fitness)
        best_solution = population[best_index]
        best_fitness = fitness[best_index]

        # print(f"Generation {generation + 1}: Best Solution = {best_solution}, Fitness =
{best_fitness}")

        # Step 3: Create new population
        new_population = []
        for _ in range(population_size):
            # Select parents
            parent1, parent2 = selection(population, fitness)
            # Crossover to create offspring
            offspring = crossover(parent1, parent2)
            # Mutate offspring
```

```
            offspring = mutate(offspring)
            new_population.append(offspring)

        # Step 6: Replace old population with new population
        population = np.array(new_population)

    return best_solution, best_fitness

# Run the Genetic Algorithm
best_solution, best_fitness = genetic_algorithm()
print(f"Best Solution Found: {best_solution}, Fitness: {best_fitness}")
```

OUTPUT:

```
Best Solution Found: -9.290037411642935, Fitness: 86.30479510972536
```

<u>Program 2:</u> Particle Swarm Optimization for Function Optimization:

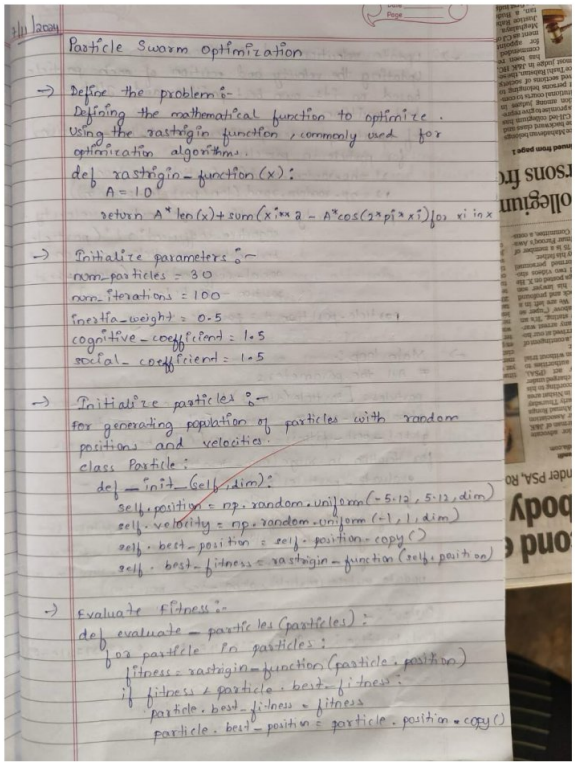
Particle Swarm Optimization (PSO) is inspired by the social behavior of birds flocking or fish schooling. PSO is used to find optimal solutions by iteratively improving a candidate solution with regard to a given measure of quality. Implement the PSO algorithm using Python to optimize a mathematical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

Implementation Steps:

1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of particles, inertia weight, cognitive and social coefficients.
3. Initialize Particles: Generate an initial population of particles with random positions and velocities.
4. Evaluate Fitness: Evaluate the fitness of each particle based on the optimization function.
5. Update Velocities and Positions: Update the velocity and position of each particle based on its own best position and the global best position.
6. Iterate: Repeat the evaluation, updating, and position adjustment for a fixed number of

iterations or until convergence criteria are met.
7. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:



Particle Swarm optimization

-> Define the problem :-
Defining the mathematical function to optimize.
Using the rastrigin function, commonly used for optimization algorithms.

```
def rastrigin_function(x):
    A = 10
    return A*len(x)+sum(x**2 - A*cos(2*pi*xi)) for xi in x
```

-> Initialize parameters :-

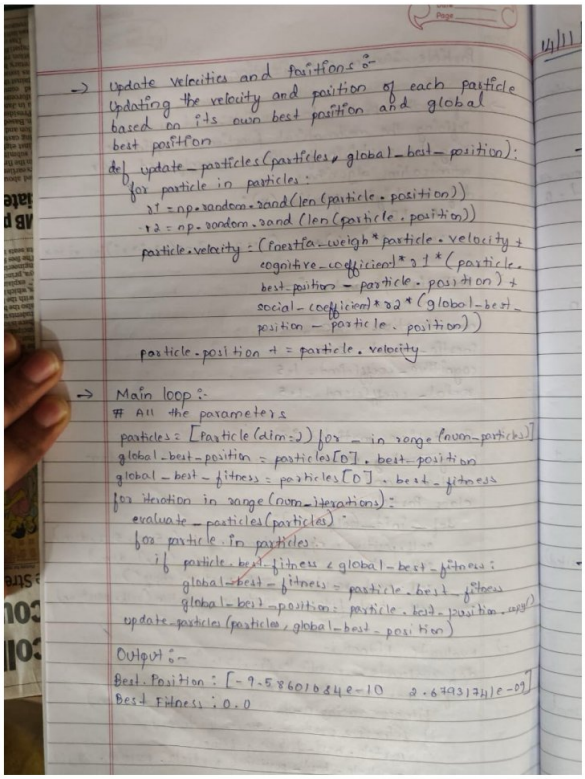
```
num_particles = 30
num_iterations = 100
inertia_weight = 0.5
cognitive_coefficient = 1.5
social_coefficient = 1.5
```

-> Initialize particles :-
for generating population of particles with random positions and velocities.

```
class Particle:
    def __init__(self, dim):
        self.position = np.random.uniform(-5.12, 5.12, dim)
        self.velocity = np.random.uniform(-1, 1, dim)
        self.best_position = self.position.copy()
        self.best_fitness = rastrigin_function(self.position)
```

-> Evaluate fitness :-

```
def evaluate_particles(particles):
    for particle in particles:
        fitness = rastrigin_function(particle.position)
        if fitness < particle.best_fitness:
            particle.best_fitness = fitness
            particle.best_position = particle.position.copy()
```



-> Update velocities and positions :-
Updating the velocity and position of each particle based on its own best position and global best position

```
def update_particles(particles, global_best_position):
    for particle in particles:
        r1 = np.random.rand(len(particle.position))
        r2 = np.random.rand(len(particle.position))
        particle.velocity = (inertia_weight*particle.velocity +
                             cognitive_coefficient*r1*(particle.
                             best_position - particle.position) +
                             social_coefficient*r2*(global_best_
                             position - particle.position))
        particle.position += particle.velocity
```

-> Main loop :-

```
# All the parameters
particles = [Particle(dim=2) for _ in range(num_particles)]
global_best_position = particles[0].best_position
global_best_fitness = particles[0].best_fitness
for iteration in range(num_iterations):
    evaluate_particles(particles)
    for particle in particles:
        if particle.best_fitness < global_best_fitness:
            global_best_fitness = particle.best_fitness
            global_best_position = particle.best_position.copy()
    update_particles(particles, global_best_position)
```

Output :-

```
Best Position: [-9.58601084e-10  2.67931741e-09]
Best Fitness: 0.0
```

Code:

```
#lab-3: pso
import numpy as np
import random

# Define the optimization problem (Rastrigin Function)
def rastrigin(x):
    A = 10
    return A * len(x) + sum([(xi**2 - A * np.cos(2 * np.pi * xi)) for xi in x])

# Particle Swarm Optimization (PSO) implementation
class Particle:
    def __init__(self, dimension, lower_bound, upper_bound):
        # Initialize the particle position and velocity randomly
        self.position = np.random.uniform(lower_bound, upper_bound, dimension)
        self.velocity = np.random.uniform(-1, 1, dimension)
        self.best_position = np.copy(self.position)
        self.best_value = rastrigin(self.position)

    def update_velocity(self, global_best_position, w, c1, c2):
        # Update the velocity of the particle
        r1 = np.random.rand(len(self.position))
        r2 = np.random.rand(len(self.position))

        # Inertia term
        inertia = w * self.velocity

        # Cognitive term (individual best)
        cognitive = c1 * r1 * (self.best_position - self.position)

        # Social term (global best)
        social = c2 * r2 * (global_best_position - self.position)

        # Update velocity
        self.velocity = inertia + cognitive + social

    def update_position(self, lower_bound, upper_bound):
        # Update the position of the particle
        self.position = self.position + self.velocity

        # Ensure the particle stays within the bounds
        self.position = np.clip(self.position, lower_bound, upper_bound)
```

```
    def evaluate(self):
        # Evaluate the fitness of the particle
        fitness = rastrigin(self.position)

        # Update the particle's best position if necessary
        if fitness < self.best_value:
            self.best_value = fitness
            self.best_position = np.copy(self.position)

def particle_swarm_optimization(dim, lower_bound, upper_bound, num_particles=30, max_iter=100,
w=0.5, c1=1.5, c2=1.5):
    # Initialize particles
    particles = [Particle(dim, lower_bound, upper_bound) for _ in range(num_particles)]

    # Initialize the global best position and value
    global_best_position = particles[0].best_position
    global_best_value = particles[0].best_value

    for i in range(max_iter):
        # Update each particle
        for particle in particles:
            particle.update_velocity(global_best_position, w, c1, c2)
            particle.update_position(lower_bound, upper_bound)
            particle.evaluate()

            # Update global best position if needed
            if particle.best_value < global_best_value:
                global_best_value = particle.best_value
                global_best_position = np.copy(particle.best_position)

        # Optionally print the progress
        if (i+1 ) % 10 == 0:
            print(f"Iteration {i+1 }/{max_iter} - Best Fitness: {global_best_value}")

    return global_best_position, global_best_value

# Set the parameters for the PSO algorithm
dim = 2              # Number of dimensions for the function
lower_bound = -5.12    # Lower bound of the search space
upper_bound = 5.12     # Upper bound of the search space
num_particles = 30     # Number of particles in the swarm
max_iter = 100         # Number of iterations
```

```
# Run the PSO
best_position, best_value = particle_swarm_optimization(dim, lower_bound, upper_bound,
num_particles, max_iter)

# Output the best solution found
print("\nBest Solution Found:")
print("Position:", best_position)
print("Fitness:", best_value)
```

OUTPUT:

```
Iteration 10/100 - Best Fitness: 1.1103296669969005
Iteration 20/100 - Best Fitness: 0.020031338560627887
Iteration 30/100 - Best Fitness: 2.788695226740856e-06
Iteration 40/100 - Best Fitness: 1.0778596895022474e-06
Iteration 50/100 - Best Fitness: 6.450946443692374e-10
Iteration 60/100 - Best Fitness: 2.0463630789890885e-11
Iteration 70/100 - Best Fitness: 1.0658141036401503e-14
Iteration 80/100 - Best Fitness: 0.0
Iteration 90/100 - Best Fitness: 0.0
Iteration 100/100 - Best Fitness: 0.0

