VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

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Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled " Bio Inspired Systems (23CS5BSBIS)" carried out by **Santosh Hanamappa Jambagi (1BM22CS244),** 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/SantoshJambagi2004/Bio_Inspired_Systems

Program 1: Genetic Algorithm for Optimization on Problems

Algorithm:

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1) Genetic Algorithm For Optimization Problems:

Pseudocode:

```
function GeneticAlgorithm():
    // Initialize parameters
    Initialize parameters(population_size, mutation_rate,
        crossover_rate, num_generations, range_min, range_max)

    // create initial population
    population = InitializePopulation(population_size, range_min,
                                      range_max)

    for generation in 1 to num_generations:
        // Evaluate fitness
        fitness = EvaluateFitness(population)

        new_population = [ ]
        // generate new population
        for i from 1 to population_size/2:
            parent1, parent2 = Selection(population, fitness)

            offspring1, offspring2 = Crossover(parent1, parent2)
            new_population.append(Mutate(offspring1))
            new_population.append(Mutate(offspring2))

    population = new_population
    best_fitness = Max(fitness)
    best_solution = population[Arg Max(fitness)]

    return best_solution, FitnessFunction(best_solution)
```

```
population_size = 100
num_generations = 50
mutation_rate = 0.1
crossover_rate = 0.7
x_range = (-10, 10)

def initialize_population(size, x_range):
    return np.random.uniform(x_range[0], x_range[1], size)

def objective_function(x):
    return x**2

def crossover(parent1, parent2):
    return (parent1 + parent2)/2  # simple averaging fn

def mutate(offspring, mutation_rate, x_range):
    if np.random.rand() < mutation_rate:
        return np.random.uniform(x_range[0], x_range[1])
    return offspring.
```

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

Algorithm:

2) Particle Swarm Optimization for Function Optimization.

1. Objective Function

```
def objective_function(x):
    return x**2
```

2. PSO Algorithm:

```
def pso(num_particles, max_iter, w, c1, c2, dim):
    # initialize particles' positions & velocities
    positions = np.random.uniform(-10, 10, (num_particles, dim))

    # Random velocities
    velocities = np.random.uniform(-1, 1, (num_particles, dim))

    personal_best_positions = positions.copy()

    personal_best_scores = np.array([objective_function(pos)
                                     for pos in positions])

    global_best_position = personal_best_positions[np.argmin
                                     (personal_best_scores)]

    global_best_score = np.min(personal_best_scores)
```

3. Main PSO Loop:

```
for iter in range(max_iter):
    for i in range(num_particles):
    # update velocity and position
    r1, r2 = np.random.rand(2)    # random number for each particle
    velocities[i] = w * velocities[i] + c1*r1*(personal_best_positions[i]
    positions[i] + c2*r2*(global_best_position
```

```
        positions[i] = positions[i] + velocities[i]

        # evaluate fitness of the new position
        fitness = objective_function(position[i])

        # Update personal best
        if fitness < personal_best_scores[i]:
            personal_best_scores[i] = fitness
            personal_best_positions[i] = positions[i]
```

4. Update Global best

```
min_score_index = np.argmin(personal_best_scores)
if (personal_best_scores[min_score_index] < global_best_score:
    global_best_score = personal_best_scores[min_score_index]
    global_best_position = personal_best_positions[min_scores_index]

return global_best_position, global_best_score
```

5. Initialize values

```
num_particles = 30
max_iter      = 100
w  = 0.7        # inertia weight
c1 = 1.5        # cognitive coefficient
c2 = 1.5        # social coefficient
dim = 1
```

