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

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in
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CERTIFICATE

This is to certify that the Lab work entitled " Bio Inspired Systems (23CS5BSBIS)" carried out by **Samraat Dabolay (1BM22CS236),** who is a 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/samraatd/BIS-LAB

Program 1: Genetic Algorithm for Optimization Problems

Problem Statement: Implement a Genetic Algorithm using Python to solve a basic optimization problem, such as finding the maximum value of a mathematical function.

Algorithm:

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Algorithm 1 : Genetic Algorithm for Optimisation Problems

```
Initialise_population ( bounds , n ) {
        random.uniform ( bounds [0], bounds [1] , 1 ) }

Evaluate - fitness ( population ) {
        ~~objective~~ function ( i ) for i in population }

Roulette - wheel ( pop , scores ) {
        total ← sum (scores)
        prob ← 1 - score / total for each score
        selection ← random.choice ( len (pop) , p )
        p ← prob / sum (prob)
        return pop [ selection ]

Crossover ( p1 , p2 , α ):
    return offspring = alpha * p1 [0] + (1 - α) * p2[0

Mutation ( individuals , bounds , rate ) :
    if random ( ) < rate :
        return [ random.uniform ( bounds [0], bounds[
    return individual

Genetic - Algorithm ( bounds , iter , n-pop , rate ) :
    pop ← initialise population ( bounds , n - pop )
    best , best - eval ← pop [0] , function ( pop [0] )
```

for gen in range (iter):
scores ← evaluate - fitness (pop)
for i in range (n - pop):
if scores[i] < best - eval:
best, best - eval ← pop[i], scores[i]

children = [ ]
for _ in range (n - pop):
p1 ← roulette - wheel (pop, scores)
p2 ← roulette - wheel (pop, scores)

child ← crossover (p1, p2)
child ← mutation (child, bounds, rate)
Add child to children list
pop ← children
return [best, best - eval]

Input:
Range / bounds = [-10, 10]
Total iterations = 50
Population size = 100
Mutation rate = 0.1
Alpha = 0.5

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Code:

```
import numpy as np


# Objective function: f(x) = x^2
def objective(x):
    return x[0] ** 2 + 2*x[0] + 1
```

```
# Initialization: generate initial population
def initialize_population(bounds, n_pop):
    return [np.random.uniform(bounds[0], bounds[1], 1).tolist() for _ in range(n_pop)]


# Fitness evaluation
def evaluate_fitness(pop):
    return [objective(ind) for ind in pop]


# Roulette wheel selection
def roulette_wheel_selection(pop, scores):
    total_fitness = sum(scores)
    probabilities = [1 - (score / total_fitness) for score in scores]
    selection_ix = np.random.choice(len(pop), p=np.array(probabilities) / sum(probabilities))
    return pop[selection_ix]


# Crossover: linear combination of parents
def crossover(p1, p2, alpha=0.5):
    offspring = alpha * p1[0] + (1 - alpha) * p2[0]
    return [offspring]  # Ensure offspring is a list


# Mutation: random value within bounds
def mutation(individual, bounds, r_mut):
    if np.random.rand() < r_mut:
        return [np.random.uniform(bounds[0], bounds[1])]
    return individual


# Genetic algorithm
def genetic_algorithm(bounds, n_iter, n_pop, r_mut):
    # Initialize population
    pop = initialize_population(bounds, n_pop)
    best, best_eval = pop[0], objective(pop[0])


    for gen in range(n_iter):
        # Evaluate fitness
        scores = evaluate_fitness(pop)
```

```
        # Check for new best solution
        for i in range(n_pop):
            if scores[i] < best_eval:
                best, best_eval = pop[i], scores[i]
                print(f">{gen}, new best f({pop[i]}) = {scores[i]:.6f}")


        # Select parents and create offspring
        children = []
        for _ in range(n_pop):
            p1 = roulette_wheel_selection(pop, scores)
            p2 = roulette_wheel_selection(pop, scores)
            offspring = crossover(p1, p2)
            offspring = mutation(offspring, bounds, r_mut)  # Pass as list
            children.append(offspring)


        # Replace population with new offspring
        pop = children


    return [best, best_eval]


# Define range for input
bounds = [-10.0, 10.0]
# Define the total iterations
n_iter = 50
# Define the population size
n_pop = 100
# Mutation rate
r_mut = 0.1


# Perform the genetic algorithm search
best, score = genetic_algorithm(bounds, n_iter, n_pop, r_mut)
print('Done!')
print(f'f({best}) = {score:.6f}')
```

Output:

```
>0, new best f([-5.666534385599229]) = 21.776543
>0, new best f([1.080175298094792]) = 4.327129
>0, new best f([-1.5931328574092856]) = 0.351807
>0, new best f([-1.5653111777364508]) = 0.319577
>0, new best f([-0.8482241989814483]) = 0.023036
>0, new best f([-1.0705269641866977]) = 0.004974
>1, new best f([-0.9332442167834278]) = 0.004456
>1, new best f([-1.022829583444282]) = 0.000521
>6, new best f([-0.9958642058435989]) = 0.000017
>14, new best f([-0.9989132354583119]) = 0.000001
>40, new best f([-0.999748411998941]) = 0.000000
Done!
f([-0.999748411998941]) = 0.000000
```

Program 2: Particle Swarm Optimization for Function Optimization

Problem Statement: Implement the PSO algorithm using Python to optimize a mathematical function.

Algorithm:

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Algorithm 2 : Particle Swarm Optimization

Fitness - function (x_1, x_2) :

$f_1 \leftarrow x1 - 2(x2) + 3$

$f_2 \leftarrow 2x1 + x2 - 8$

$z \leftarrow f1^2 + f2^2$

return z

Update - velocity (particle, velocity , pbest , gbest) :

Inertia

$\omega \leftarrow$ random . uniform (w-min, max)

Social & Cognitive components

$c_1 \leftarrow c$

$c_2 \leftarrow c$

$r_1 \leftarrow$ random . uniform (0 , max)