Best Solution Found:
Position: [-1.63024230e-09  1.14735681e-09]
Fitness: 0.0
```

<u>Program 3:</u> Ant Colony Optimization for the Traveling Salesman Problem:

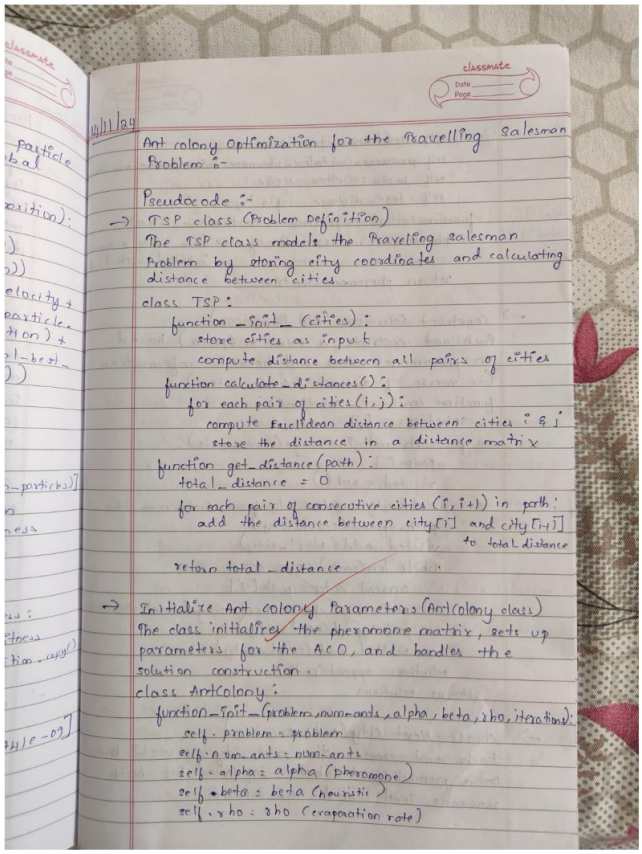
The foraging behavior of ants has inspired the development of optimization algorithms that
can solve complex problems such as the Traveling Salesman Problem (TSP). Ant Colony
Optimization (ACO) simulates the way ants find the shortest path between food sources and
their nest. Implement the ACO algorithm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

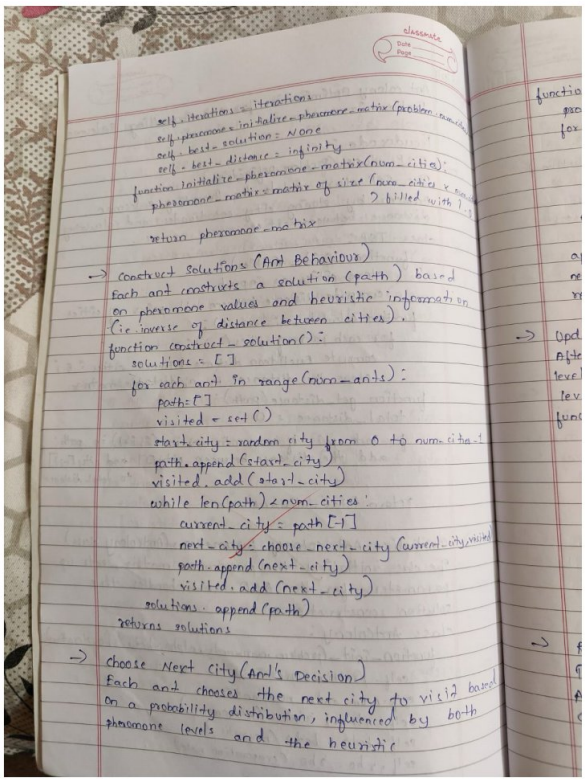
Implementation Steps:

1. Define the Problem: Create a set of cities with their coordinates.
2. Initialize Parameters: Set the number of ants, the importance of pheromone (alpha), the
importance of heuristic information (beta), the evaporation rate (rho), and the initial pheromone value.
3. Construct Solutions: Each ant constructs a solution by probabilistically choosing the

next
city based on pheromone trails and heuristic information.
4. Update Pheromones: After all ants have constructed their solutions, update the pheromone trails based on the quality of the solutions found.
5. Iterate: Repeat the construction and updating process for a fixed number of iterations or
until convergence criteria are met.
6. Output the Best Solution: Keep track of and output the best solution found during the
iterations.

Algorithm:

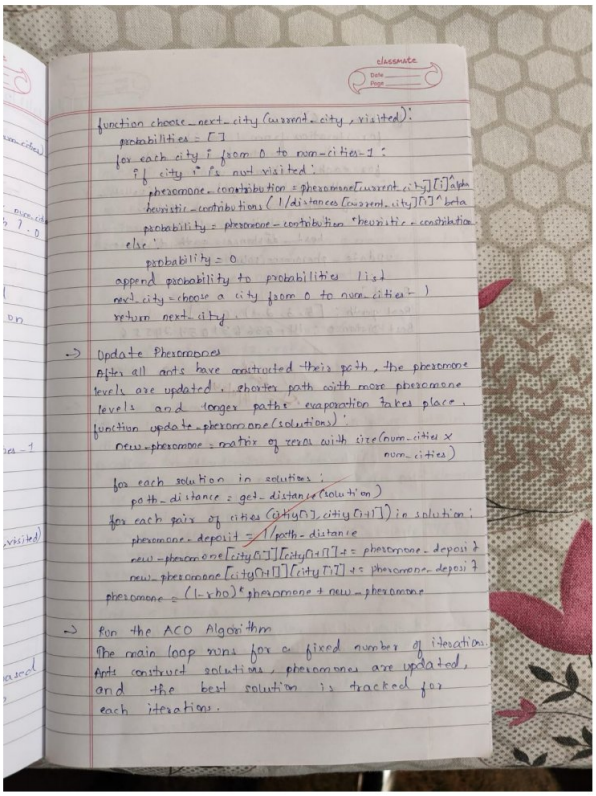




self.iterations = iterations
self.pheromone = initialize_pheromone_matrix(problem_size)
self.best_solution = None
self.best_distance = infinity
function initialize_pheromone_matrix(num_cities):
pheromone_matrix = matrix of size (num_cities x num_cities) filled with 1.0
return pheromone_matrix

→ Construct Solutions (Ant Behaviour)
Each ant constructs a solution (path) based on pheromone values and heuristic information (i.e. inverse of distance between cities).
function construct_solutions():
solutions = []
for each ant in range(num_ants):
path = []
visited = set()
start_city = random city from 0 to num_cities-1
path.append(start_city)
visited.add(start_city)
while len(path) < num_cities:
current_city = path[-1]
next_city = choose_next_city(current_city, visited)
path.append(next_city)
visited.add(next_city)
solutions.append(path)
returns solutions

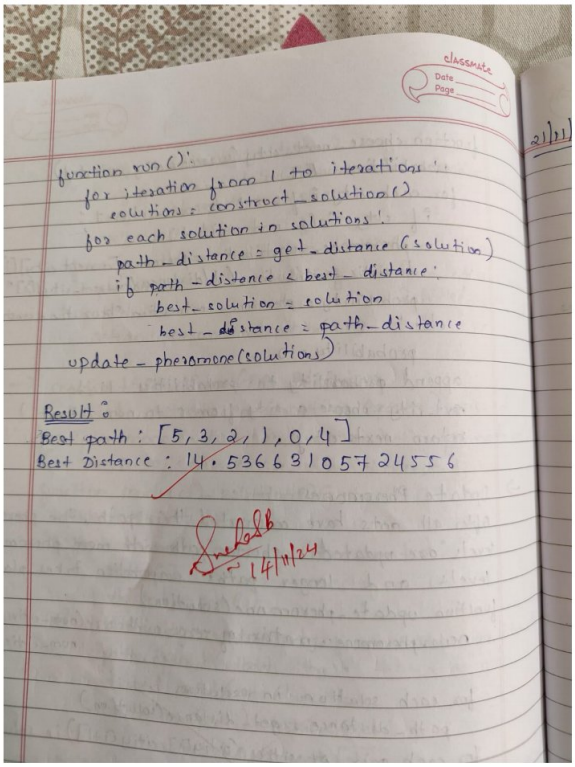
→ Choose Next City (Ant's Decision)
Each ant chooses the next city to visit based on a probability distribution, influenced by both pheromone levels and the heuristic



function choose_next_city(current_city, visited):
probabilities = []
for each city i from 0 to num_cities-1:
if city i is not visited:
pheromone_contribution = pheromone[current_city][i]^alpha
heuristic_contribution = (1/distances[current_city][i])^beta
probability = pheromone_contribution * heuristic_contribution
else:
probability = 0
append probability to probabilities list
next_city = choose a city from 0 to num_cities-1
return next_city

→ Update Pheromones
After all ants have constructed their path, the pheromone levels are updated, shorter path with more pheromone levels and longer paths evaporation takes place.
function update_pheromone(solutions):
new_pheromone = matrix of zeros with size (num_cities x num_cities)
for each solution in solutions:
path_distance = get_distance(solution)
for each pair of cities (city[i], city[i+1]) in solution:
pheromone_deposit = 1/path_distance
new_pheromone[city[i]][city[i+1]] += pheromone_deposit
new_pheromone[city[i+1]][city[i]] += pheromone_deposit
pheromone = (1-rho)*pheromone + new_pheromone

→ For the ACO Algorithm
The main loop runs for a fixed number of iterations. Ants construct solutions, pheromones are updated, and the best solution is tracked for each iterations.



Code:

```
#ant colony
import numpy as np
import matplotlib.pyplot as plt

# 1. Define the Problem: Create a set of cities with their coordinates
cities = np.array([
    [0, 0],  # City 0
    [1, 5],  # City 1
    [5, 1],  # City 2
    [6, 4],  # City 3
    [7, 8],  # City 4
])

# Calculate the distance matrix between each pair of cities
def calculate_distances(cities):
    num_cities = len(cities)
```

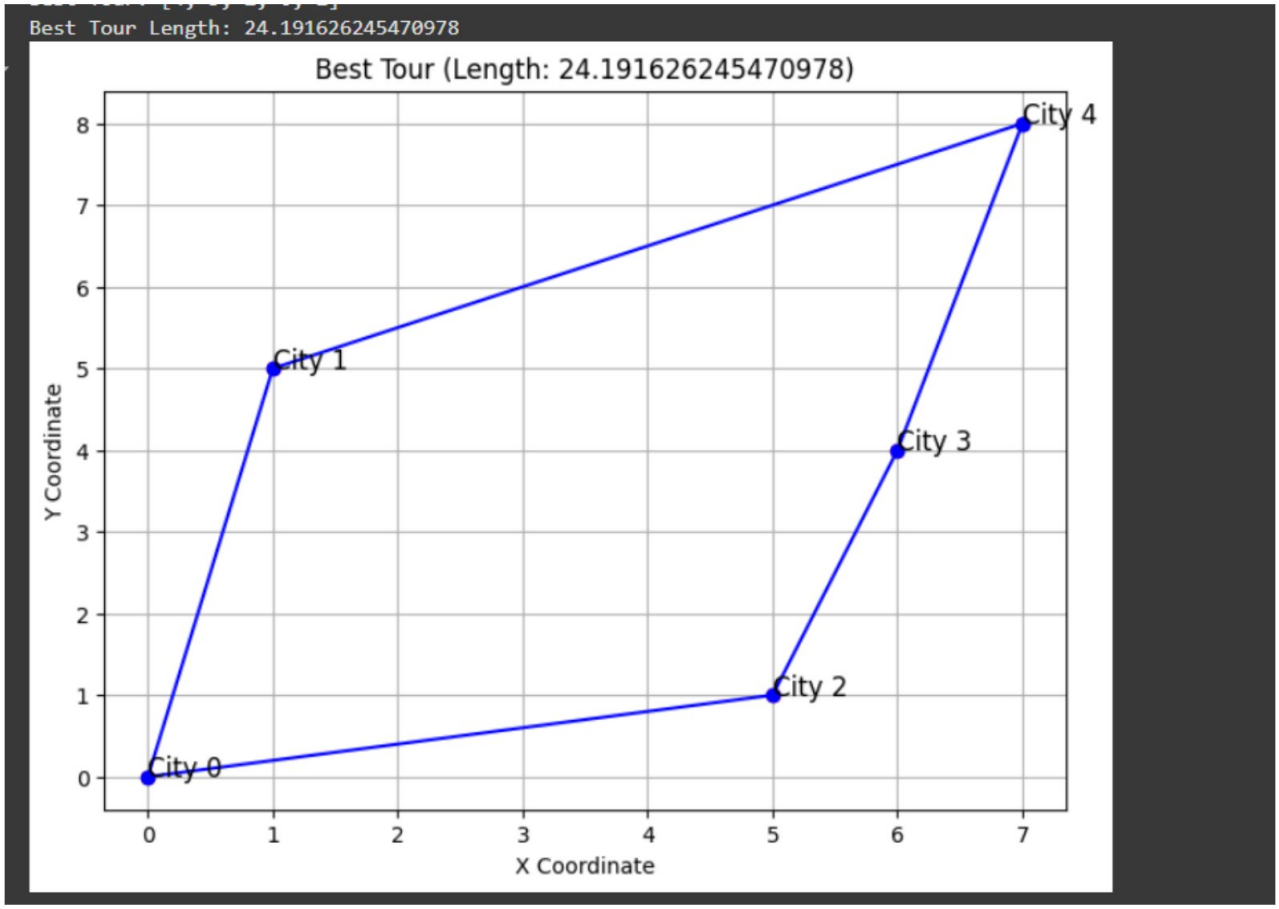
```
    distances = np.zeros((num_cities, num_cities))

    for i in range(num_cities):
        for j in range(num_cities):
            distances[i][j] = np.linalg.norm(cities[i] - cities[j])

    return distances

distances = calculate_distances(cities)