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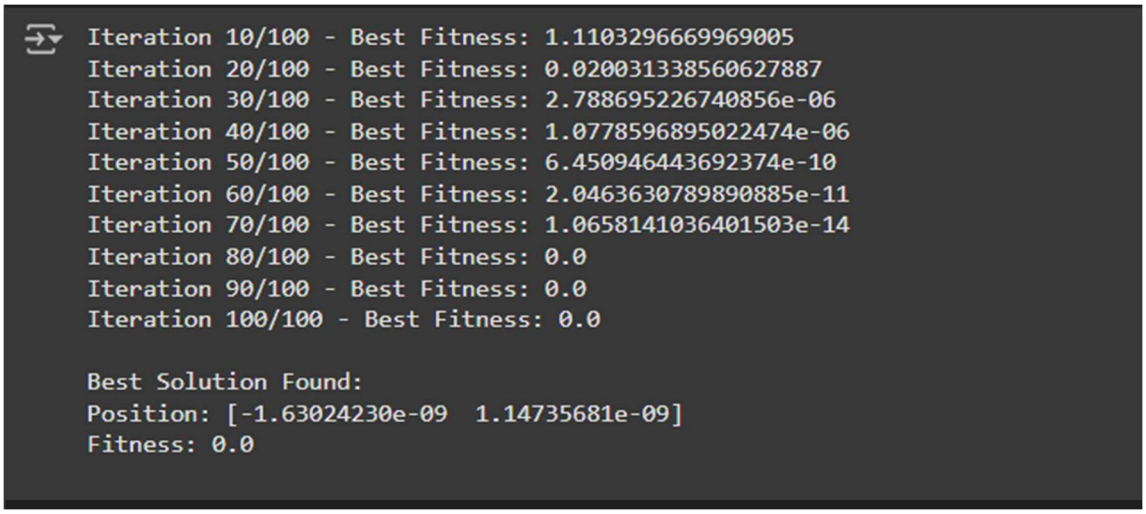
Code:

```
#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:



Program 3: Ant Colony Optimization for the Traveling Salesman Problem

Algorithm:

3) Ant colony Optimization for the Travelling Salesman Problem:

1. Initialize necessary parameters
   N (Number of ants) ← 20
   M (Number of cities) ← 10
   alpha ← Influence of pheromone (b/w 1 & 2)
   beta ← Influence of heuristic (—— " ——)
   rho ← pheromone evaporation rate (b/w 0 & 1)
   Q ← pheromone deposit factor
   max_iterations ←

2. Initialize pheromone trail (T) on edges
   T(i,j) = T0 for all edges (i,j)
   Initialize cost or distance matrix D
   D(i,j) ← the distance between cities i and j

3. for i in range(max_iterations):

   for k in range(N):
   path[k] ← [ ]
   visited[k] ← [ ]
   current_city ← random_start_city
   visited[k].add(current_city)

   // construct solution by moving from city to city
   while not all cities are visited by ant k do:

$$P(i,j) = [T(i,j)^{alpha} * \eta(i,j)^{beta}] / sum(T(i,j)^{alpha} * \eta(i,j)^{beta})$$

where $\eta(i,j) = 1/D(i,j)$ (inverse Distance)

// 6 select the next city j based on calculated prob

// 7 Add city j to the ant's path and mark it as visited

```
path[k].append(j)
visited[k].add(j)
current_city[k] ← j
```

// 8 Calculate the length of the path for ant k

```
Length[k] ← total distance
```

// 9 Update the best solution if the current path is shorter

```
If Length[k] < best_length:
    best_solution ← path[k]
    best_path ← Length[k]
```

// Update pheromone trail after all ants have completed their tours

```
for edge(i,j) do:
    T(i,j) ← (1 - rho) * T(i,j)
```

// Deposit pheromone trail after all ants have completed their tours