$r_2 \leftarrow$ random . uniform (0 , max)

new - velocity $\leftarrow$ [0 ..... num - particle]

for $i \leftarrow 0$ to num particle

new - velocity [i] $\leftarrow$ w * velocity [i] + c1 * r1 * (pbest [i] - particle [i]) + c2 * r2 * (gbest [i] - particle [i])

return new - velocity

Update - position (particle , velocity) :

new - particle $\leftarrow$ particle + velocity

return new - particle

pso_2d (population, dimension, pos_min, pos_max, generation, fitness_criteria):

```
particles ← [[random.uniform(pos_min, pos_max)
        for j ← 0 to dimension] for
            i ← 0 to population]

pbest_pos ← particles
pbest_fitness ← fitness_function (p[0], p[1])
                    for all p in particles

gbest_index ← min (pbest_fitness)
gbest_pos ← pbest_pos [gbest_index]
velocity ← [0... dimension] for i in range of
                    population

for t ← 0 to generation
    if average (pbest_fitness) <= fitness_criteria
        break
    else
        for n ← 0 to population
            velocity[n] ← update_velocity (
                    particles[n], velocity[n],
                    pbest_pos[n], gbest_pos)

            particles[n] ← update_position (
                    particles[n], velocity[n])

        pbest_fitness ← fitness_function (p[0], p[1])
        gbest_index ← min (pbest_fitness)
        gbest_pos ← pbest_pos [gbest_index]
```

Inputs :

population = 100

dimension = 2

pos_min = -100.0

pos_max = 100

generation = 100

fitness_criterion = 10e-6

SSO
7/11/24.

Code:

```
import random
import numpy as np
from matplotlib import pyplot as plt
def fitness_function(x1,x2):
  f1=x1+2*-x2+3
  f2=2*x1+x2-8
  z = f1**2+f2**2
  return z


def update_velocity(particle, velocity, pbest, gbest, w_min=0.5, max=1.0, c=0.1):
  # Initialise new velocity array
  num_particle = len(particle)
  new_velocity = np.array([0.0 for i in range(num_particle)])
  # Randomly generate r1, r2 and inertia weight from normal distribution
  r1 = random.uniform(0,max)
  r2 = random.uniform(0,max)
  w = random.uniform(w_min,max)
  c1 = c
  c2 = c
  # Calculate new velocity
  for i in range(num_particle):
    new_velocity[i] = w*velocity[i] + c1*r1*(pbest[i]-particle[i])+c2*r2*(gbest[i]-particle[i])
  return new_velocity
```

```
def update_position(particle, velocity):
  # Move particles by adding velocity
  new_particle = particle + velocity
  return new_particle



def pso_2d(population, dimension, position_min, position_max, generation, fitness_criterion):
  # Initialisation
  # Population
  particles = [[random.uniform(position_min, position_max) for j in range(dimension)] for i in
range(population)]
  # Particle's best position
  pbest_position = particles
  # Fitness
  pbest_fitness = [fitness_function(p[0],p[1]) for p in particles]
  # Index of the best particle
  gbest_index = np.argmin(pbest_fitness)
  # Global best particle position
  gbest_position = pbest_position[gbest_index]
  # Velocity (starting from 0 speed)
  velocity = [[0.0 for j in range(dimension)] for i in range(population)]


  # Loop for the number of generation
  for t in range(generation):
    # Stop if the average fitness value reached a predefined success criterion
    if np.average(pbest_fitness) <= fitness_criterion:
      break
    else:
      for n in range(population):
        # Update the velocity of each particle
        velocity[n] = update_velocity(particles[n], velocity[n], pbest_position[n], gbest_position)
        # Move the particles to new position
        particles[n] = update_position(particles[n], velocity[n])
    # Calculate the fitness value
    pbest_fitness = [fitness_function(p[0],p[1]) for p in particles]
    # Find the index of the best particle
```

```
    gbest_index = np.argmin(pbest_fitness)
    # Update the position of the best particle
    gbest_position = pbest_position[gbest_index]


  # Print the results
  print('Global Best Position: ', gbest_position)
  print('Best Fitness Value: ', min(pbest_fitness))
  print('Average Particle Best Fitness Value: ', np.average(pbest_fitness))
  print('Number of Generation: ', t)


population = 100
dimension = 2
position_min = -100.0
position_max = 100.0
generation = 100
fitness_criterion = 10e-6


pso_2d(population, dimension, position_min, position_max, generation, fitness_criterion)
```

Output:

```
Global Best Position:  [2.6000003  2.80000327]
Best Fitness Value:  5.3854415182325324e-11
Average Particle Best Fitness Value:  8.509552783246299e-06
Number of Generation:  86
```

Program 3: Ant Colony Optimization for the Traveling Salesman Problem

Problem Statement: Implement the ACO algorithm using Python to solve the TSP, where the objective is to find the shortest possible route that visits a list of cities and returns to the origin city.

Algorithm:

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Algorithm 3 Ant Colony Optimization for TSP

```
Inputcity ( ) :
    n ← no of cities
    cities ← list of city
    for i ← 0 to n
        input city [i] x,y coords.

    return cities

Distance (p1, p2) :
    return sqrt( sum( (p1 - p2) ** 2 ) )

Build _ Path ( n, pheromone, points , α , β ) :
    visited ← for i ← 0 to n all false
    visited [current] ← true
    current ← random( n-points )
    path ← [current]
    path - length ← 0

    while false in visited :
        probabilities ← [0 .... n] all zeros array
        unvisited ← find point which is not visited
                    using array

        for i , unvisited - point in unvisited :
            pherone - value ← pherone [current, unvisited point]
                                  ** α

            distance - value ← distance (points [current],
                         points [unvisited - point] ) ** β

            probabilities [i] = pherone _ value / distance - value
```

Sum and normalise probabi...

next_point ← random (unvisited , p = probabilities

path. append (next - point)

path - length += distance (points [current - point]

points[next - point])

visited [next - point] ← True

current - point ← next - point

return path, path_length

Update - pheromones (pheromone , paths , path - lengths ,

rho, Q) :

pheromone ← pheromone * rho

for path , path - length in their arrays :

for i ← 0 to n-1

pheromone [path[i] , path[i+1]] ← phe...