# 2. Initialize Parameters
num_ants = 10
num_cities = len(cities)
alpha = 1.0  # Influence of pheromone
beta = 5.0   # Influence of heuristic (inverse distance)
rho = 0.5    # Evaporation rate
num_iterations = 30
initial_pheromone = 1.0

# Pheromone matrix initialization
pheromone = np.ones((num_cities, num_cities)) * initial_pheromone

# 3. Heuristic information (Inverse of distance)
def heuristic(distances):
    with np.errstate(divide='ignore'):  # Ignore division by zero
        return 1 / distances

eta = heuristic(distances)

# 4. Choose next city probabilistically based on pheromone and heuristic info
def choose_next_city(pheromone, eta, visited):
    probs = []
    for j in range(num_cities):
        if j not in visited:
            pheromone_ij = pheromone[visited[-1], j] ** alpha
            heuristic_ij = eta[visited[-1], j] ** beta
            probs.append(pheromone_ij * heuristic_ij)
        else:
            probs.append(0)
    probs = np.array(probs)
    return np.random.choice(range(num_cities), p=probs / probs.sum())

# Construct solution for a single ant
def construct_solution(pheromone, eta):
```

```
    tour = [np.random.randint(0, num_cities)]
    while len(tour) < num_cities:
        next_city = choose_next_city(pheromone, eta, tour)
        tour.append(next_city)
    return tour

# 5. Update pheromones after all ants have constructed their tours
def update_pheromones(pheromone, all_tours, distances, best_tour):
    pheromone *= (1 - rho)  # Evaporate pheromones

    # Add pheromones for each ant's tour
    for tour in all_tours:
        tour_length = sum([distances[tour[i], tour[i + 1]] for i in range(-1, num_cities - 1)])
        for i in range(-1, num_cities - 1):
            pheromone[tour[i], tour[i + 1]] += 1.0 / tour_length

    # Increase pheromones on the best tour
    best_length = sum([distances[best_tour[i], best_tour[i + 1]] for i in range(-1, num_cities - 1)])
    for i in range(-1, num_cities - 1):
        pheromone[best_tour[i], best_tour[i + 1]] += 1.0 / best_length

# 6. Main ACO Loop: Iterate over multiple iterations to find the best solution
def run_aco(distances, num_iterations):
    pheromone = np.ones((num_cities, num_cities)) * initial_pheromone
    best_tour = None
    best_length = float('inf')

    for iteration in range(num_iterations):
        all_tours = [construct_solution(pheromone, eta) for _ in range(num_ants)]
        all_lengths = [sum([distances[tour[i], tour[i + 1]] for i in range(-1, num_cities - 1)]) for tour in
all_tours]

        current_best_length = min(all_lengths)
        current_best_tour = all_tours[all_lengths.index(current_best_length)]

        if current_best_length < best_length:
            best_length = current_best_length
            best_tour = current_best_tour

        update_pheromones(pheromone, all_tours, distances, best_tour)

        print(f"Iteration {iteration + 1}, Best Length: {best_length}")

    return best_tour, best_length
```

```
# Run the ACO algorithm
best_tour, best_length = run_aco(distances, num_iterations)

# 7. Output the Best Solution
print(f"Best Tour: {best_tour}")
print(f"Best Tour Length: {best_length}")

# 8. Plot the Best Route
def plot_route(cities, best_tour):
    plt.figure(figsize=(8, 6))
    for i in range(len(cities)):
        plt.scatter(cities[i][0], cities[i][1], color='red')
        plt.text(cities[i][0], cities[i][1], f"City {i}", fontsize=12)

    # Plot the tour as lines connecting the cities
    tour_cities = np.array([cities[i] for i in best_tour] + [cities[best_tour[0]]])  # Complete the loop by
returning to the start
    plt.plot(tour_cities[:, 0], tour_cities[:, 1], linestyle='-', marker='o', color='blue')

    plt.title(f"Best Tour (Length: {best_length})")
    plt.xlabel("X Coordinate")
    plt.ylabel("Y Coordinate")
    plt.grid(True)
    plt.show()

# Call the plot function
plot_route(cities, best_tour)
```

OUTPUT:

```
Iteration 1, Best Length: 24.191626245470978
Iteration 2, Best Length: 24.191626245470978
Iteration 3, Best Length: 24.191626245470978
Iteration 4, Best Length: 24.191626245470978
Iteration 5, Best Length: 24.191626245470978
Iteration 6, Best Length: 24.191626245470978
Iteration 7, Best Length: 24.191626245470978
Iteration 8, Best Length: 24.191626245470978
Iteration 9, Best Length: 24.191626245470978
Iteration 10, Best Length: 24.191626245470978
Iteration 11, Best Length: 24.191626245470978
Iteration 12, Best Length: 24.191626245470978
Iteration 13, Best Length: 24.191626245470978
Iteration 14, Best Length: 24.191626245470978
Iteration 15, Best Length: 24.191626245470978
Iteration 16, Best Length: 24.191626245470978
Iteration 17, Best Length: 24.191626245470978
Iteration 18, Best Length: 24.191626245470978
Iteration 19, Best Length: 24.191626245470978
Iteration 20, Best Length: 24.191626245470978
Iteration 21, Best Length: 24.191626245470978
Iteration 22, Best Length: 24.191626245470978
Iteration 23, Best Length: 24.191626245470978
Iteration 24, Best Length: 24.191626245470978
Iteration 25, Best Length: 24.191626245470978
Iteration 26, Best Length: 24.191626245470978
Iteration 27, Best Length: 24.191626245470978
Iteration 28, Best Length: 24.191626245470978
Iteration 29, Best Length: 24.191626245470978
Iteration 30, Best Length: 24.191626245470978
Best Tour: [4, 3, 2, 0, 1]
Best Tour Length: 24.191626245470978
```



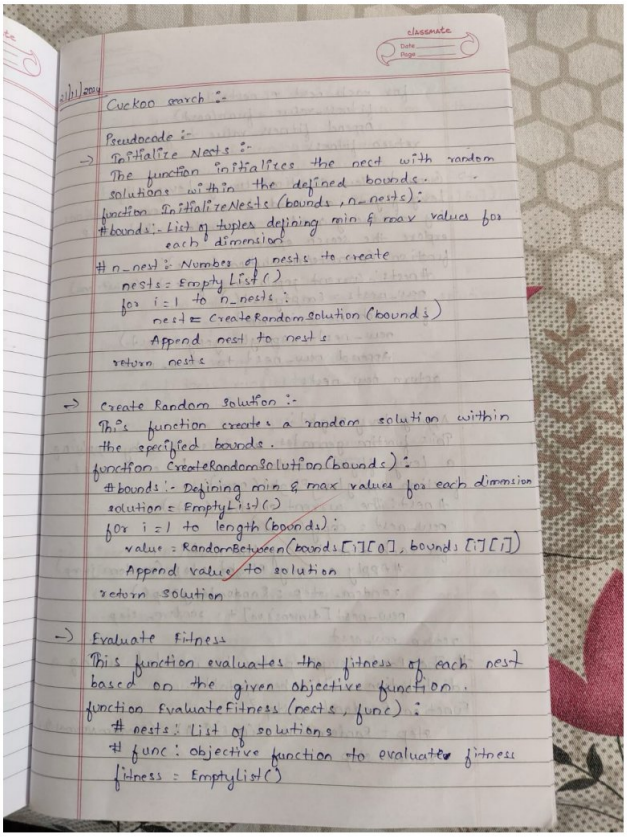
<u>Program 4:</u> Cuckoo Search (CS):

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.

Implementation Steps:

1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of nests, the probability of discovery, and the number of iterations.
3. Initialize Population: Generate an initial population of nests with random positions.
4. Evaluate Fitness: Evaluate the fitness of each nest based on the optimization function.
5. Generate New Solutions: Create new solutions via Lévy flights.
6. Abandon Worst Nests: Abandon a fraction of the worst nests and replace them with new random positions.
7. Iterate: Repeat the evaluation, updating, and replacement process for a fixed number of iterations or until convergence criteria are met.
8. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:



Cuckoo search :-

Pseudocode :-

→ Initialize Nests :-
The function initializes the nest with random solutions within the defined bounds.

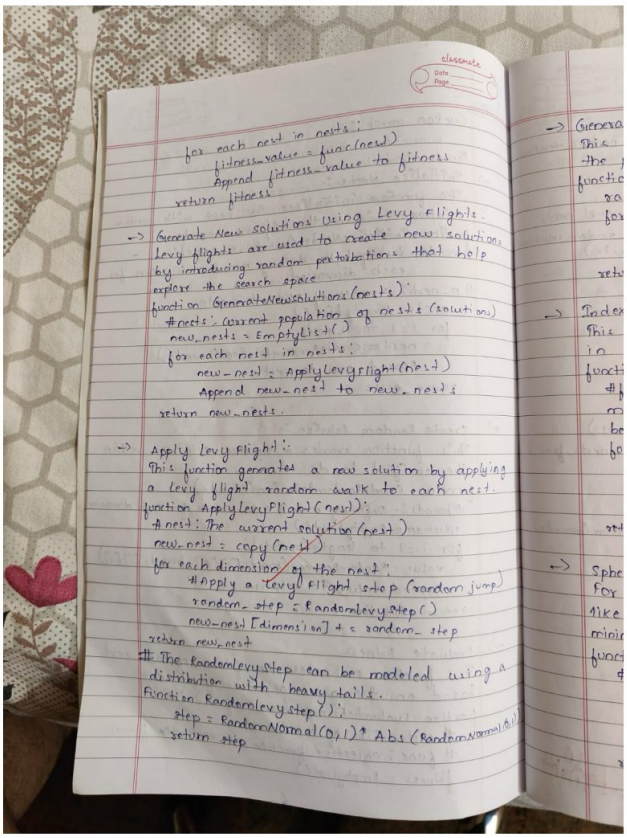
```
function InitializeNests(bounds, n_nests):
# bounds : List of tuples defining min & max values for
         each dimension
# n_nest : Number of nests to create
  nests = Empty List()
  for i = 1 to n_nests :
      nest = CreateRandomSolution(bounds)
      Append nest to nests
  return nests
```

→ Create Random Solution :-
This function creates a random solution within the specified bounds.

```
function CreateRandomSolution(bounds):
# bounds :- Defining min & max values for each dimension
  solution = EmptyList()
  for i = 1 to length(bounds):
      value = RandomBetween(bounds[i][0], bounds[i][1])
      Append value to solution
  return solution
```

→ Evaluate Fitness
This function evaluates the fitness of each nest based on the given objective function.