```
for each ant k do:
    for each edge (i,j) in path[k] do:
        T(i,j) ← T(i,j) + Q/Length[k]
```

return best_solution, best_length.

Code:

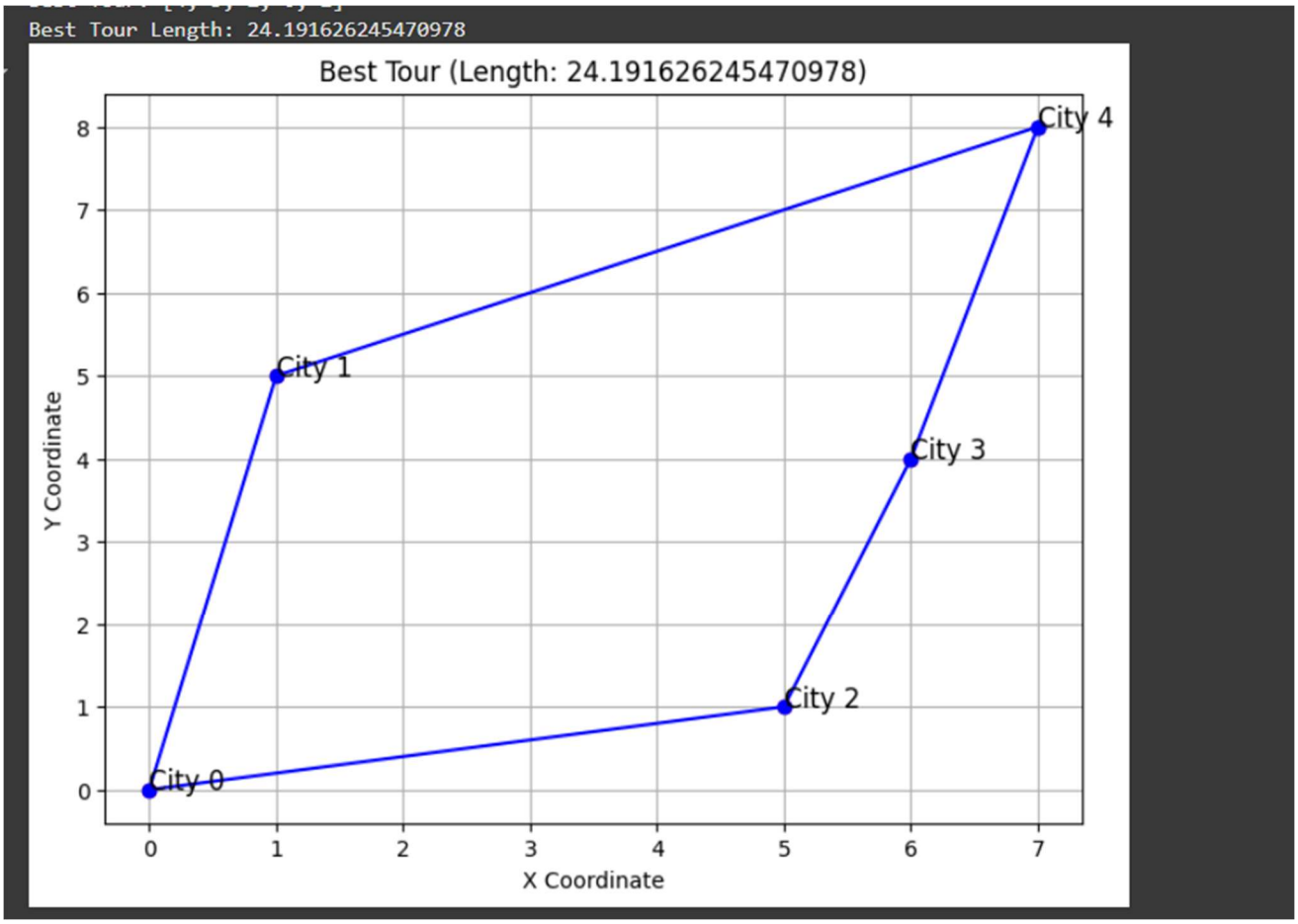
```
#ant colony
import numpy as np
import matplotlib.pyplot as plt

# 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
```



Program 4: Cuckoo Search (CS)

Algorithm:

4) Cuckoo search (CS):

```
import numpy as np

step 1: Initialise nests with random positions
def initialize_nests(N, dim, bounds):
    return np.random.uniform(bounds[0], bounds[1], (N, dim))

step 2: Fitness Evaluation function
def evaluate_fitness(nests, objective_function):
    return np.array([objective_function for nest in nests])

step 3: Levy Flight to generate new solution
def levy_flight(nests, alpha=1.0):
    N,
    for i in range(N):
        u = np.random.normal(0, 1, dim)
        v = np.random.normal(0, 1, dim)
        step = u / (np.abs(v) ** (1.0 / alpha))

        new_nests[i] = nests[i] + step * 0.01
    return new_nests.

def get_best_nest(nests, fitness):
    best_idx = np.argmin(fitness)
    return nests[best_idx], fitness[best_idx]
```

```
def cuckoo_search(N, dim, bounds, max_iter=100, pa=0.25, alpha
                                                        =1.0):