+ Q/path_len...

pheromone [path[-1], path[0]] += Q / path-length

return pheromone

Ant - Colony - Optimisation (points, n-ants , n , α , β , rho ...

n - points ← len(points)

pheromone ← [(1, 1), (1, 1) . . . .] for n-points

best - path - length ← ∞

for iter in range of n :

paths ← [ ]

path - lengths ← [ ]

for _ in range of n_ants :
path, path_length ← Build_path (n, pheromone, α, β, points)

paths. append (path)

path_lengths . append (path_length)

if path_length < best_path_length

best_path ← path

best_path_length ← path_length

pheromone ← update_pheromones (pheromones, paths, path_lengths, rho, Q)

return best_path , best_path_length

points ← input_city ( )

Inputs:

points,

n_ants = 10

n_iters = 100

α = 1

β = 1

rho = 0.5

Q = 1

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Code:

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

```
# 1. Define the Problem: Taking custom 2D city coordinates as input
def input_city_coordinates():
    """
    Function to input custom city coordinates.
    The user is prompted to input coordinates for each city.
    """
    n_cities = int(input("Enter the number of cities: "))
    cities = []


    for i in range(n_cities):
        # Taking x and y coordinates as input
        x, y = map(float, input(f"Enter coordinates for city {i + 1} (x, y): ").split())
        cities.append([x, y])


    return np.array(cities)  # Return as a NumPy array for convenience


# 2. Distance Function: Calculate Euclidean distance between two cities
def distance(point1, point2):
    return np.sqrt(np.sum((point1 - point2)**2))


# 3. Construct Solutions: Build a solution for each ant
def construct_solution(n_points, pheromone, points, alpha, beta):
    visited = [False] * n_points
    current_point = np.random.randint(n_points)  # Start from a random city
    visited[current_point] = True
    path = [current_point]
    path_length = 0


    while False in visited:
        unvisited = np.where(np.logical_not(visited))[0]
        probabilities = np.zeros(len(unvisited))


        # Calculate the probabilities for the unvisited cities
        for i, unvisited_point in enumerate(unvisited):
            pheromone_value = pheromone[current_point, unvisited_point] ** alpha
            distance_value = distance(points[current_point], points[unvisited_point]) ** beta
            probabilities[i] = pheromone_value / distance_value
```

```
            # Normalize the probabilities
            probabilities /= np.sum(probabilities)


            # Choose the next city based on probabilities
            next_point = np.random.choice(unvisited, p=probabilities)
            path.append(next_point)
            path_length += distance(points[current_point], points[next_point])
            visited[next_point] = True
            current_point = next_point


        return path, path_length


    # 4. Update Pheromones: Update pheromone levels based on the ants' solutions
    def update_pheromones(pheromone, paths, path_lengths, evaporation_rate, Q):
        pheromone *= evaporation_rate  # Evaporate all pheromones
        for path, path_length in zip(paths, path_lengths):
            for i in range(len(path) - 1):
                pheromone[path[i], path[i + 1]] += Q / path_length
            pheromone[path[-1], path[0]] += Q / path_length  # Close the loop
        return pheromone


    # 5. Main ACO Algorithm: Main function to run the ACO
    def ant_colony_optimization(points, n_ants, n_iterations, alpha, beta, evaporation_rate, Q):
        n_points = len(points)
        pheromone = np.ones((n_points, n_points))  # Initial pheromone levels
        best_path = None
        best_path_length = np.inf


        # 6. Iterate: Run the ACO for a set number of iterations
        for iteration in range(n_iterations):
            paths = []
            path_lengths = []


            # Construct solutions for each ant
            for _ in range(n_ants):
```

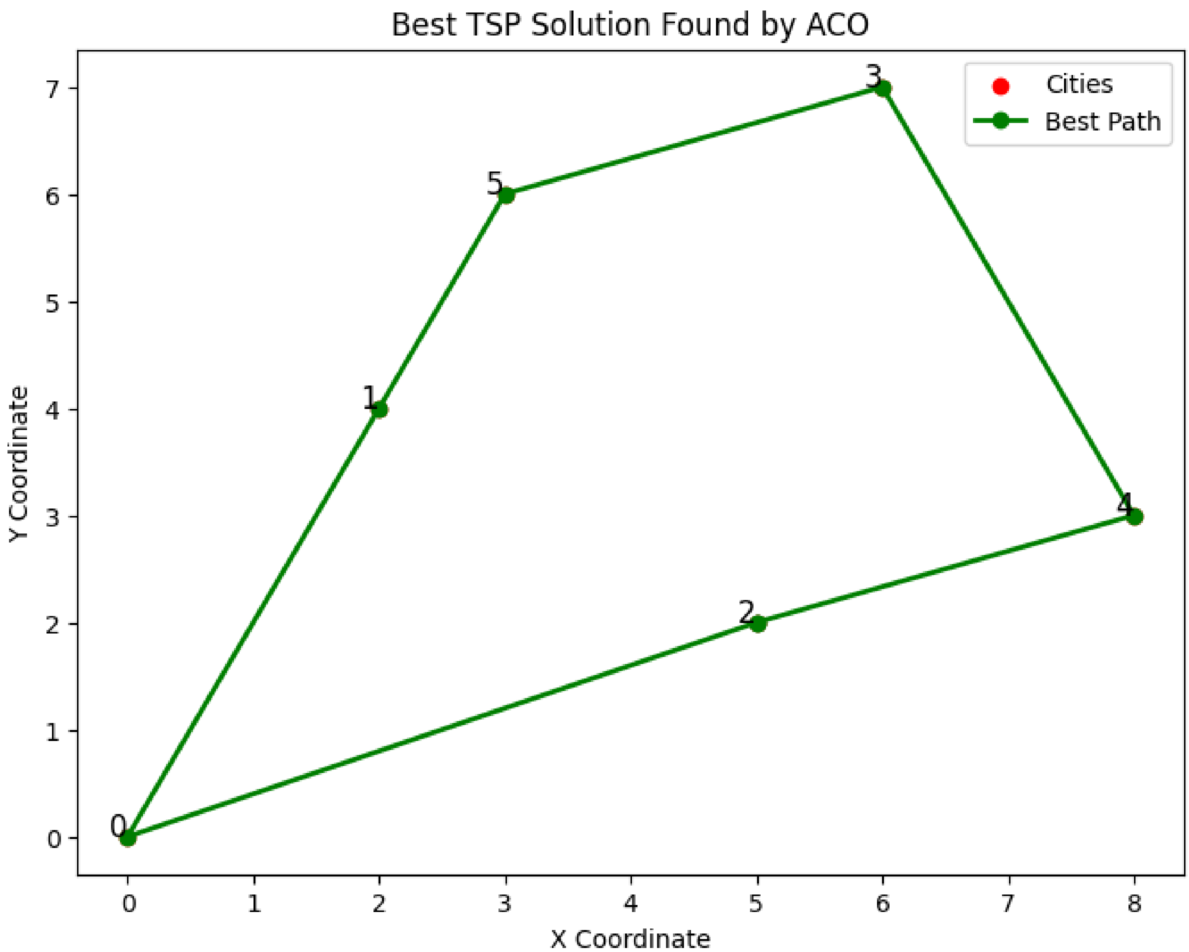
```
            path, path_length = construct_solution(n_points, pheromone, points, alpha, beta)
            paths.append(path)
            path_lengths.append(path_length)


            # Update the best solution found
            if path_length < best_path_length:
                best_path = path
                best_path_length = path_length


        # Update pheromones based on all ants' paths
        pheromone = update_pheromones(pheromone, paths, path_lengths, evaporation_rate, Q)


        # Optional: Print or log progress
        print(f"Iteration {iteration + 1}/{n_iterations}, Best Path Length: {best_path_length:.2f}")


    # Return the best path found
    return best_path, best_path_length


# 7. Output the Best Solution: Plotting the best path in 2D space
def plot_best_path(points, best_path):
    fig, ax = plt.subplots(figsize=(8, 6))
    ax.scatter(points[:, 0], points[:, 1], c='red', marker='o', label='Cities')


    # Draw the best path found by the ants
    path_points = points[best_path]
    path_points = np.vstack([path_points, path_points[0]])  # Close the loop
    ax.plot(path_points[:, 0], path_points[:, 1], c='green', linewidth=2, marker='o', label='Best
Path')


    # Display the cities' indices
    for i, point in enumerate(points):
        ax.text(point[0], point[1], str(i), fontsize=12, ha='right')


    ax.set_xlabel('X Coordinate')
    ax.set_ylabel('Y Coordinate')
```

```
    ax.set_title('Best TSP Solution Found by ACO')
    ax.legend()
    plt.show()


# Example usage with custom city inputs:
points = input_city_coordinates()  # Take custom input for city coordinates
best_path, best_path_length = ant_colony_optimization(
    points,
    n_ants=10,            # Number of ants
    n_iterations=100,     # Number of iterations
    alpha=1,              # Pheromone importance
    beta=1,               # Distance importance
    evaporation_rate=0.5, # Evaporation rate
    Q=1                   # Pheromone deposit
)


print(f"Best Path: {best_path}")
print(f"Best Path Length: {best_path_length:.2f}")


# Plot the best path found
plot_best_path(points, best_path)
```