```
function EvaluateFitness(nests, func):
  # nests : List of solutions
  # func : objective function to evaluate fitness
  fitness = EmptyList()
```



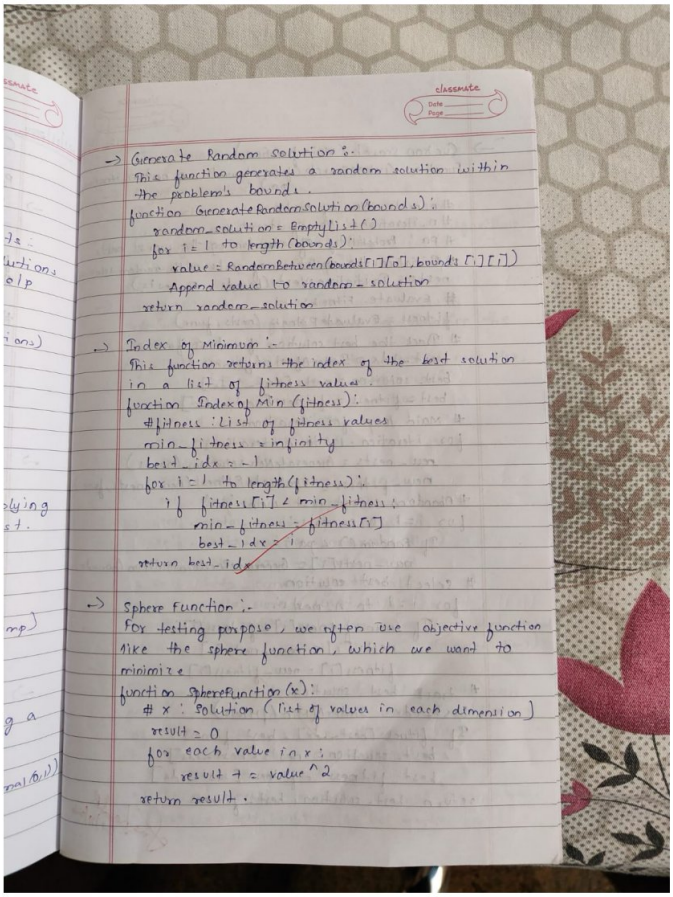
```
  for each nest in nests:
      fitness_value = func(nest)
      Append fitness_value to fitness
  return fitness
```

→ Generate New solutions Using Levy Flights
Levy flights are used to create new solutions by introducing random perturbations that help explore the search space

```
function GenerateNewSolutions(nests):
  # nests : Current population of nests (solutions)
    new_nests = EmptyList()
    for each nest in nests:
        new_nest = ApplyLevyFlight(nest)
        Append new_nest to new_nests
    return new_nests
```

→ Apply Levy Flight :-
This function generates a new solution by applying a levy flight random walk to each nest.

```
function ApplyLevyFlight(nest):
  # nest : The current solution (nest)
    new_nest = copy(nest)
    for each dimension of the nest:
        # Apply a Levy Flight step (random jump)
        random_step = RandomLevyStep()
        new_nest[dimension] += random_step
    return new_nest
# The RandomLevyStep can be modeled using a
  distribution with heavy tails.
function RandomLevyStep():
    step = RandomNormal(0,1) * Abs(RandomNormal(0,1))
    return step
```



→ Generate Random solution :-
This function generates a random solution within the problem's bounds.

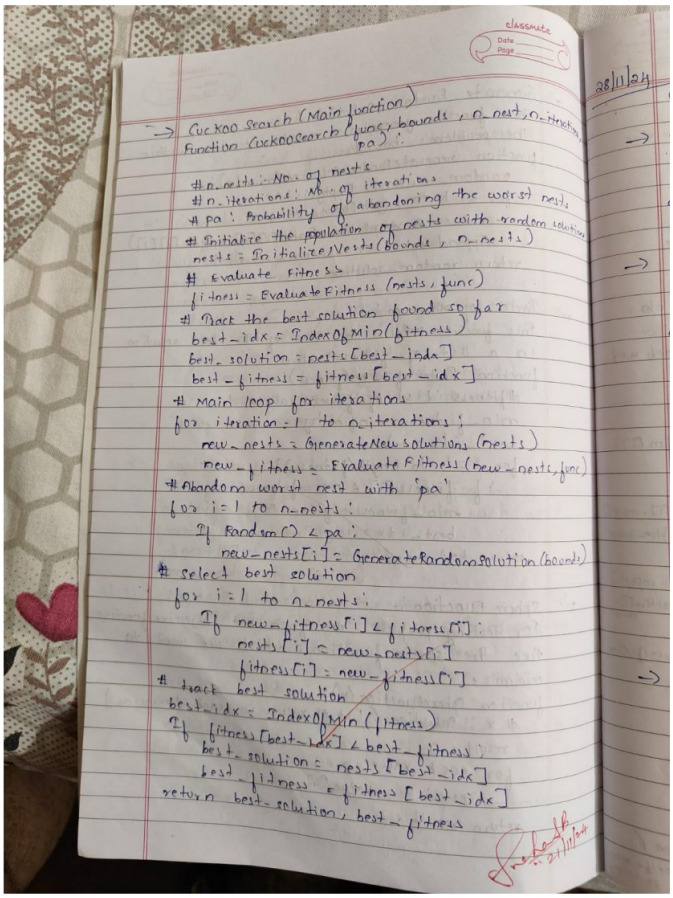
```
function GenerateRandomSolution(bounds):
    random_solution = EmptyList()
    for i = 1 to length(bounds):
        value = RandomBetween(bounds[i][0], bounds[i][1])
        Append value to random_solution
    return random_solution
```

→ Index of Minimum :-
This function returns the index of the best solution in a list of fitness values.

```
function IndexOfMin(fitness):
    #fitness : List of fitness values
    min_fitness = infinity
    best_idx = -1
    for i = 1 to length(fitness):
        if fitness[i] < min_fitness:
            min_fitness = fitness[i]
            best_idx = i
    return best_idx
```

→ Sphere Function :-
For testing purpose, we often use objective function like the sphere function, which we want to minimize

```
function SphereFunction(x):
    # x : solution (list of values in each dimension)
    result = 0
    for each value in x:
        result += value ^ 2
    return result.
```



→ Cuckoo Search (Main function)

```
Function CuckooSearch(func, bounds, n_nest, n_iterations, pa):
    #n_nests : No. of nests
    #n_iterations : No. of iterations
    # pa : Probability of abandoning the worst nests
    # Initialize the population of nests with random solutions
    nests = InitializeNests(bounds, n_nests)
    # Evaluate Fitness
    fitness = EvaluateFitness(nests, func)
    # Track the best solution found so far
    best_idx = IndexOfMin(fitness)
    best_solution = nests[best_idx]
    best_fitness = fitness[best_idx]
    # Main loop for iterations
    for iteration = 1 to n_iterations:
        new_nests = GenerateNewSolutions(nests)
        new_fitness = EvaluateFitness(new_nests, func)
    #Abandon worst nest with 'pa'
    for i = 1 to n_nests:
        If Random() < pa:
            new_nests[i] = GenerateRandomSolution(bounds)
    # Select best solution
    for i = 1 to n_nests:
        If new_fitness[i] < fitness[i]:
            nests[i] = new_nests[i]
            fitness[i] = new_fitness[i]
    # Track best solution
    best_idx = IndexOfMin(fitness)
    If fitness[best_idx] < best_fitness:
        best_solution = nests[best_idx]
        best_fitness = fitness[best_idx]
    return best_solution, best_fitness
```

Code:

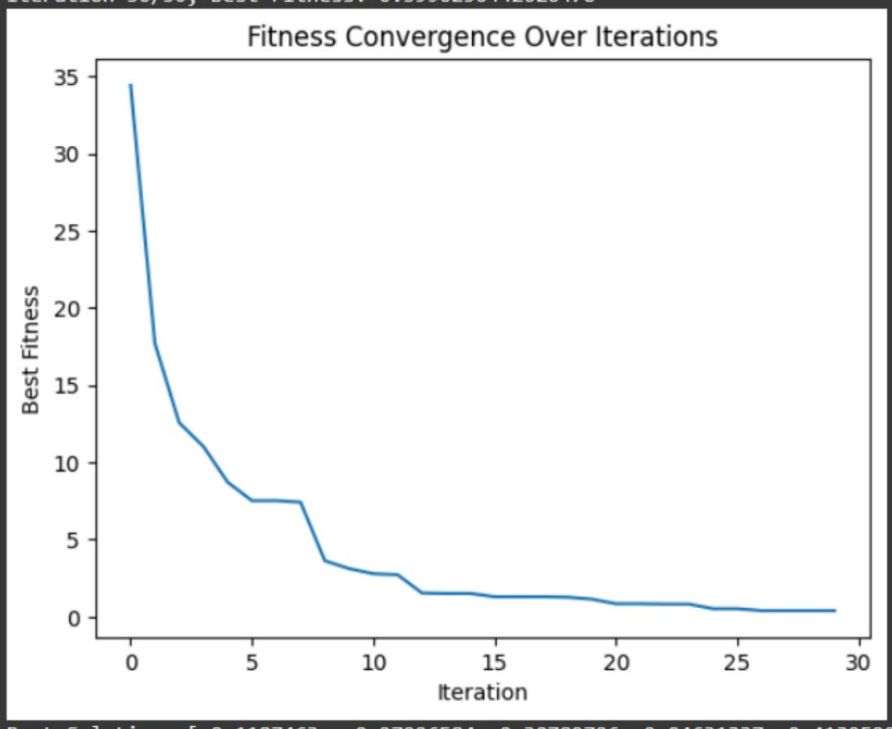
```
#cuckoo search
import numpy as np
import random
import math
import matplotlib.pyplot as plt

# Define a sample function to optimize (Sphere function in this case)
def objective_function(x):
    return np.sum(x ** 2)

# Lévy flight function
def levy_flight(Lambda):
    sigma_u = (math.gamma(1 + Lambda) * np.sin(np.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, size=1)
    v = np.random.normal(0, sigma_v, size=1)
    step = u / (abs(v) ** (1 / Lambda))
    return step

# Cuckoo Search algorithm
def cuckoo_search(num_nests=25, num_iterations=100, discovery_rate=0.25, dim=5,
lower_bound=-10, upper_bound=10):
    # Initialize nests
    nests = np.random.uniform(lower_bound, upper_bound, (num_nests, dim))
    fitness = np.array([objective_function(nest) for nest in nests])

    # Get the current best nest
    best_nest_idx = np.argmin(fitness)
    best_nest = nests[best_nest_idx].copy()
    best_fitness = fitness[best_nest_idx]

    Lambda = 1.5  # Parameter for Lévy flights
    fitness_history = []  # To track fitness at each iteration

    for iteration in range(num_iterations):
        # Generate new solutions via Lévy flight
        for i in range(num_nests):
            step_size = levy_flight(Lambda)
```

```
            new_solution = nests[i] + step_size * (nests[i] - best_nest)
            new_solution = np.clip(new_solution, lower_bound, upper_bound)
            new_fitness = objective_function(new_solution)

            # Replace nest if new solution is better
            if new_fitness < fitness[i]:
                nests[i] = new_solution
                fitness[i] = new_fitness

        # Discover some nests with probability 'discovery_rate'
        random_nests = np.random.choice(num_nests, int(discovery_rate * num_nests), replace=False)
        for nest_idx in random_nests:
            nests[nest_idx] = np.random.uniform(lower_bound, upper_bound, dim)
            fitness[nest_idx] = objective_function(nests[nest_idx])

        # Update the best nest
        current_best_idx = np.argmin(fitness)
        if fitness[current_best_idx] < best_fitness:
            best_fitness = fitness[current_best_idx]
            best_nest = nests[current_best_idx].copy()

        # Store fitness for plotting
        fitness_history.append(best_fitness)

        # Print the best solution at each iteration (optional)
        print(f"Iteration {iteration+1}/{num_iterations}, Best Fitness: {best_fitness}")

    # Plot fitness convergence graph
    plt.plot(fitness_history)
    plt.title('Fitness Convergence Over Iterations')
    plt.xlabel('Iteration')
    plt.ylabel('Best Fitness')
    plt.show()