    # Initialize nests
    nests = initialize_nests(N, dim, bounds)
    # Evaluate fitness of initial nests
    fitness = evaluate_fitness(nests, objective_function)
    # Track the best nest
    best_nest, best_fitness = get_best_nest(nests, fitness)

    # Iterate over max_iter
    for i in range(max_iter):
        # Generate new solutions via levy flights
        new_nests = levy_flight(nests, alpha)

        new_fitness = evaluate_fitness(new_nests, objective_fn)

        nests, fitness = abandon_worst_nests(nests, fitness,
                                    new_nests, new_fitness, pa)

        # Track the best solution found
        current_best_nest, current_best_fitness =
                                    get_best_nest(nests, fitness)

        # If the current soln is better, update the best solution
        if current_best_fitness < best_fitness:
            best_nest = current_best_nest
            best_fitness = current_best_fitness

    return best_nest, best_fitness

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N = 20          # Number of nests
dim = 2         # problem dimension
bounds = (-5,5)  # search space bounds
```
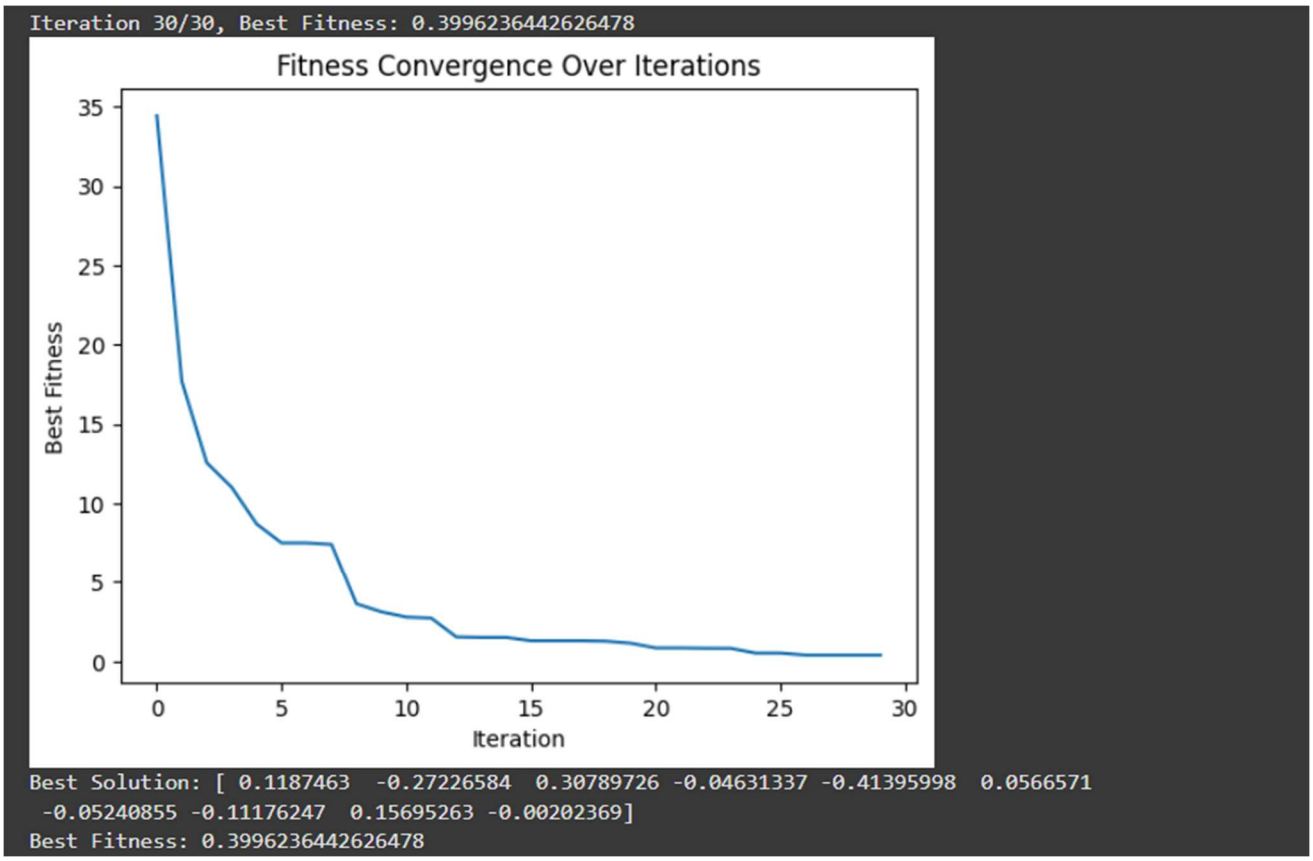

Code:

