

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



B.M.S. COLLEGE OF ENGINEERING

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CERTIFICATE

This is to certify that the Lab work entitled “ Bio Inspired Systems (23CS5BSBIS)” carried out by **Shreyansh Sethiya (1BM22CS269)** 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/Shreyanshsethiya/BISLAB>

Program 1

Genetic Algorithm for Optimization Problems

Algorithm:

29/10/24

Genetic Algorithm

Objective function:

$$f(x) = x^2$$

The goal is to find the value of x (within a defined range) that maximizes this function

Pseudo Code \rightarrow

FUNCTION Objective-function(x):

RETURN x^2

FUNCTION initialize-population(pop_size , lower-bound, upper-bound):

RETURN random values in range [lower-bound, upper-bound] of size pop_size

FUNCTION evaluate-fitness($population$):

RETURN Objective-function($population$)

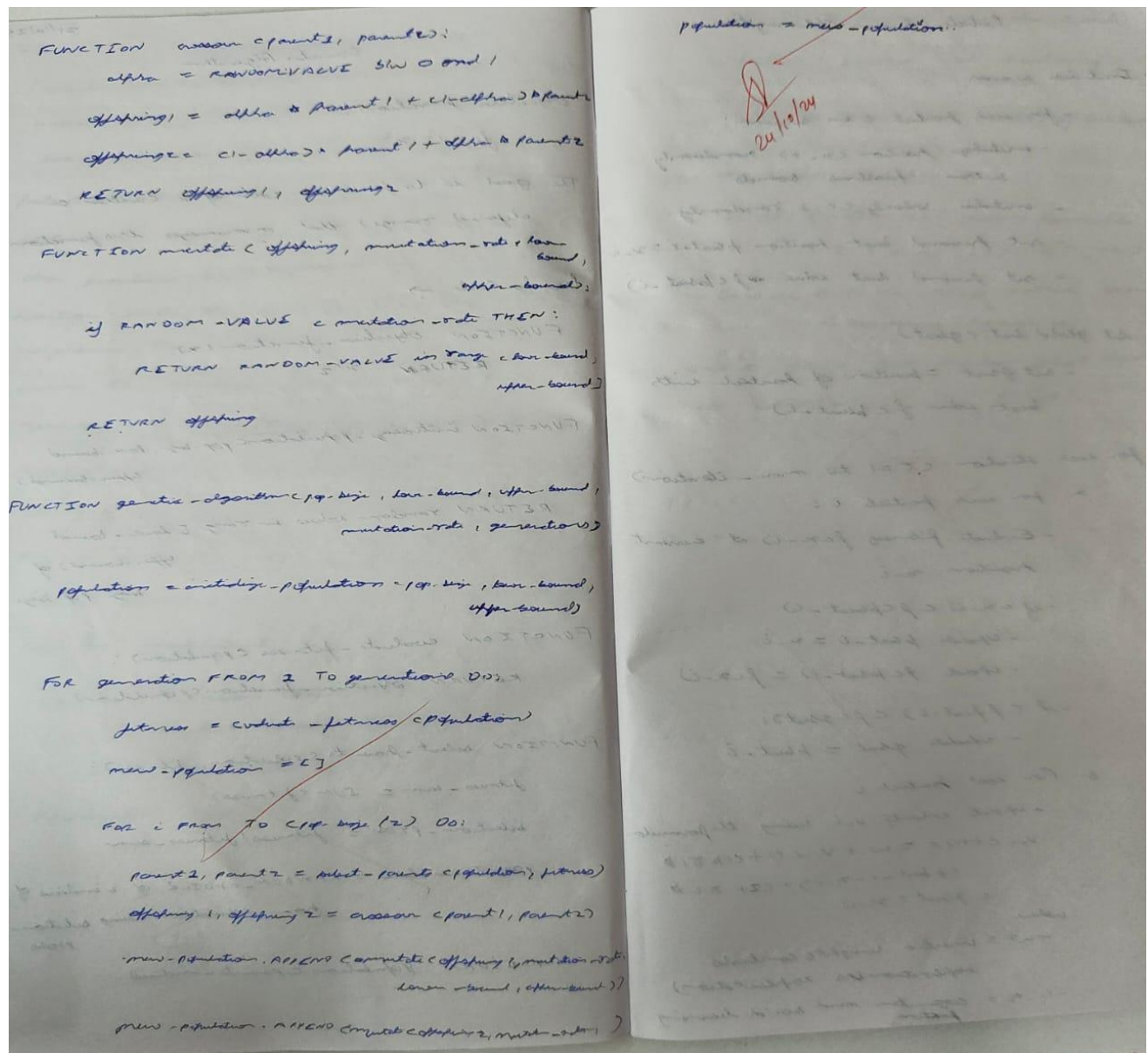
FUNCTION select-parents($population$, fitness):