    # Return the best solution found
    return best_nest, best_fitness

# Example usage
best_nest, best_fitness = cuckoo_search(num_nests=30, num_iterations=30, dim=10,
lower_bound=-5, upper_bound=5)
print("Best Solution:", best_nest)
print("Best Fitness:", best_fitness)
```

OUTPUT:

```
Iteration 1/30, Best Fitness: 34.421347350368414
Iteration 2/30, Best Fitness: 17.701267864864427
Iteration 3/30, Best Fitness: 12.572246094152595
Iteration 4/30, Best Fitness: 11.025968548544025
Iteration 5/30, Best Fitness: 8.713786692960158
Iteration 6/30, Best Fitness: 7.5206125475077785
Iteration 7/30, Best Fitness: 7.5206125475077785
Iteration 8/30, Best Fitness: 7.426062303628502
Iteration 9/30, Best Fitness: 3.6305424687807872
Iteration 10/30, Best Fitness: 3.122312407680085
Iteration 11/30, Best Fitness: 2.7935374916676268
Iteration 12/30, Best Fitness: 2.7258275326189683
Iteration 13/30, Best Fitness: 1.5451154817432429
Iteration 14/30, Best Fitness: 1.5138101828809285
Iteration 15/30, Best Fitness: 1.5138101828809285
Iteration 16/30, Best Fitness: 1.300269684490209
Iteration 17/30, Best Fitness: 1.300269684490209
Iteration 18/30, Best Fitness: 1.300269684490209
Iteration 19/30, Best Fitness: 1.2738498249584989
Iteration 20/30, Best Fitness: 1.1445834652176474
Iteration 21/30, Best Fitness: 0.8487556087655604
Iteration 22/30, Best Fitness: 0.8487556087655604
Iteration 23/30, Best Fitness: 0.8289231635578032
Iteration 24/30, Best Fitness: 0.8242402471719793
Iteration 25/30, Best Fitness: 0.5258270013075049
Iteration 26/30, Best Fitness: 0.5258270013075049
Iteration 27/30, Best Fitness: 0.3996236442626478
Iteration 28/30, Best Fitness: 0.3996236442626478
Iteration 29/30, Best Fitness: 0.3996236442626478
Iteration 30/30, Best Fitness: 0.3996236442626478
```

```
Iteration 30/30, Best Fitness: 0.3996236442626478
```




```
Best Solution: [ 0.1187463  -0.27226584  0.30789726 -0.04631337 -0.41395998  0.0566571
 -0.05240855 -0.11176247  0.15695263 -0.00202369]
Best Fitness: 0.3996236442626478
```

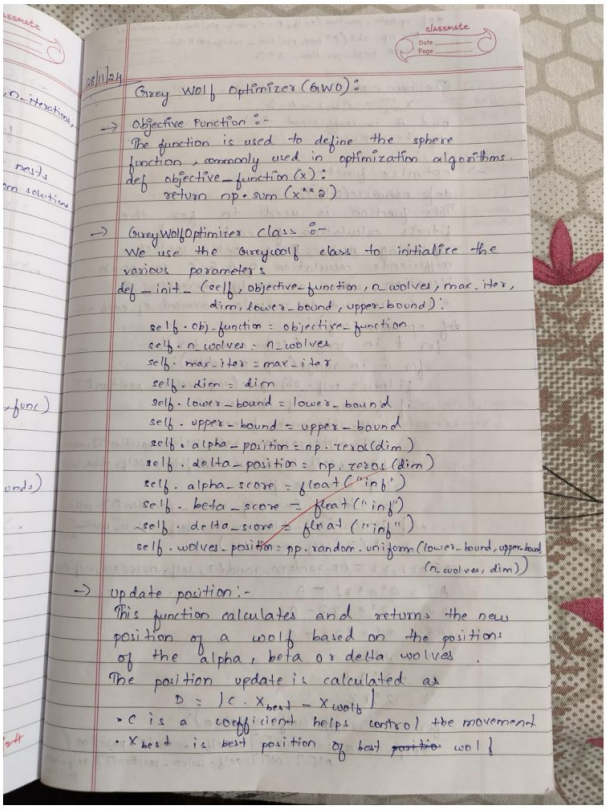
<u>Program 5:</u> Grey Wolf Optimizer (GWO):

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.

Implementation Steps:

1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of wolves and the number of iterations.
3. Initialize Population: Generate an initial population of wolves with random positions.
4. Evaluate Fitness: Evaluate the fitness of each wolf based on the optimization function.
5. Update Positions: Update the positions of the wolves based on the positions of alpha, beta, and delta wolves.
6. Iterate: Repeat the evaluation and position updating process for a fixed number of iterations or until convergence criteria are met.
7. Output the Best Solution: Track and output the best solution found during the iterations

Algorithm:



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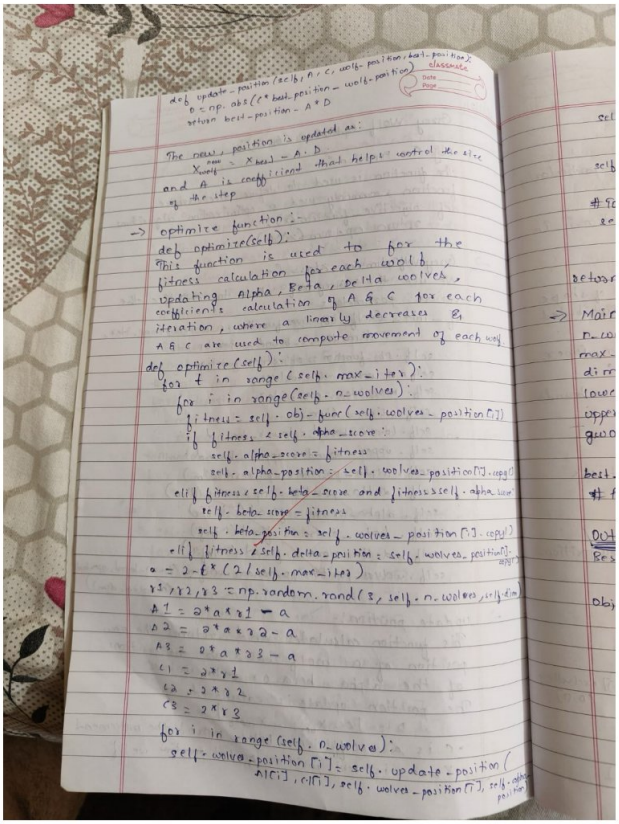
Grey Wolf Optimizer (GWO):-

→ Objective Function :-
The function is used to define the sphere function, commonly used in optimization algorithms.
def objective_function(x):
    return np.sum(x**2)

→ GreyWolfOptimizer class :-
We use the GreyWolf class to initialize the various parameters
def __init__(self, objective_function, n_wolves, max_iter, dim, lower_bound, upper_bound):
    self.obj_function = objective_function
    self.n_wolves = n_wolves
    self.max_iter = max_iter
    self.dim = dim
    self.lower_bound = lower_bound
    self.upper_bound = upper_bound
    self.alpha_position = np.zeros(dim)
    self.delta_position = np.zeros(dim)
    self.alpha_score = float("inf")
    self.beta_score = float("inf")
    self.delta_score = float("inf")
    self.wolves_position = np.random.uniform(lower_bound, upper_bound, (n_wolves, dim))

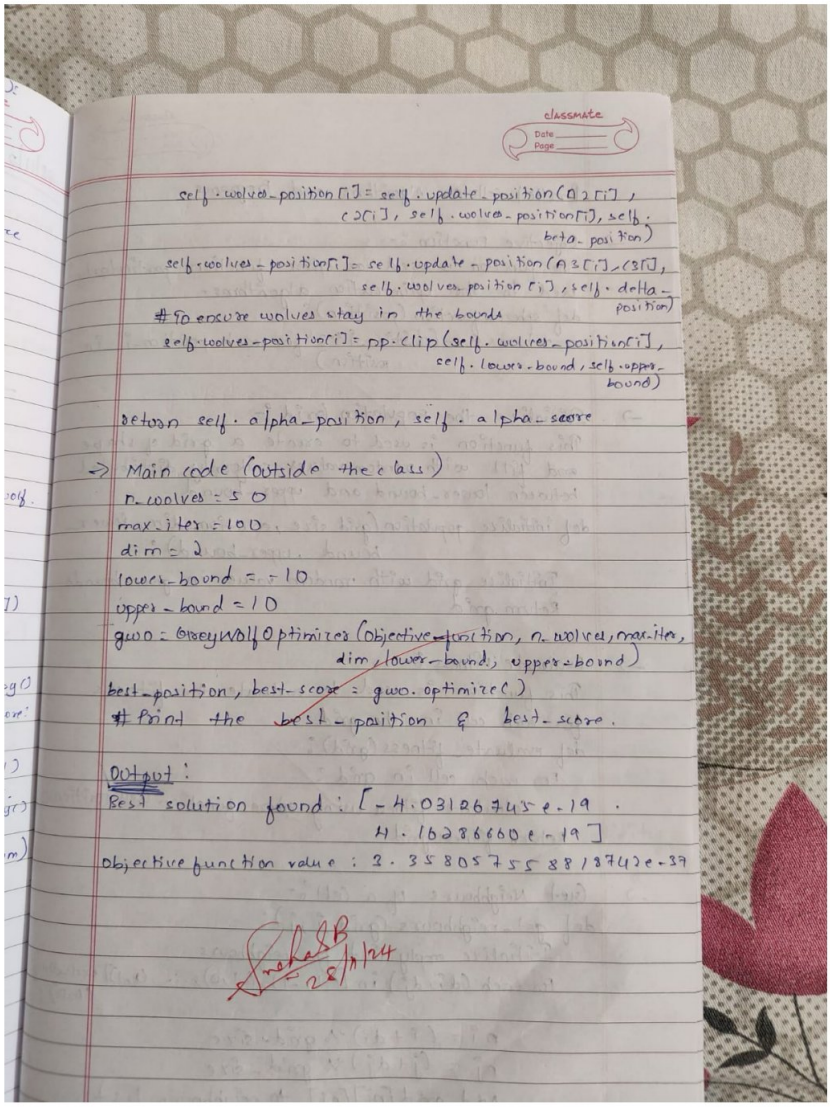
→ update position :-
This function calculates and returns the new position of a wolf based on the position of the alpha, beta or delta wolves.
The position update is calculated as
$D = |C \cdot X_{best} - X_{wolf}|$
• C is a coefficient helps control the movement
• X_{best} is best position of best ~~position~~ wolf



def update_position(self, A, C, wolf_position, best_position):
    D = np.abs(C * best_position - wolf_position)
    return best_position - A * D

The new position is updated as:
$X_{wolf}^{new} = X_{best} - A \cdot D$
and A is coefficient that helps control the size of the step

→ optimize function :-
def optimize(self):
This function is used to for the fitness calculation for each wolf, updating alpha, beta, delta wolves, coefficients calculation of A & C for each iteration, where a linearly decreases & A & C are used to compute movement of each wolf
def optimize(self):
    for t in range(self.max_iter):
        for i in range(self.n_wolves):
            fitness = self.obj_func(self.wolves_position[i])
            if fitness < self.alpha_score:
                self.alpha_score = fitness
                self.alpha_position = self.wolves_position[i].copy()
            elif fitness < self.beta_score and fitness > self.alpha_score:
                self.beta_score = fitness
                self.beta_position = self.wolves_position[i].copy()
            elif fitness < self.delta_position = self.wolves_position[i].copy()
        a = 2 - t * (2 / self.max_iter)
        r1, r2, r3 = np.random.rand(3, self.n_wolves, self.dim)
        A1 = 2*a*r1 - a
        A2 = 2*a*r2 - a
        A3 = 2*a*r3 - a
        C1 = 2*r1
        C2 = 2*r2
        C3 = 2*r3
        for i in range(self.n_wolves):
            self.wolves_position[i] = self.update_position(A[i], C[i], self.wolves_position[i], self.alpha_position



Code:

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

# Step 1: Define the Problem (a mathematical function to optimize)
def objective_function(x):
    return np.sum(x**2)  # Example: Sphere function (minimize sum of squares)

# Step 2: Initialize Parameters
num_wolves = 5  # Number of wolves in the pack
```