```
#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
```



Program 5: Grey Wolf Optimizer (GWO)

Algorithm:

28/11/24

5) Grey Wolf Optimizer (GWO):

Pseudocode:

Step 1: Randomly initialize Grey Wolf Optimization population of N particles X_i $(i = 1, 2, \ldots, n)$

Step 2: Calculate the fitness of each individuals

sort grey wolf population based on fitness value

alpha_wolf = wolf with least fitness value

beta_wolf = wolf with second least fitness value

gamma_wolf = wolf with third least fitness value

Step 3: For Iter in range(max_iter):

calculate the value of a

$a = 2 * (1 - Iter / max\_iter)$

For i in range (N):

a. compute the value of A1, A2, A3 and C1, C2, C3

$A1 = a * (2 * r1 - 1)$, $A2 = a * (2 * r2 - 1)$, $A3 = a * (2 * r3 - 1)$

$C1 = 2 * r1$, $C2 = 2 * r2$, $C3 = 2 * r3$

b. compute X1, X2, X3

$X1 = alpha\_wolf.position - A1 * abs(C1 * alpha\_wolf\_position - ith\_wolf\_pos)$

$X2 = beta\_wolf\_position - A2 * abs(C2 * beta\_wolf\_position - ith\_wolf.position)$

$X3 = gamma\_wolf\_position - A3 * abs(C3 * gamma\_wolf\_position - ith\_wolf\_position)$

c. compute new solution & it's fitness

$Xnew = (X1 + X2 + X3) / 3$

$fnew = fitness(Xnew)$

d. Update the ith_wolf greedily

if (fnew < ith_wolf.fitness)

ith_wolf.position = Xnew

ith_wolf.fitness = fnew

End for

#compute new alpha, beta and gamma

alpha_wolf = wolf with least fitness values

beta_wolf = wolf with second least fitness values

gamma_wolf = wolf with third least fitness value.

End for

Step 4: Return best wolf in the population.

Code:

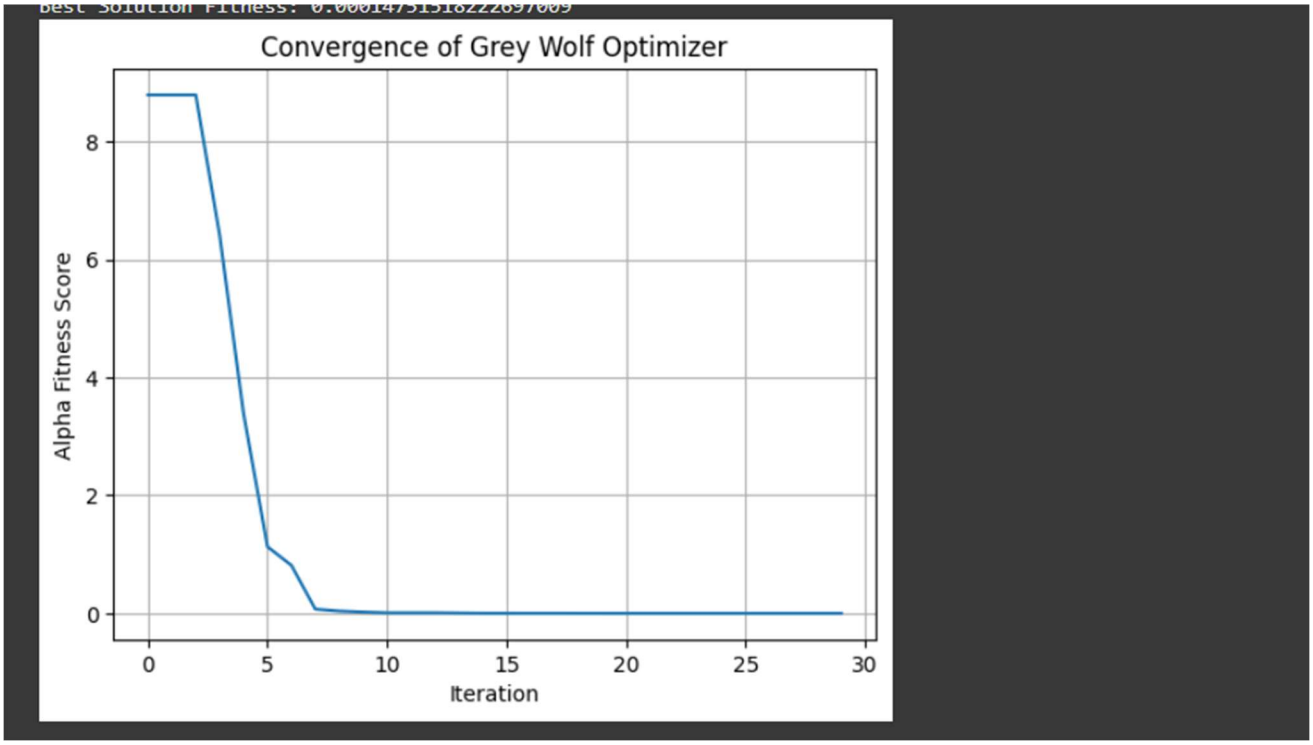
```
#GWO
import numpy as np
import matplotlib.pyplot as plt