Output:

```
Enter the number of cities: 6
Enter coordinates for city 1 (x, y): 0 0
Enter coordinates for city 2 (x, y): 2 4
Enter coordinates for city 3 (x, y): 5 2
Enter coordinates for city 4 (x, y): 6 7
Enter coordinates for city 5 (x, y): 8 3
Enter coordinates for city 6 (x, y): 3 6
Iteration 1/100, Best Path Length: 18.86
Iteration 2/100, Best Path Length: 18.86
Iteration 3/100, Best Path Length: 18.86
Iteration 4/100, Best Path Length: 18.86
Iteration 5/100, Best Path Length: 18.86
Iteration 6/100, Best Path Length: 18.86
Iteration 7/100, Best Path Length: 18.86
Iteration 8/100, Best Path Length: 18.86
Iteration 9/100, Best Path Length: 17.50
Iteration 10/100, Best Path Length: 17.50
Iteration 11/100, Best Path Length: 17.50
Iteration 12/100, Best Path Length: 17.50
Iteration 13/100, Best Path Length: 17.50
Iteration 14/100, Best Path Length: 17.50
Iteration 15/100, Best Path Length: 17.50
Iteration 16/100, Best Path Length: 17.50
Iteration 17/100, Best Path Length: 17.50
Iteration 18/100, Best Path Length: 17.50
```

```
Iteration 92/100, Best Path Length: 17.50
Iteration 93/100, Best Path Length: 17.50
Iteration 94/100, Best Path Length: 17.50
Iteration 95/100, Best Path Length: 17.50
Iteration 96/100, Best Path Length: 17.50
Iteration 97/100, Best Path Length: 17.50
Iteration 98/100, Best Path Length: 17.50
Iteration 99/100, Best Path Length: 17.50
Iteration 100/100, Best Path Length: 17.50
Best Path: [2, 4, 3, 5, 1, 0]
Best Path Length: 17.50
```



Program 4: Cuckoo Search (CS)

Problem Statement: Implement cuckoo search algorithm to optimize a function using nests and eggs.

Algorithm:

21/11/24

Algorithm 4: Cuckoo Search Algorithm

```
objective_function(x):
    return x[0]**2

levy_flight(num, β=1.5):
    sigma_u ← ( gamma(1+β) * sin(π * β/2) / (gamma((1+β)/2) * β * 2**((β-1)/2)) )**(1/β)

    u ← random.normal(0, sigma_u, num)
    v ← random.normal(0, 1, num)

    return u / |v|^(1/β)


cuckoo_search(iter, num_nests, pa=0.25):
    num_dim ← 1
    nests ← random.rand(num_nests, num_dim)
    fitness ← objective_function(nests)
    best_nest ← nests[np.argmin(fitness)]
    best_fitness ← np.min(fitness)
    for _ in range(iter):
        for i ← 0 to num_nests:
            new_nest ← nests[i] + levy_flight(num_d...)

            new_fitness ← objective_function(new_nest)

            if new_fitness < fitness[i]:
                nests[i] ← new_nest
                fitness[i] ← new_fitness
```

worst_nests ← argsort (fitness) [- int(pa * num_nests):]
for j in worst_nests:
    nests[j] ← random (num_dim) * 10 - 5
    fitness[j] ← objective_function (nests[j])