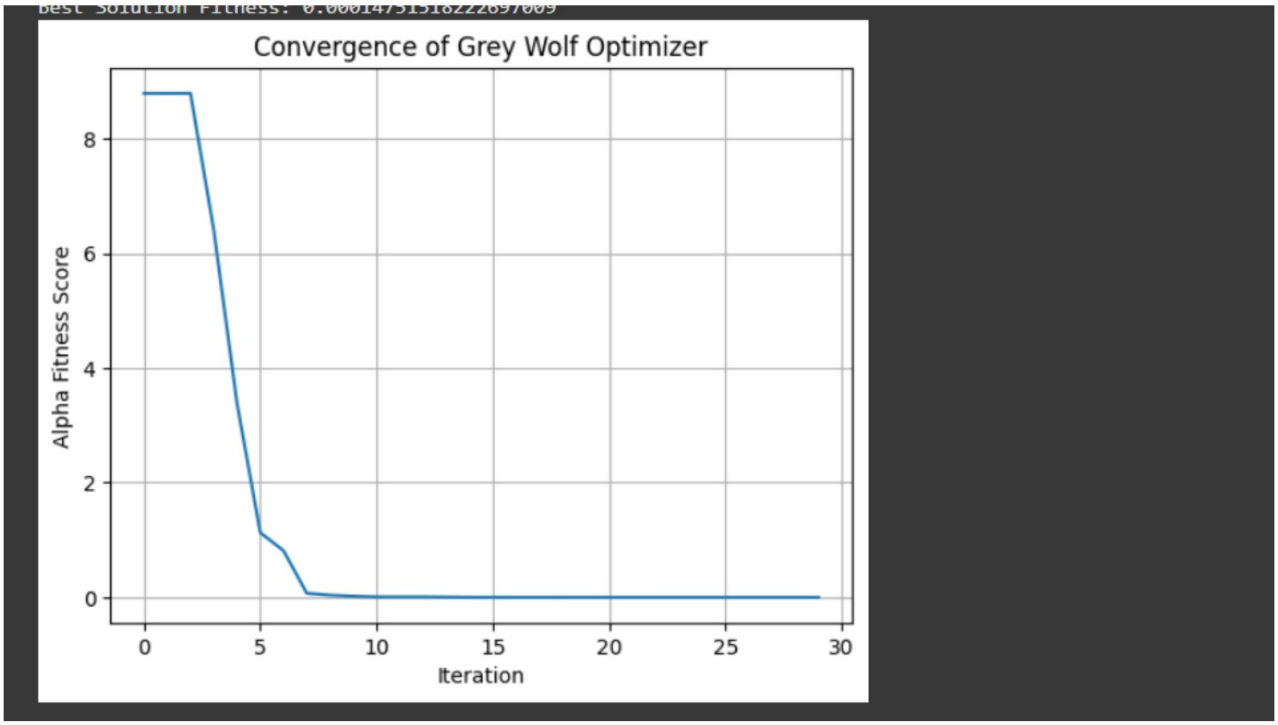
```
num_dimensions = 2  # Number of dimensions (for the optimization problem)
num_iterations = 30  # Number of iterations
lb = -10  # Lower bound of search space
ub = 10  # Upper bound of search space

# Step 3: Initialize Population (Generate initial positions randomly)
wolves = np.random.uniform(lb, ub, (num_wolves, num_dimensions))

# Initialize alpha, beta, delta wolves
alpha_pos = np.zeros(num_dimensions)
beta_pos = np.zeros(num_dimensions)
delta_pos = np.zeros(num_dimensions)

alpha_score = float('inf')  # Best (alpha) score
beta_score = float('inf')   # Second best (beta) score
delta_score = float('inf')  # Third best (delta) score

# To store the alpha score over iterations for graphing
alpha_score_history = []

# Step 4: Evaluate Fitness and assign Alpha, Beta, Delta wolves
def evaluate_fitness():
    global alpha_pos, beta_pos, delta_pos, alpha_score, beta_score, delta_score

    for wolf in wolves:
        fitness = objective_function(wolf)

        # Update Alpha, Beta, Delta wolves based on fitness
        if fitness < alpha_score:
            delta_score = beta_score
            delta_pos = beta_pos.copy()

            beta_score = alpha_score
            beta_pos = alpha_pos.copy()

            alpha_score = fitness
            alpha_pos = wolf.copy()
        elif fitness < beta_score:
```

```
            delta_score = beta_score
            delta_pos = beta_pos.copy()

            beta_score = fitness
            beta_pos = wolf.copy()
        elif fitness < delta_score:
            delta_score = fitness
            delta_pos = wolf.copy()

# Step 5: Update Positions
def update_positions(iteration):
    a = 2 - iteration * (2 / num_iterations)  # a decreases linearly from 2 to 0

    for i in range(num_wolves):
        for j in range(num_dimensions):
            r1 = np.random.random()
            r2 = np.random.random()

            # Position update based on alpha
            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

            # Position update based on beta
            r1 = np.random.random()
            r2 = np.random.random()
            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

            # Position update based on delta
            r1 = np.random.random()
            r2 = np.random.random()
            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

            # Update wolf position
            wolves[i, j] = (X1 + X2 + X3) / 3

            # Apply boundary constraints
            wolves[i, j] = np.clip(wolves[i, j], lb, ub)

# Step 6: Iterate (repeat evaluation and position updating)
for iteration in range(num_iterations):
    evaluate_fitness()  # Evaluate fitness of each wolf
    update_positions(iteration)  # Update positions based on alpha, beta, delta

    # Record the alpha score for this iteration
    alpha_score_history.append(alpha_score)

    # Optional: Print current best score
    print(f"Iteration {iteration+1}/{num_iterations}, Alpha Score: {alpha_score}")

# Step 7: Output the Best Solution
print("Best Solution:", alpha_pos)
print("Best Solution Fitness:", alpha_score)

# Plotting the convergence graph
plt.plot(alpha_score_history)
plt.title('Convergence of Grey Wolf Optimizer')
plt.xlabel('Iteration')
plt.ylabel('Alpha Fitness Score')
plt.grid(True)
plt.show()
```

OUTPUT:

```
Iteration 1/30, Alpha Score: 8.789922247101906
Iteration 2/30, Alpha Score: 8.789922247101906
Iteration 3/30, Alpha Score: 8.789922247101906
Iteration 4/30, Alpha Score: 6.409956649485766
Iteration 5/30, Alpha Score: 3.383929841190778
Iteration 6/30, Alpha Score: 1.1292299489236237
Iteration 7/30, Alpha Score: 0.8136628488047792
Iteration 8/30, Alpha Score: 0.07110881373527288
Iteration 9/30, Alpha Score: 0.03823180120070083
Iteration 10/30, Alpha Score: 0.021111314445105462
Iteration 11/30, Alpha Score: 0.00874782100259989
Iteration 12/30, Alpha Score: 0.00874782100259989
Iteration 13/30, Alpha Score: 0.00874782100259989
Iteration 14/30, Alpha Score: 0.005066807028932165
Iteration 15/30, Alpha Score: 0.0011746187200998674
Iteration 16/30, Alpha Score: 0.0011746187200998674
Iteration 17/30, Alpha Score: 0.0008078646351838173
Iteration 18/30, Alpha Score: 0.0008078646351838173
Iteration 19/30, Alpha Score: 0.0006302256737926024
Iteration 20/30, Alpha Score: 0.0005272190797352655
Iteration 21/30, Alpha Score: 0.00035614966782860404
Iteration 22/30, Alpha Score: 0.0003270119398391142
Iteration 23/30, Alpha Score: 0.00022723766847392013
Iteration 24/30, Alpha Score: 0.00022152382849585967
Iteration 25/30, Alpha Score: 0.00022152382849585967
Iteration 26/30, Alpha Score: 0.00020102313789207912
Iteration 27/30, Alpha Score: 0.0001974565833678501
Iteration 28/30, Alpha Score: 0.0001547675581999543
Iteration 29/30, Alpha Score: 0.00014751518222697009
Iteration 30/30, Alpha Score: 0.00014751518222697009
Best Solution: [ 0.00643925 -0.01029812]
Best Solution Fitness: 0.00014751518222697009
```



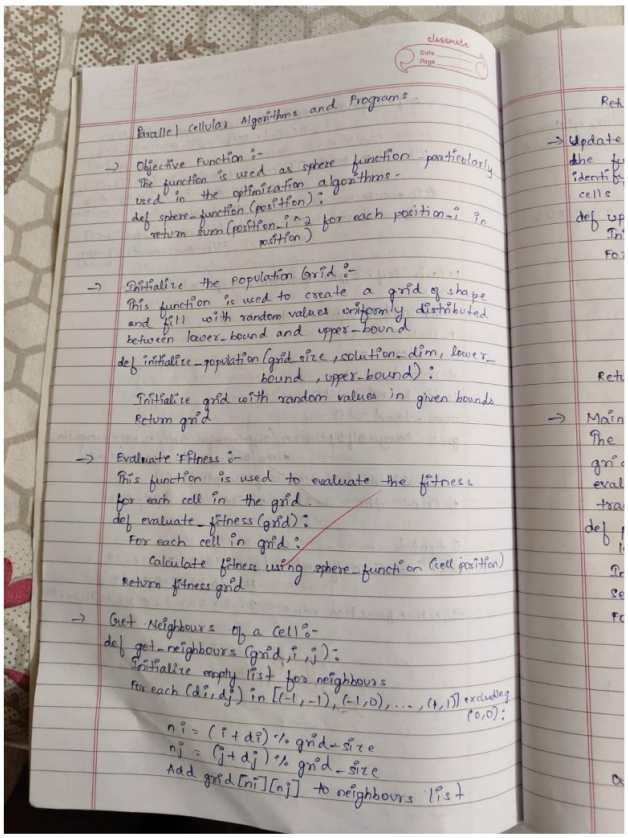
<u>Program 6:</u> Parallel Cellular Algorithms and Programs:

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 large-scale optimization problems and can be implemented on parallel computing architectures for enhanced performance.