# 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
```



Program 6: Parallel Cellular Algorithms and Programs

Algorithm:

6) Parallel Cellular Algorithms and programs

Function ParallelCellularAlgorithm:

```
Define objectiveFunction()
InitializeGrid(GridSize)
For each cell in the grid:
    Randomly initialize cell's position in the solution space
# Evaluate Fitness
For each cell in the grid:
    EvaluateFitness(cell)

# Update states
For iteration = 1 to MaxIterations:
    For each cell in the grid:
        neighbours = GetNeighbours(cell, neighbourhood)
        newState = calculateNewState(cell, neighbours)
        cell.state = newState

    For each in the grid:
        EvaluateFitness(cell)

    TrackBestSolution()

Output BestSolution()
```

```
Initialize parameters
Set GridSize = (rows, cols)
Set NumCells = rows * cols
Set MaxIterations = 1000
Set convergenceThreshold = 0.001
```

```
Function InitializeGrid(Gridsize):
    Initialize cells with random positions

Function EvaluateFitness(cell):
    cell.fitness = ObjectiveFunction(cell.state)

Function GetNeighbours(cell, neighbourhood)
    return the list of neighbouring cells.

Function CalculateNewState(cell, neighbours)
    Return new state for the cell based on predefined
    rules.

Function TrackBestSolution():
    bestsolution = min(bestSolution, cell)
```

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
```

Program 7: Optimization via Gene Expression Algorithms

Algorithm:

7) Optimization via Gene Expression Algorithms:

```
Function GeneExpressionAlgorithm:
    #step 1
    Define objectiveFunction()

    #step 2: Initialize parameters
    Set population=100, NumGenes=10, MutationRate=0.05,
    CrossoverRate=0.7, NumGenerations=1000

    #step 3: Initialize population
    population = InitializePopulation(populationSize, NumGenes)

    #step 4: Evaluate Fitness
    For each individual in population:
        EvaluateFitness(individual)

    For generation=1 to NumGenerations:
        selected = SelectIndividuals(population)
        offspring = Crossover(selected)
        MutateOffspring(offspring, MutationRate)

    For each individual in offspring:
        individual.solution = DecodeGenes(individuals.genes)
        EvaluateFitness(individual)

        TrackBestSolution()

o   output BestSolution.
```

Date: Page:

```
Function Initialize population (population size, Num Genes):
    Return [GenerateRandom Genes(Num Genes)]

Function EvaluateFitness (individual):
    individual.fitness = Objective Function (individual.genes)

Function crossover (selected):
    Return [Perform crossover (selected[i], selected[i+1])]

Function Mutate OffSpring (offspring, MutationRate):
    For each individual in offspring:
        If Random() < MutationRate:
            Mutate (individual)

Function TrackBestSolution():
    bestsolution = min (best Solution, individual)
```

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
```