Current_best ← np.argmin (fitness)
current_best_fitness ← fitness [current_best]
if current_best_fitness < best_fitness:
    best_fitness ← current_best_fitness
    best_nest ← nests [current_best]

return best_nest, best_fitness

Inputs: num_iterations = 1000
num_nests = 25
pa = 0.25
β = 1.5

21/11/24

Code:

```
import numpy as np


# Objective function for 1D (x^2)
def objective_function_1d(x):
    return x[0]**2  # x is a 1D array, even though we just care about the first element


# Lévy Flight to generate new solutions
```

```
def levy_flight(num_dim, beta=1.5):
    sigma_u = (np.math.gamma(1 + beta) * np.sin(np.pi * beta / 2) /
            np.math.gamma((1 + beta) / 2) * beta * (2 ** ((beta - 1) / 2)))**(1 / beta)
    u = np.random.normal(0, sigma_u, num_dim)  # Lévy-distributed steps
    v = np.random.normal(0, 1, num_dim)
    return u / np.abs(v) ** (1 / beta)


# Cuckoo Search Algorithm for 1D
def cuckoo_search_1d(num_iterations, num_nests, pa=0.25):
    num_dim = 1  # 1D problem
    nests = np.random.rand(num_nests, num_dim) * 10 - 5  # Random initialization within [-5, 5]
    fitness = np.apply_along_axis(objective_function_1d, 1, nests)  # Evaluate initial fitness
    best_nest = nests[np.argmin(fitness)]
    best_fitness = np.min(fitness)


    for _ in range(num_iterations):
        for i in range(num_nests):
            new_nest = nests[i] + levy_flight(num_dim)  # Generate new solution using Lévy flight
            new_fitness = objective_function_1d(new_nest)


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


        # Abandon the worst nests
        worst_nests = np.argsort(fitness)[-int(pa * num_nests):]
        for j in worst_nests:
            nests[j] = np.random.rand(num_dim) * 10 - 5  # Randomly initialize new nests
            fitness[j] = objective_function_1d(nests[j])


        # Update best solution found so far
        current_best_idx = np.argmin(fitness)
        current_best_fitness = fitness[current_best_idx]
        if current_best_fitness < best_fitness:
            best_fitness = current_best_fitness
            best_nest = nests[current_best_idx]
```

```
    return best_nest, best_fitness  # Return the best solution and its fitness


# Run the cuckoo search on the 1D problem
best_solution, best_fitness = cuckoo_search_1d(num_iterations=1000, num_nests=25)
print(f"Best solution found: {best_solution} with objective value: {best_fitness}")
```

Output:

```
Best solution found: [2.93269108e-05] with objective value: 8.600676942579324e-10
```

Program 5: Grey Wolf Optimizer (GWO)

Problem Statement: Implement grey wolf optimizer using alpha, beta and gamma wolves.

Algorithm:

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Algorithm 5 : Grey Wolf Optimization

Initialize_wolves (search_space, num_wolves):
    dim ← len (search_space)
    wolves ← zeros ((num_wolves, dim))
    for i ← 0 to num_wolves:
        wolves [i] ← random.uniform (
                search_space [:, 0],
                search_space [:, 1])

    return wolves

Fitness_function (x):
    return np.sum (x**2)

GWO_algorithm (search_space, num_wolves,
                max_iterations):

    dim ← len (search_space)

    wolves ← initialise_wolves (search_space,
                num_wolves)

    alpha ← zeros (dim)
    beta ← zeros (dim)
    gamma ← zeros (dim)

    alpha_fit = beta_fit = gamma_fit ← float('i

    best_fit ← float ('inf')

```
for iter in range (max)
    a ← 2 - (iteration / max) * 2
    for i ← 0 to num_wolves:
        fitness ← fitness_function(wolves[i])
        if fitness < alpha_fitness:
            copy beta wolf & fitness to gamma
            copy alpha wolf & fitness to beta
            alpha_wolf ← wolves[i].copy()
            alpha_fitness ← fitness

        elif fitness < beta_fitness:
            copy beta wolf & fitness to gamma
            beta_wolf ← wolves[i].copy()
            beta_fitness ← fitness

        elif fitness < gamma_fitness:
            gamma_wolf ← wolves[i].copy()
            gamma_fitness ← fitness

    if alpha_fitness < best_fitness:
        best_fitness ← alpha_fitness

    for i ← 0 to num_wolves:
        for j ← 0 to dims:
            r1 & r2 random floats
            A1 ← 2*a*r1 - a
            C1 ← 2*r2
            D_alpha ← abs(C1 * alpha_wolf[j]
                                - wolves[i, j])

            X1 ← alpha_wolf[j] - A1 * D_alpha
```

New r1 & r2 random floats

A2 ← 2 * a * r1 − a

C2 ← 2 * r2

D-beta ← abs (C2 * beta-wolf [j]
- wolves [i, j])

x2 ← beta-wolf [j] − A2 * D-beta

New r1 & r2 random floats

A3 ← 2 * a * r1 − a

C3 ← 2 * r2

D-gamma ← abs (C3 * gamma-wolf [j]
- wolves [i, j])

x3 ← gamma-wolf [j] − A3 * D-gamma

wolves [i, j] ← (x1 + x2 + x3) / 3

wolves [i, j] ← clip (wolves [i, j] ,
search-space [j, 0] ,
search-space [j, 1])

Inputs:

search-space = array ([−5, 5], [−5, 5])