Implementation Steps:

1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the number of cells, grid size, neighborhood structure, and number of iterations.
3. Initialize Population: Generate an initial population of cells with random positions in the solution space.
4. Evaluate Fitness: Evaluate the fitness of each cell based on the optimization function.
5. Update States: Update the state of each cell based on the states of its neighboring cells and predefined update rules.
6. Iterate: Repeat the evaluation and state updating process for a fixed number of iterations or until convergence criteria are met.
7. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:



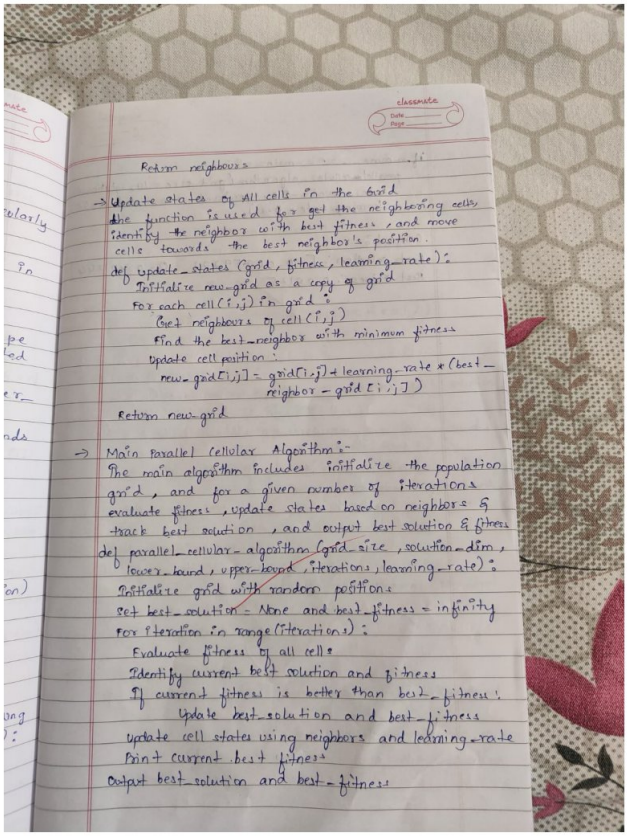
Parallel Cellular Algorithms and Programs

→ Objective Function :-
The function is used as sphere function particularly used in the optimization algorithms.
def sphere_function(position):
return sum(position_i ^ 2 for each position_i in position)

→ Initialize the Population Grid :-
This function is used to create a grid of shape and fill with random values uniformly distributed between lower_bound and upper_bound
def initialize_population(grid_size, solution_dim, lower_bound, upper_bound):
Initialize grid with random values in given bounds
Return grid

→ Evaluate Fitness :-
This function is used to evaluate the fitness for each cell in the grid.
def evaluate_fitness(grid):
For each cell in grid:
Calculate fitness using sphere_function(cell position)
Return fitness grid

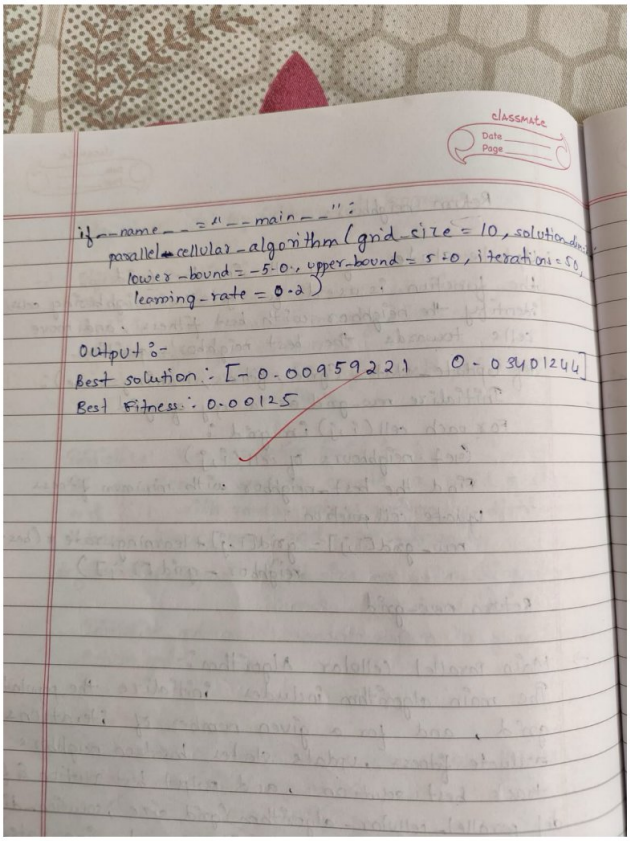
→ Get Neighbours of a Cell :-
def get_neighbours(grid, i, j):
Initialize empty list for neighbours
for each (di, dj) in [(-1,-1), (-1,0), ..., (1,1)] excluding (0,0):
ni = (i + di) % grid_size
nj = (j + dj) % grid_size
Add grid[ni][nj] to neighbours list



Return neighbours

→ Update states of all cells in the Grid
the function is used for get the neighboring cells, identify the neighbor with best fitness, and move cells towards the best neighbor's position.
def update_states(grid, fitness, learning_rate):
Initialize new_grid as a copy of grid
For each cell (i,j) in grid:
Get neighbours of cell (i,j)
Find the best_neighbor with minimum fitness
Update cell position:
new_grid[i,j] = grid[i,j] + learning_rate * (best_neighbor - grid[i,j])
Return new_grid

→ Main Parallel Cellular Algorithm :-
The main algorithm includes initialize the population grid, and for a given number of iterations evaluate fitness, update states based on neighbors & track best solution, and output best solution & fitness.
def parallel_cellular_algorithm(grid_size, solution_dim, lower_bound, upper_bound, iterations, learning_rate):
Initialize grid with random positions
Set best_solution = None and best_fitness = infinity
For iteration in range(iterations):
Evaluate fitness of all cells
Identify current best solution and fitness
If current fitness is better than best_fitness:
Update best_solution and best_fitness
Update cell states using neighbors and learning_rate
Print current best fitness
Output best_solution and best_fitness



Code:

```
#pcap
import numpy as np

# Define the problem: A simple optimization function (e.g., Sphere Function)
def optimization_function(position):
    """Example: Sphere Function for minimization."""
    return sum(x**2 for x in position)

# Initialize Parameters
GRID_SIZE = (10, 10)  # Grid size (rows, columns)
NEIGHBORHOOD_RADIUS = 1  # Moore neighborhood radius
DIMENSIONS = 2  # Number of dimensions in the solution space
ITERATIONS = 30  # Number of iterations

# Initialize Population
def initialize_population(grid_size, dimensions):
    """Initialize a grid with random positions."""
    population = np.random.uniform(-10, 10, size=(grid_size[0], grid_size[1], dimensions))
```

```
    return population

# Evaluate Fitness
def evaluate_fitness(population):
    """Calculate the fitness of all cells."""
    fitness = np.zeros((population.shape[0], population.shape[1]))
    for i in range(population.shape[0]):
        for j in range(population.shape[1]):
            fitness[i, j] = optimization_function(population[i, j])
    return fitness

# Get Neighborhood
def get_neighborhood(grid, x, y, radius):
    """Get the neighbors of a cell within the specified radius."""
    neighbors = []
    for i in range(-radius, radius + 1):
        for j in range(-radius, radius + 1):
            if i == 0 and j == 0:
                continue  # Skip the current cell
            ni, nj = x + i, y + j
            if 0 <= ni < grid.shape[0] and 0 <= nj < grid.shape[1]:
                neighbors.append((ni, nj))
    return neighbors

# Update States
def update_states(population, fitness):
    """Update the state of each cell based on its neighbors."""
    new_population = np.copy(population)
    for i in range(population.shape[0]):
        for j in range(population.shape[1]):
            neighbors = get_neighborhood(population, i, j, NEIGHBORHOOD_RADIUS)
            best_neighbor = population[i, j]
            best_fitness = fitness[i, j]

            # Find the best position among neighbors
            for ni, nj in neighbors:
                if fitness[ni, nj] < best_fitness:
                    best_fitness = fitness[ni, nj]
                    best_neighbor = population[ni, nj]

            # Update the cell state (move towards the best neighbor)
            new_population[i, j] = (population[i, j] + best_neighbor) / 2  # Average position
    return new_population
```

```
# Main Algorithm
def parallel_cellular_algorithm():
    """Implementation of the Parallel Cellular Algorithm."""
    population = initialize_population(GRID_SIZE, DIMENSIONS)
    best_solution = None
    best_fitness = float('inf')

    for iteration in range(ITERATIONS):
        # Evaluate fitness
        fitness = evaluate_fitness(population)

        # Track the best solution
        min_fitness = np.min(fitness)
        if min_fitness < best_fitness:
            best_fitness = min_fitness
            best_solution = population[np.unravel_index(np.argmin(fitness), fitness.shape)]

        # Update states based on neighbors
        population = update_states(population, fitness)

        # Print progress
        print(f"Iteration {iteration + 1}: Best Fitness = {best_fitness}")

    print("\nBest Solution Found:")
    print(f"Position: {best_solution}, Fitness: {best_fitness}")

# Run the algorithm
if __name__ == "__main__":
    parallel_cellular_algorithm()
```

OUTPUT:

```
Iteration 1: Best Fitness = 0.43918427791098213
Iteration 2: Best Fitness = 0.43918427791098213
Iteration 3: Best Fitness = 0.062221279350329436
Iteration 4: Best Fitness = 0.030149522005462108
Iteration 5: Best Fitness = 0.015791278460696168
Iteration 6: Best Fitness = 0.0025499667118763104
Iteration 7: Best Fitness = 0.0025499667118763104
Iteration 8: Best Fitness = 0.00019007166980743008
Iteration 9: Best Fitness = 0.00019007166980743008
Iteration 10: Best Fitness = 1.0432171933623911e-05
Iteration 11: Best Fitness = 8.406928148912647e-06
Iteration 12: Best Fitness = 5.511032710180021e-07
Iteration 13: Best Fitness = 4.3084388056725156e-07
Iteration 14: Best Fitness = 2.315054420755622e-07
Iteration 15: Best Fitness = 5.245753459404661e-08
Iteration 16: Best Fitness = 5.245753459404661e-08
Iteration 17: Best Fitness = 4.341357920017173e-08
Iteration 18: Best Fitness = 1.145644119860328e-08
Iteration 19: Best Fitness = 3.147791691706415e-09
Iteration 20: Best Fitness = 2.8192306881167533e-09
Iteration 21: Best Fitness = 9.788374665398935e-11
Iteration 22: Best Fitness = 9.788374665398935e-11
Iteration 23: Best Fitness = 9.788374665398935e-11
Iteration 24: Best Fitness = 9.788374665398935e-11
Iteration 25: Best Fitness = 7.537171686605552e-11
Iteration 26: Best Fitness = 7.234639306921671e-11
Iteration 27: Best Fitness = 7.028872029493468e-11
Iteration 28: Best Fitness = 3.340290444524624e-11
Iteration 29: Best Fitness = 1.4953679944431498e-11
Iteration 30: Best Fitness = 1.0817118995466254e-11

Best Solution Found:
Position: [-2.92599538e-06 -1.50188883e-06], Fitness: 1.0817118995466254e-11
```

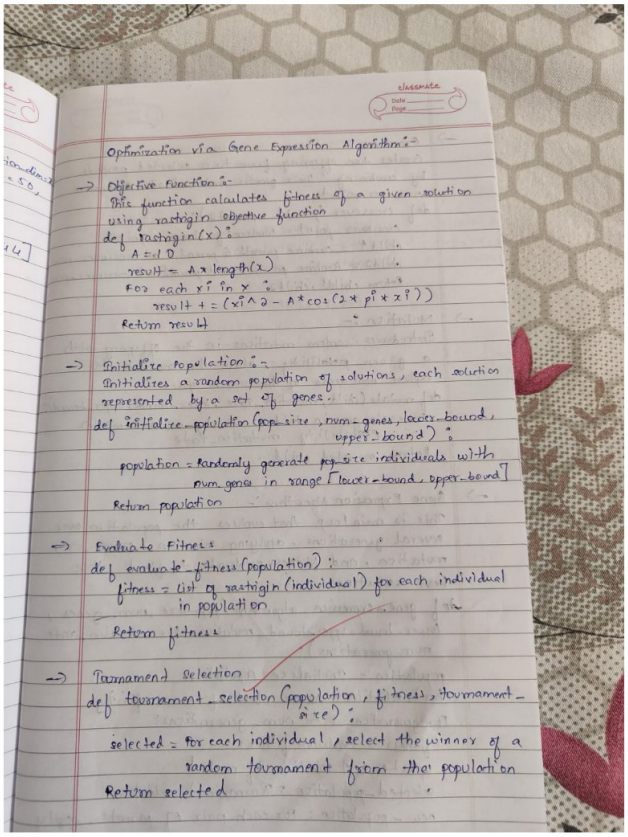
<u>Program 7:</u> Optimization via Gene Expression Algorithms:

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.