fitness-sum = SUM(fitness)

selection-prob = fitness / fitness-sum

parents-indices = RANDOM-CHOICE of 2 indices of $population$ using selection-prob

RETURN $population$ [parents-indices]



Code:

```
import random
```

```
# Set a random seed for reproducibility
random.seed(42)
```

```
def fitness(chromosome):
    x = int("".join(map(str, chromosome)), 2)
    return x ** 2
```

```
def binary_string_to_chromosome(binary_string):
```

```

    return [int(bit) for bit in binary_string]

def generate_population_from_input():
    population = []
    for _ in range(population_size):
        while True:
            binary_string = input("Enter a binary string of size 5 (e.g., '11001'): ")
            if len(binary_string) == 5 and all(bit in '01' for bit in binary_string):
                population.append(binary_string_to_chromosome(binary_string))
                break
            else:
                print("Invalid input. Please enter a binary string of size 5.")
    return population

def select_pair(population, fitnesses):
    total_fitness = sum(fitnesses)
    selection_probs = [f / total_fitness for f in fitnesses]
    parent1 = population[random.choices(range(len(population)), selection_probs)[0]]
    parent2 = population[random.choices(range(len(population)), selection_probs)[0]]
    return parent1, parent2

def crossover(parent1, parent2):
    point = random.randint(1, len(parent1) - 1)
    offspring1 = parent1[:point] + parent2[point:]
    offspring2 = parent2[:point] + parent1[point:]
    return offspring1, offspring2

def mutate(chromosome, mutation_rate):
    return [gene if random.random() > mutation_rate else 1 - gene for gene in chromosome]

# Parameters
population_size = 4
generations = 20
mutation_rate = 0.01

# Initialize population from user input
population = generate_population_from_input()

for generation in range(generations):
    fitnesses = [fitness(chromosome) for chromosome in population]

    new_population = []

```

```

# Create new population
while len(new_population) < population_size:
    parent1, parent2 = select_pair(population, fitnesses)
    offspring1, offspring2 = crossover(parent1, parent2)
    new_population.append(mutate(offspring1, mutation_rate))
    new_population.append(mutate(offspring2, mutation_rate))

# Ensure the new population has the right size
population = new_population[:population_size]

# Get the maximum fitness
fitnesses = [fitness(chromosome) for chromosome in population]
max_fitness = max(fitnesses)

print(f"Maximum Possible Fitness: {max_fitness}")

```

Output:

```

Enter a binary string of size 5 (e.g., '11001'): 11011
Enter a binary string of size 5 (e.g., '11001'): 01011
Enter a binary string of size 5 (e.g., '11001'): 11100
Enter a binary string of size 5 (e.g., '11001'): 01101
Maximum Possible Fitness: 841

```

Program 2

Ant Colony Optimization

Algorithm:

Ant Colony Optimization for Traveling Salesman

Objective \rightarrow To find the shortest possible route of salesman that visits a list of cities and returns to the origin city using ant colony.