num-wolves = 10

max-iter = 100

Code:

```
import numpy as np

def initialize_wolves(search_space, num_wolves):
    dimensions = len(search_space)
    wolves = np.zeros((num_wolves, dimensions))
    for i in range(num_wolves):
        wolves[i] = np.random.uniform(search_space[:, 0], search_space[:, 1])
    return wolves

def fitness_function(x):
    # Define your fitness function to evaluate the quality of a solution
    # Example: Sphere function (minimize the sum of squares)
    return np.sum(x**2)

def gwo_algorithm(search_space, num_wolves, max_iterations):
    dimensions = len(search_space)

    # Initialize wolves
    wolves = initialize_wolves(search_space, num_wolves)

    # Initialize alpha, beta, and gamma wolves
    alpha_wolf = np.zeros(dimensions)
    beta_wolf = np.zeros(dimensions)
    gamma_wolf = np.zeros(dimensions)

    # Initialize the fitness of alpha, beta, gamma wolves
    alpha_fitness = float('inf')
    beta_fitness = float('inf')
    gamma_fitness = float('inf')

    # Store the best fitness found
    best_fitness = float('inf')

    for iteration in range(max_iterations):
        a = 2 - (iteration / max_iterations) * 2  # Parameter a decreases linearly from 2 to 0

        #print(f"Iteration {iteration + 1}/{max_iterations}")

        # Evaluate the fitness of all wolves
        for i in range(num_wolves):
            fitness = fitness_function(wolves[i])
```

```
        # Print the fitness of the current wolf
       # print(f"Wolf {i+1} Fitness: {fitness}")

        # Update alpha, beta, gamma wolves based on fitness
        if fitness < alpha_fitness:
            gamma_wolf = beta_wolf.copy()
            gamma_fitness = beta_fitness
            beta_wolf = alpha_wolf.copy()
            beta_fitness = alpha_fitness
            alpha_wolf = wolves[i].copy()
            alpha_fitness = fitness
        elif fitness < beta_fitness:
            gamma_wolf = beta_wolf.copy()
            gamma_fitness = beta_fitness
            beta_wolf = wolves[i].copy()
            beta_fitness = fitness
        elif fitness < gamma_fitness:
            gamma_wolf = wolves[i].copy()
            gamma_fitness = fitness

    # Print the best fitness for this iteration
    #print(f"Best Fitness in this Iteration: {alpha_fitness}")

    # Store the best overall fitness found so far
    if alpha_fitness < best_fitness:
        best_fitness = alpha_fitness

    # Update positions of wolves
    for i in range(num_wolves):
        for j in range(dimensions):
            r1 = np.random.random()
            r2 = np.random.random()

            A1 = 2 * a * r1 - a
            C1 = 2 * r2

            D_alpha = np.abs(C1 * alpha_wolf[j] - wolves[i, j])
            X1 = alpha_wolf[j] - A1 * D_alpha

            r1 = np.random.random()
            r2 = np.random.random()

            A2 = 2 * a * r1 - a
```

```
            C2 = 2 * r2

            D_beta = np.abs(C2 * beta_wolf[j] - wolves[i, j])
            X2 = beta_wolf[j] - A2 * D_beta

            r1 = np.random.random()
            r2 = np.random.random()

            A3 = 2 * a * r1 - a
            C3 = 2 * r2

            D_gamma = np.abs(C3 * gamma_wolf[j] - wolves[i, j])
            X3 = gamma_wolf[j] - A3 * D_gamma

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

            # Ensure the new position is within the search space bounds
            wolves[i, j] = np.clip(wolves[i, j], search_space[j, 0], search_space[j, 1])

    print(f"Optimal Solution Found: {alpha_wolf}")
    print(f"Optimal Fitness: {best_fitness}")
    return alpha_wolf  # Return the best solution found

# Example usage
search_space = np.array([[-5, 5], [-5, 5]])  # Define the search space for the optimization problem
num_wolves = 10  # Number of wolves in the pack
max_iterations = 100  # Maximum number of iterations

# Run the GWO algorithm
optimal_solution = gwo_algorithm(search_space, num_wolves, max_iterations)

# Print the optimal solution
print("Optimal Solution:", optimal_solution)
```

Output:

```
Optimal Solution Found: [ 1.51778516e-13 -1.31752029e-13]
Optimal Fitness: 4.039531525040229e-26
Optimal Solution: [ 1.51778516e-13 -1.31752029e-13]
```

Program 6: Parallel Cellular Algorithms and Programs

Problem Statement: Implement the parallel cellular algorithm to optimize the function.

Algorithm:

Algorithm 6 Parallel Cellular Algorithms

custom - function (x) :
    return sum (x ** 2)

Initialize - population (grid - size , dim , lower, upper)
    population ← random (lower , upper , (grid - size ,
        grid-size , dim))
    return population

Evaluate - fitness (population , fitness _ function) :
    fitness ← zeros (population . shape [: -1])
    for i in range (population . Shape [0])
        for j in range (population . shape [1])
            fitness [i] [j] ← ~~fitne~~ custom - function
                (population [i , j])

    return fitness

update _ States (pop , fit , radius , lower , upper) :
    grid - size , _ , dim ← ~~population~~ . shape
    new - pop ← pop . copy ( )
    for i in 0 to grid - size :
        for j in 0 to grid - size :
            neighbours ← get - neighbors (i , j , grid - size ,
                radius)
            best - neighbor ← None
            best - fitness ← float (inf)

        for ni , nj in neighbors :
            if fitness [ni , nj] < best - fitness .
                best - fitness ← fitness [ni , nj]
                best - neighbor ← (ni , nj)

```
if best_neighbors:
    ni, nj ← best_neighbors
    new_population [i, j] ← pop[ni, nj] +
                            random(-0.5, 0.5, d
    new_population [i, j] ← clip(new_populat
                    [i, j], lower, upper)

return new_population

get_neighbors( i, j, grid_size, radius):
    neighbors ← [ ]
    for di in range (-radius, radius + 1):
        for dj in range (-radius, radius + 1):
            ni, nj ← (i + di) % grid_size,
                     (j + dj) % grid_size

            if (di != 0 or dj != 0):
                neighbors.append ((ni, nj))

    return neighbors

Parallel_cellular_Algorithm (grid_size, dim, lower,
    upper, max_iters, radius, fitness_func).
        population ← initialise_population (grid_size,
                        dim, lower, upper)

        fitness ← evaluate_fitness (population,
                        fitness_function)

        min_fitness ← fitness.min( )
        if min_fitness < best_fitness
            best_fitness ← min_fitness
```

```
best_sol ← None
best_fit ← ∞

for iter in max_iters :
        pop ← update_states ( population, fitness,
              radius, lower, upper)

        fitness ← evaluate_fitness ( pop,
                  fitness_function)

        min_fitness ← fitness.min( )
        if min_fitness < best_fitness :
            best_fitness ← min_fitness
            best_sol ← population [np.
                 unravel_index ( fitness.min( ),
                 fitness.shape )]

        print (iteration , fitness)

return best_sol, best_fit
```