Implementation Steps:

1. Define the Problem: Create a mathematical function to optimize.
2. Initialize Parameters: Set the population size, number of genes, mutation rate, crossover rate, and number of generations.
3. Initialize Population: Generate an initial population of random genetic sequences.
4. Evaluate Fitness: Evaluate the fitness of each genetic sequence based on the optimization function.
5. Selection: Select genetic sequences based on their fitness for reproduction.
6. Crossover: Perform crossover between selected sequences to produce offspring.
7. Mutation: Apply mutation to the offspring to introduce variability.
8. Gene Expression: Translate genetic sequences into functional solutions.
9. Iterate: Repeat the selection, crossover, mutation, and gene expression processes for a fixed number of generations or until convergence criteria are met.
10. Output the Best Solution: Track and output the best solution found during the iterations.

Algorithm:



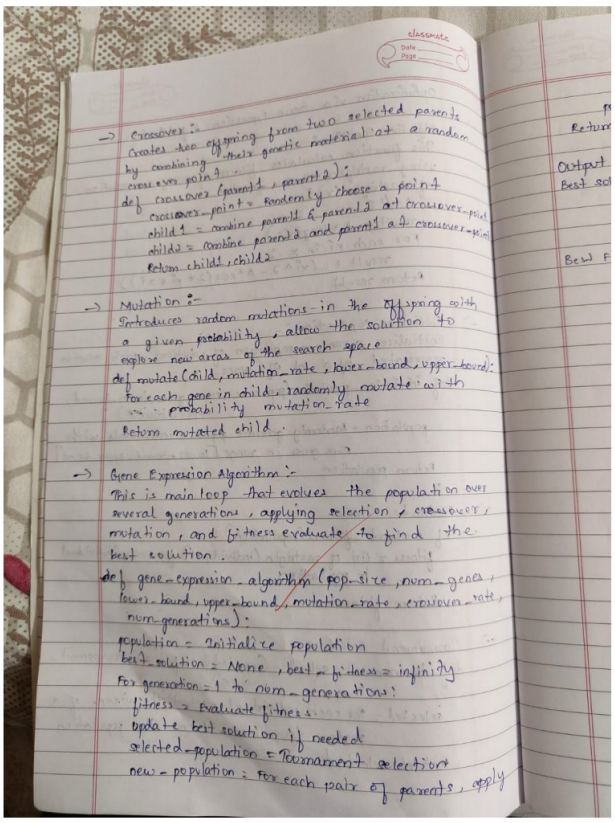
Optimization via Gene Expression Algorithm:-

→ Objective function :-
This function calculates fitness of a given solution using rastrigin objective function
def rastrigin(x):
A = 10
result = A * length(x)
For each xi in x:
result += (xi^2 - A*cos(2 * pi * xi))
Return result

→ Initialize population :-
Initializes a random population of solutions, each solution represented by a set of genes
def initialize_population(pop_size, num_genes, lower_bound, upper_bound):
population = randomly generate pop_size individuals with num_genes in range [lower_bound, upper_bound]
Return population

→ Evaluate Fitness
def evaluate_fitness(population):
fitness = list of rastrigin(individual) for each individual in population
Return fitness

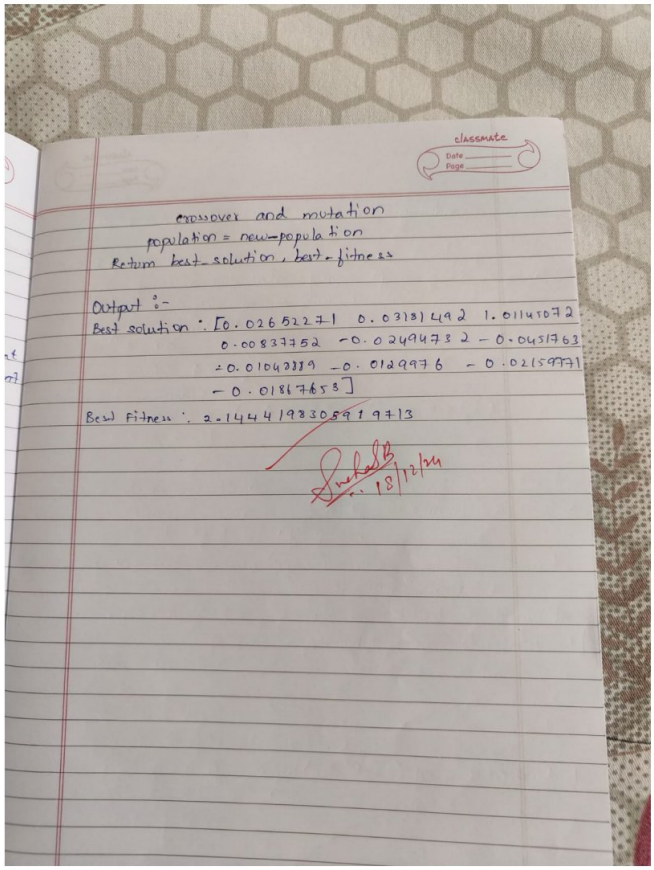
→ Tournament selection
def tournament_selection(population, fitness, tournament_size):
selected = for each individual, select the winner of a random tournament from the population
Return selected



→ Crossover :-
Creates the offspring from two selected parents by combining their genetic material at a random crossover point
def crossover(parent1, parent2):
crossover_point = Randomly choose a point
child1 = combine parent1 & parent2 at crossover_point
child2 = combine parent2 and parent1 at crossover_point
Return child1, child2

→ Mutation :-
Introduces random mutations in the offspring with a given probability, allow the solution to explore new areas of the search space
def mutate(child, mutation_rate, lower_bound, upper_bound):
For each gene in child: randomly mutate with probability mutation_rate
Return mutated child

→ Gene Expression Algorithm :-
This is main loop that evolves the population over several generations, applying selection, crossover, mutation, and fitness evaluate to find the best solution.
def gene_expression_algorithm(pop_size, num_genes, lower_bound, upper_bound, mutation_rate, crossover_rate, num_generations):
population = initialize population
best_solution = None, best_fitness = infinity
For generation = 1 to num_generations:
fitness = Evaluate fitness
update best solution if needed
selected_population = Tournament selection
new_population = for each pair of parents, apply



Code:

```
import numpy as np
import random

# 1. Define the Problem: Optimization Function (e.g., Sphere Function)
def optimization_function(solution):
    """Sphere Function for minimization (fitness evaluation)."""
    return sum(x**2 for x in solution)

# 2. Initialize Parameters
POPULATION_SIZE = 50  # Number of genetic sequences (solutions)
GENES = 5  # Number of genes per solution
MUTATION_RATE = 0.1  # Probability of mutation
CROSSOVER_RATE = 0.7  # Probability of crossover
GENERATIONS = 30  # Number of generations to evolve
```

```
# 3. Initialize Population
def initialize_population(pop_size, genes):
    """Generate initial population of random genetic sequences."""
    return np.random.uniform(-10, 10, (pop_size, genes))

# 4. Evaluate Fitness
def evaluate_fitness(population):
    """Evaluate the fitness of each genetic sequence."""
    fitness = [optimization_function(solution) for solution in population]
    return np.array(fitness)

# 5. Selection: Tournament Selection
def select_parents(population, fitness, num_parents):
    """Select parents using tournament selection."""
    parents = []
    for _ in range(num_parents):
        tournament = random.sample(range(len(population)), 3)  # Randomly select 3 candidates
        best = min(tournament, key=lambda idx: fitness[idx])
        parents.append(population[best])
    return np.array(parents)

# 6. Crossover: Single-Point Crossover
def crossover(parents, crossover_rate):
    """Perform crossover between pairs of parents."""
    offspring = []
    for i in range(0, len(parents), 2):
        if i + 1 >= len(parents):
            break
        parent1, parent2 = parents[i], parents[i + 1]
        if random.random() < crossover_rate:
            point = random.randint(1, len(parent1) - 1)  # Single crossover point
            child1 = np.concatenate((parent1[:point], parent2[point:]))
            child2 = np.concatenate((parent2[:point], parent1[point:]))
        else:
            child1, child2 = parent1, parent2  # No crossover
        offspring.extend([child1, child2])
    return np.array(offspring)

# 7. Mutation
def mutate(offspring, mutation_rate):
    """Apply mutation to introduce variability."""
    for i in range(len(offspring)):
        for j in range(len(offspring[i])):
```

```
            if random.random() < mutation_rate:
                offspring[i][j] += np.random.uniform(-1, 1)  # Random small change
    return offspring

# 8. Gene Expression: Functional Solution (No transformation needed for this case)
def gene_expression(population):
    """Translate genetic sequences into functional solutions."""
    return population  # Genetic sequences directly represent solutions here.

# 9. Main Function: Gene Expression Algorithm
def gene_expression_algorithm():
    """Implementation of Gene Expression Algorithm for optimization."""
    # Initialize population
    population = initialize_population(POPULATION_SIZE, GENES)
    best_solution = None
    best_fitness = float('inf')

    for generation in range(GENERATIONS):
        # Evaluate fitness
        fitness = evaluate_fitness(population)

        # Track the best solution
        min_fitness_idx = np.argmin(fitness)
        if fitness[min_fitness_idx] < best_fitness:
            best_fitness = fitness[min_fitness_idx]
            best_solution = population[min_fitness_idx]

        # Selection
        parents = select_parents(population, fitness, POPULATION_SIZE // 2)

        # Crossover
        offspring = crossover(parents, CROSSOVER_RATE)

        # Mutation
        offspring = mutate(offspring, MUTATION_RATE)

        # Gene Expression
        population = gene_expression(offspring)

        # Print progress
        print(f"Generation {generation + 1}: Best Fitness = {best_fitness}")

    # Output the best solution
    print("\nBest Solution Found:")
```

```
    print(f"Position: {best_solution}, Fitness: {best_fitness}")

# 10. Run the Algorithm
if __name__ == "__main__":
    gene_expression_algorithm()
```

OUTPUT:

```
Generation 1: Best Fitness = 55.82997756903893
Generation 2: Best Fitness = 26.410565738143625
Generation 3: Best Fitness = 21.857647823851615
Generation 4: Best Fitness = 20.016914182036285
Generation 5: Best Fitness = 20.016914182036285
Generation 6: Best Fitness = 20.016914182036285
Generation 7: Best Fitness = 13.81760087982789
Generation 8: Best Fitness = 13.81760087982789
Generation 9: Best Fitness = 12.077725051361178
Generation 10: Best Fitness = 10.461698723345474
Generation 11: Best Fitness = 8.933105023570093
Generation 12: Best Fitness = 6.619449963941974
Generation 13: Best Fitness = 3.1567413435369454
Generation 14: Best Fitness = 3.1567413435369454
Generation 15: Best Fitness = 3.1567413435369454
Generation 16: Best Fitness = 2.74585545305795
Generation 17: Best Fitness = 2.7031453676198964
Generation 18: Best Fitness = 2.078188177116774
Generation 19: Best Fitness = 1.5193087227027497
Generation 20: Best Fitness = 1.4413606561895607
Generation 21: Best Fitness = 0.8501569187378994
Generation 22: Best Fitness = 0.4209372164676112
Generation 23: Best Fitness = 0.3893761873774093
Generation 24: Best Fitness = 0.3893761873774093
Generation 25: Best Fitness = 0.3893761873774093
Generation 26: Best Fitness = 0.3741053651316379
Generation 27: Best Fitness = 0.1381555631914642
Generation 28: Best Fitness = 0.12238160343023853
Generation 29: Best Fitness = 0.12238160343023853
Generation 30: Best Fitness = 0.12238160343023853

Best Solution Found:
Position: [-0.03614343 -0.00257499  0.02260677  0.31412563  0.14792784], Fitness: 0.12238160343023853
```