Initialization \rightarrow

- Number of ants \rightarrow A fixed number of ants are used to explore the solutions space. Each ant is treated as an individual agent to construct a solution.
- Number of iterations \rightarrow Runs for a fixed number of iterations.

Pheromone Parameters:

Concentration

- α : Weight of the pheromone in the decision-making process.
- β : Weight of the heuristic (inverse distance) in the decision-making process.
- ρ : Evaporation rate of the pheromone, which simulates how old pheromones dissipate over time.
- Distance Matrix: Euclidean distance b/w each pair of cities is pre-computed.

2) Construction of Ant Tour \Rightarrow

- For each ant a tour is constructed.

Each ant starts at a random city

From the starting city, it repeatedly chooses the next city to visit based on the following factors \Rightarrow

Pheromone concentration \Rightarrow The stronger the pheromone on an edge

Heuristic information \Rightarrow The inverse of the distance b/w cities. The shorter the distance, the more likely an ant to choose that edge.

Probability calculation \Rightarrow $(\text{Alpha}) \alpha$ and $(\text{heuristic information}) \beta$ to calculate the probability

Ant select the ants with greater probability, and a degree of randomness is also included to encourage exploration.

This process continues until all cities are visited.

3) Pheromone Update:

- After all ants have completed their tours, the pheromone matrix is updated \Rightarrow

Pheromone Evaporation: All pheromone values are reduced by a factor $(1 - \rho)$,

simulating the natural evaporation of pheromones over time

write pseudocode
of this
24/11/24

Code:

```
import random
import numpy as np
import operator

FUNCTIONS = {'+': operator.add, '-': operator.sub, '*': operator.mul, '/': operator.truediv}
TERMINALS = ['x', 1, 2, 3, 4] # x and constants

def random_gene(length=10):
    return [random.choice(list(FUNCTIONS.keys()) + TERMINALS) for _ in range(length)]

def decode_chromosome(chromosome, x):
    stack = []
    for gene in chromosome:
        if gene in FUNCTIONS: # If it's a function, pop arguments and apply
            if len(stack) < 2: # Avoid errors if stack has fewer than 2 elements
                stack.append(0)
                continue
            b = stack.pop()
            a = stack.pop()
            try:
                result = FUNCTIONS[gene](a, b)
            except ZeroDivisionError:
                result = 1 # Avoid division by zero
            stack.append(result)
        elif gene == 'x':
            stack.append(x)
        else:
            stack.append(gene)
    return stack[0] if stack else 0 # Return top of stack as output

def fitness_function(chromosome, target_function, x_values):
    predictions = [decode_chromosome(chromosome, x) for x in x_values]
    targets = [target_function(x) for x in x_values]
    mse = np.mean([(p - t) ** 2 for p, t in zip(predictions, targets)])
    return mse
```

```

def selection(population, fitnesses):
    total_fitness = sum(1 / (f + 1e-6) for f in fitnesses) # Avoid division by zero
    probabilities = [(1 / (f + 1e-6)) / total_fitness for f in fitnesses]
    return population[np.random.choice(len(population), p=probabilities)]

def mutate(chromosome, mutation_rate=0.1):
    new_chromosome = chromosome[:]
    for i in range(len(new_chromosome)):
        if random.random() < mutation_rate:
            new_chromosome[i] = random.choice(list(FUNCTIONS.keys()) + TERMINALS)
    return new_chromosome

def crossover(parent1, parent2):
    point = random.randint(1, len(parent1) - 1)
    child1 = parent1[:point] + parent2[point:]
    child2 = parent2[:point] + parent1[point:]
    return child1, child2

def ant_colony_optimization(cost_matrix, n_ants=10, n_iterations=100, evaporation_rate=0.5,
alpha=1, beta=2):
    n_nodes = len(cost_matrix)
    pheromones = np.ones((n_nodes, n_nodes)) # Initialize pheromones

    def calculate_probability(i, j, visited):
        if j in visited:
            return 0
        return (pheromones[i][j] ** alpha) * ((1 / cost_matrix[i][j]) ** beta)

    def construct_solution():
        path = [random.randint(0, n_nodes - 1)]
        while len(path) < n_nodes:
            i = path[-1]
            probabilities = [calculate_probability(i, j, path) for j in range(n_nodes)]
            total = sum(probabilities)
            probabilities = [p / total if total > 0 else 0 for p in probabilities]
            next_node = np.random.choice(range(n_nodes), p=probabilities)
            path.append(next_node)
        path.append(path[0]) # Return to start
        return path

    def path_cost(path):
        return sum(cost_matrix[path[i]][path[i + 1]] for i in range(len(path) - 1))