Inputs:
grid_size = 10
dim = 1
lower = -5
upper = 5
max_iters = 100
radius = 1

Code:

```
import numpy as np
import random

# Define any optimization function to minimize (can be changed as needed)
def custom_function(x):
    return x**2  # Example function: x^2 to minimize

# Initialize the population (grid of cells) with random values
def initialize_population(grid_size, dim, lower_bound, upper_bound):
    # Initialize a grid of cells with random positions
    population = np.random.uniform(lower_bound, upper_bound, (grid_size, grid_size, dim))
    return population

# Evaluate the fitness of each cell in the grid
def evaluate_fitness(population, fitness_function):
    # Calculate fitness of each cell based on the optimization function
    fitness = np.zeros(population.shape[:-1])  # Create an empty fitness matrix
    for i in range(population.shape[0]):
        for j in range(population.shape[1]):
            fitness[i, j] = fitness_function(population[i, j])  # Assign fitness value
    return fitness

# Update the state of each cell based on the best neighbor within a neighborhood
def update_states(population, fitness, neighborhood_radius, lower_bound, upper_bound):
    grid_size, _, dim = population.shape
    new_population = population.copy()  # Make a copy to store updated values

    # Iterate over each cell in the grid
    for i in range(grid_size):
        for j in range(grid_size):
            # Get the neighbors of the current cell
            neighbors = get_neighbors(i, j, grid_size, neighborhood_radius)
            best_neighbor = None
            best_fitness = float('inf')

            # Find the best neighbor based on fitness
            for ni, nj in neighbors:
                if fitness[ni, nj] < best_fitness:
                    best_fitness = fitness[ni, nj]
                    best_neighbor = (ni, nj)

            # Update the current cell towards the best neighbor
```

```
            if best_neighbor:
                ni, nj = best_neighbor
                # Add a small random perturbation to the updated cell value
                new_population[i, j] = population[ni, nj] + np.random.uniform(-0.5, 0.5, dim)
                # Ensure the new population is within bounds
                new_population[i, j] = np.clip(new_population[i, j], lower_bound, upper_bound)

    return new_population

# Get the neighbors of a cell within a given neighborhood radius
def get_neighbors(i, j, grid_size, radius):
    neighbors = []
    for di in range(-radius, radius + 1):
        for dj in range(-radius, radius + 1):
            ni, nj = (i + di) % grid_size, (j + dj) % grid_size
            if (di != 0 or dj != 0):  # Exclude the cell itself
                neighbors.append((ni, nj))
    return neighbors

# Main function to run the parallel cellular algorithm
def parallel_cellular_algorithm(grid_size, dim, lower_bound, upper_bound, max_iterations,
neighborhood_radius, fitness_function):
    # Initialize the population (grid of cells)
    population = initialize_population(grid_size, dim, lower_bound, upper_bound)

    # Initialize fitness of the population
    fitness = evaluate_fitness(population, fitness_function)

    best_solution = None
    best_fitness = float('inf')

    # Iterate to update states (based on number of iterations)
    for iteration in range(max_iterations):
        # Update states based on neighbor interactions
        population = update_states(population, fitness, neighborhood_radius, lower_bound,
upper_bound)

        # Re-evaluate fitness
        fitness = evaluate_fitness(population, fitness_function)

        # Track the best solution found so far
        min_fitness = fitness.min()
        if min_fitness < best_fitness:
```

```
            best_fitness = min_fitness
            best_solution = population[np.unravel_index(fitness.argmin(), fitness.shape)]

        # Print output every 10 iterations
        if (iteration + 1) % 10 == 0:
            print(f"Iteration {iteration + 1}/{max_iterations}, Best Fitness: {best_fitness}")

    return best_solution, best_fitness

# Parameters for the algorithm
grid_size = 10  # Number of cells per side (10x10 grid = 100 cells)
dim = 1  # One-dimensional solution space (this can be extended to higher dimensions if needed)
lower_bound = -5  # Lower bound for the solution space (can be adjusted for different problem
ranges)
upper_bound = 5  # Upper bound for the solution space
max_iterations = 100  # Number of iterations (how long to run the algorithm)
neighborhood_radius = 1  # Radius for neighborhood search (defines how far neighboring cells
are considered)

# Run the parallel cellular algorithm
best_solution, best_fitness = parallel_cellular_algorithm(grid_size, dim, lower_bound,
upper_bound, max_iterations, neighborhood_radius, custom_function)

# Output the best solution found
print("\nBest Solution Found:", best_solution)
print("Best Fitness Value:", best_fitness)
```

Output:

```
Iteration 10/100, Best Fitness: 6.1517480231833636e-06
Iteration 20/100, Best Fitness: 1.6757075383394441e-07
Iteration 30/100, Best Fitness: 5.953459053884453 4e-08
Iteration 40/100, Best Fitness: 5.9534590538844534e-08
Iteration 50/100, Best Fitness: 5.9534590538844534e-08
Iteration 60/100, Best Fitness: 5.9534590538844534e-08
Iteration 70/100, Best Fitness: 5.9534590538844534e-08
Iteration 80/100, Best Fitness: 5.9534590538844534e-08
Iteration 90/100, Best Fitness: 5.9534590538844534e-08
Iteration 100/100, Best Fitness: 5.3029915870773e-10

Best Solution Found: [2.30282253e-05]
Best Fitness Value: 5.3029915870773e-10
```

Program 7:Optimization via Gene Expression Algorithms

Problem Statement: Implement gene expression to optimize the math function using crossover and mutation rates.

Algorithm:

Algorithm 7 : Optimization via Gene Expression

Function (x):
    return sum (x**2)

Initialize_Population (pop_size, num_genes, lower, upper
    pop ← random (lower, upper, (pop_size, num_genes
    return pop

Evaluate_fitness (pop, ~~fitness~~ function):
    fitness ← zeros (pop.shape [0])
    for i in range pop.shape [0] :
        fitness [i] ← ~~fitness~~ function (pop [i])
    return fitness

Selection (pop , fitness , num_selected):
    prob ← fitness / fitness.sum()
    indices ← random.choice (range (len (pop)),
            size = num_selected , p = prob)
    selected_pop ← pop [indices]
    return selected_pop

Crossover (selected_pop , crossover):
    new_pop ← [ ]
    num_individuals ← len (selected_pop)
    for i in range 0 to num_individuals - 1 , step 2 :
        p1 , p2 ← selected_pop [i] , selected_pop [i+1]
        if len (p1) > 1 and random < crossover :
            crossover_point ← random (1, len (p1) -
            child 1 ← concatenate (p1 [: crossover_point
                p2 [crossover_point :])

```
        child2 ← concatenate (p2[: crossover_point ],
                     p1[ crossover_point : ])
        new_pop. extend([p1, p2])

    if num_individuals % 2 == 1 :
        new_pop append (selected_pop [-1])

    return new_pop

Mutation (pop, rate, lower, upper) :
    for i in range (pop.shape[0]) :
        if random < rate :
            gene ← random (0, pop.shape[1] - 1)
            pop[i, gene] ← random_uniform (lower,
                                            upper)

    .
    return pop

Gene_expression (individual, function) :
    return function (individual)

Gene_Expression_Algorithm (pop_size, num_genes, lower, upper,
  max_gen, mutation_rate, crossover_rate, function) :
    pop ← initialise_population (pop_size, num_genes,
             lower, upper)

    ~~best ← ~~
    best_sol ← NIL
    best_fit ← ∞

    for gen in 0 to max_gen :
        fitness ← evaluate_fitness (pop, function)
        min_fitness ← fitness.min()
        if min_fitness < best_fit :
            best_fit ← min_fitness
            best_sol ← pop [min(fitness)]

        selected_pop ← selection (pop, fitness,
                         pop_size // 2)
```

offspring-pop ← crossover (selected-pop
crossover-rate)

pop ← mutation (offspring-pop, mutation,
lower, upper)

print (Generation, fitness)

return best-sol, best-fit

Inputs:

pop-size = 50
num-genes = 1
lower = -5
upper = 5
max-gen = 100
mutation-rate = 0.1
crossover_rate = 0.7