```

```

best_path = None
best_cost = float('inf')

for iteration in range(n_iterations):
    solutions = [construct_solution() for _ in range(n_ants)]
    costs = [path_cost(solution) for solution in solutions]
    for i, cost in enumerate(costs):
        if cost < best_cost:
            best_cost = cost
            best_path = solutions[i]

    pheromones *= (1 - evaporation_rate) # Evaporation
    for i, solution in enumerate(solutions):
        for j in range(len(solution) - 1):
            pheromones[solution[j]][solution[j + 1]] += 1 / costs[i]

    print(f"Iteration {iteration + 1}: Best Cost = {best_cost}")

print("Best Path:", best_path)
print("Best Cost:", best_cost)

cost_matrix = [
    [0, 2, 2, 5, 7],
    [2, 0, 4, 8, 2],
    [2, 4, 0, 1, 3],
    [5, 8, 1, 0, 2],
    [7, 2, 3, 2, 0]
]
ant_colony_optimization(cost_matrix, n_ants=5, n_iterations=20)

```

Output:

```

Iteration 15: Best Cost = 9
Iteration 16: Best Cost = 9
Iteration 17: Best Cost = 9
Iteration 18: Best Cost = 9
Iteration 19: Best Cost = 9
Iteration 20: Best Cost = 9
Best Path: [1, 0, 2, 3, 4, 1]
Best Cost: 9

```

Program 3

Particle Swarm Optimization

Algorithm:

Particle Swarm Optimization

1) Initialize swarm

- for each particle i in swarm:
 - initialize position x_i randomly within problem bounds
 - initialize velocity v_i randomly
 - set personal best position $p_{best} = x_i$
 - set personal best value $f(p_{best})$

2) Set global best (g_{best})

- set g_{best} = position of particle with best value of $f(p_{best})$

3) for each iteration ($t=1$ to max-iteration)

a. for each particle i :

- Evaluate fitness $f(x_i)$ at current position x_i
- if $f(x_i) < f(p_{best})$
 - update $p_{best} = x_i$
 - update $f(p_{best}) = f(x_i)$
- if $f(p_{best}) < f(g_{best})$
 - update $g_{best} = p_{best}$

b. For each particle i

- update velocity v_i using the formula
$$v_i(t+1) = \omega + v_i(t) + c_1 r_1 (p_{best} - x_i) + c_2 r_2 (g_{best} - x_i)$$
where:

where:

- ω = inertia weight (controls exploration vs exploitation)
- c_1, c_2 = cognitive and social learning factors

- r_1, r_2 = random value b/w 0 and 1

- p_{best-i} = personal best position of Particle i

- g_{best} = global best position of the swarm

c. For each Particle i

- update position $x-i$ using formula

$$x-i(t+1) = x-i(t) + v-i(t+1)$$

- Ensure that $x-i$ stays within bounds
(boundary handling)

4) Output global best position g_{best} and
its corresponding value $f(g_{best})$