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Code:

```
import numpy as np
import random

# Define any optimization function to minimize (can be changed as needed)
def custom_function(x):
    # Example function: x^2 to minimize
    return np.sum(x ** 2)  # Ensuring the function works for multidimensional inputs
```

```
# Initialize population of genetic sequences (each individual is a sequence of genes)
def initialize_population(population_size, num_genes, lower_bound, upper_bound):
    # Create a population of random genetic sequences
    population = np.random.uniform(lower_bound, upper_bound, (population_size, num_genes))
    return population

# Evaluate the fitness of each individual (genetic sequence) in the population
def evaluate_fitness(population, fitness_function):
    fitness = np.zeros(population.shape[0])
    for i in range(population.shape[0]):
        fitness[i] = fitness_function(population[i])  # Apply the fitness function to each individual
    return fitness

# Perform selection: Choose individuals based on their fitness (roulette wheel selection)
def selection(population, fitness, num_selected):
    # Select individuals based on their fitness (higher fitness, more likely to be selected)
    probabilities = fitness / fitness.sum()  # Normalize fitness to create selection probabilities
    selected_indices = np.random.choice(range(len(population)), size=num_selected,
p=probabilities)
    selected_population = population[selected_indices]
    return selected_population

# Perform crossover: Combine pairs of individuals to create offspring
def crossover(selected_population, crossover_rate):
    new_population = []
    num_individuals = len(selected_population)

    for i in range(0, num_individuals - 1, 2):  # Iterate in steps of 2, skipping the last one if odd
        parent1, parent2 = selected_population[i], selected_population[i + 1]
        if len(parent1) > 1 and random.random() < crossover_rate:  # Only perform crossover if
more than 1 gene
            crossover_point = random.randint(1, len(parent1) - 1)  # Choose a random crossover
point
            offspring1 = np.concatenate((parent1[:crossover_point], parent2[crossover_point:]))
            offspring2 = np.concatenate((parent2[:crossover_point], parent1[crossover_point:]))
            new_population.extend([offspring1, offspring2])  # Create two offspring
        else:
            new_population.extend([parent1, parent2])  # No crossover, retain the parents

    # If the number of individuals is odd, carry the last individual without crossover
    if num_individuals % 2 == 1:
        new_population.append(selected_population[-1])
```

```
    return np.array(new_population)

# Perform mutation: Introduce random changes in offspring
def mutation(population, mutation_rate, lower_bound, upper_bound):
    for i in range(population.shape[0]):
        if random.random() < mutation_rate:  # Apply mutation based on the rate
            gene_to_mutate = random.randint(0, population.shape[1] - 1)  # Choose a random gene to
mutate
            population[i, gene_to_mutate] = np.random.uniform(lower_bound, upper_bound)  #
Mutate the gene
    return population

# Gene expression: In this context, it is how we decode the genetic sequence into a solution
def gene_expression(individual, fitness_function):
    return fitness_function(individual)

# Main function to run the Gene Expression Algorithm
def gene_expression_algorithm(population_size, num_genes, lower_bound, upper_bound,
max_generations, mutation_rate, crossover_rate, fitness_function):
    # Step 2: Initialize the population of genetic sequences
    population = initialize_population(population_size, num_genes, lower_bound, upper_bound)

    best_solution = None
    best_fitness = float('inf')

    # Step 9: Iterate for the specified number of generations
    for generation in range(max_generations):
        # Step 4: Evaluate fitness of the current population
        fitness = evaluate_fitness(population, fitness_function)

        # Track the best solution found so far
        min_fitness = fitness.min()
        if min_fitness < best_fitness:
            best_fitness = min_fitness
            best_solution = population[np.argmin(fitness)]

        # Step 5: Perform selection (choose individuals based on fitness)
        selected_population = selection(population, fitness, population_size // 2)  # Select half of
the population

        # Step 6: Perform crossover to generate new individuals
        offspring_population = crossover(selected_population, crossover_rate)
```

```
        # Step 7: Perform mutation on the offspring population
        population = mutation(offspring_population, mutation_rate, lower_bound, upper_bound)

        # Print output every 10 generations
        if (generation + 1) % 10 == 0:
            print(f"Generation {generation + 1}/{max_generations}, Best Fitness: {best_fitness}")

    # Step 10: Output the best solution found
    return best_solution, best_fitness

# Parameters for the algorithm
population_size = 50  # Number of individuals in the population
num_genes = 1  # Number of genes (for a 1D problem, this is just 1, extendable for higher
dimensions)
lower_bound = -5  # Lower bound for the solution space
upper_bound = 5  # Upper bound for the solution space
max_generations = 100  # Number of generations to evolve the population
mutation_rate = 0.1  # Mutation rate (probability of mutation per gene)
crossover_rate = 0.7  # Crossover rate (probability of crossover between two parents)

# Run the Gene Expression Algorithm
best_solution, best_fitness = gene_expression_algorithm(
    population_size, num_genes, lower_bound, upper_bound,
    max_generations, mutation_rate, crossover_rate, custom_function)

# Output the best solution found
print("\nBest Solution Found:", best_solution)
print("Best Fitness Value:", best_fitness)
```

Output:

```
Generation 10/100, Best Fitness: 0.02125657210893126
Generation 20/100, Best Fitness: 0.020266700998504673
Generation 30/100, Best Fitness: 0.020266700998504673
Generation 40/100, Best Fitness: 0.0065667627493710655
Generation 50/100, Best Fitness: 0.00089546902711783
Generation 60/100, Best Fitness: 0.00089546902711783
Generation 70/100, Best Fitness: 0.0006225317320463783
Generation 80/100, Best Fitness: 0.0006225317320463783
Generation 90/100, Best Fitness: 0.0006225317320463783
Generation 100/100, Best Fitness: 0.0006225317320463783

Best Solution Found: [-0.02495059]
Best Fitness Value: 0.0006225317320463783
```