Signature
05/11/2024

Code:

```
import random
import numpy as np
from matplotlib import pyplot as plt
from matplotlib import animation

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):
    new_velocity = np.zeros_like(particle)
    r1 = random.uniform(0, max)
    r2 = random.uniform(0, max)
    w = random.uniform(w_min, max)

    for i in range(len(particle)):
        new_velocity[i] = (w * velocity[i] +
                           c * r1 * (pbest[i] - particle[i]) +
                           c * r2 * (gbest[i] - particle[i]))
    return new_velocity

def update_position(particle, velocity):
    new_particle = particle + velocity
    return new_particle

def pso_2d(population, dimension, position_min, position_max, generation, fitness_criterion):
    # Initialization
    particles = np.array([[random.uniform(position_min, position_max) for _ in range(dimension)] for
                           _ in range(population)])
    pbest_position = particles.copy()
```

```

pbest_fitness = np.array([fitness_function(p[0], p[1]) for p in particles])

gbest_index = np.argmin(pbest_fitness)
gbest_position = pbest_position[gbest_index]

velocity = np.zeros((population, dimension))

images = [] # For animation

for t in range(generation):
    if np.average(pbest_fitness) <= fitness_criterion:
        break

    for n in range(population):
        velocity[n] = update_velocity(particles[n], velocity[n], pbest_position[n], gbest_position)
        particles[n] = update_position(particles[n], velocity[n])

    pbest_fitness = np.array([fitness_function(p[0], p[1]) for p in particles])
    for n in range(population):
        if pbest_fitness[n] < fitness_function(pbest_position[n][0], pbest_position[n][1]):
            pbest_position[n] = particles[n]

    gbest_index = np.argmin(pbest_fitness)
    gbest_position = pbest_position[gbest_index]

    # Plotting the current positions of the particles
    fig = plt.figure(figsize=(10, 10))
    ax = fig.add_subplot(111, projection='3d')
    ax.set_xlabel('x')
    ax.set_ylabel('y')
    ax.set_zlabel('z')

    x = np.linspace(position_min, position_max, 80)
    y = np.linspace(position_min, position_max, 80)
    X, Y = np.meshgrid(x, y)
    Z = fitness_function(X, Y)
    ax.plot_wireframe(X, Y, Z, color='r', linewidth=0.2)

    ax.scatter3D(
        particles[:, 0],
        particles[:, 1],
        [fitness_function(p[0], p[1]) for p in particles],

```

```

        c='b'
    )

    # Capture the frame for animation
    plt.title(f'Generation: {t + 1}')
    plt.tight_layout()
    plt.savefig(f'frame_{t}.png')
    plt.close(fig)

# Create animation
frames = [plt.imread(f'frame_{i}.png') for i in range(t)]
fig, ax = plt.subplots(figsize=(10, 10))
ax.axis('off')
image = ax.imshow(frames[0])

def update(frame):
    image.set_array(frames[frame])
    return image,

ani = animation.FuncAnimation(fig, update, frames=len(frames), interval=100)
ani.save('./pso_simple.gif', writer='pillow')

# 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 Generations: ', t)

# Run the PSO algorithm
pso_2d(population=30, dimension=2, position_min=-10, position_max=10, generation=100,
fitness_criterion=1e-3)

```

Output:

```

Global Best Position:  [2.59992843 2.79914636]
Best Fitness Value:    3.6691186243893878e-06
Average Particle Best Fitness Value:  0.0007223322365523365
Number of Generations:  45

```

Program 4

Cuckoo Search Algorithm

Algorithm:

Cuckoo Search Algorithm

bounds code \rightarrow

#2) Define the objective function to be optimized
def objective-function(x):

#3) Initialize Parameters

N = 20 # Number of Nests

pa = 0.25 # Probability of discovery

MaxIter = 100 # Maximum number of iterations

dimensions = 2 # Dimensionality of the problem

lowerBound = -5 # Lower bound of search space

upperBound = 5 # Upper bound of search space

#4) Initialize Population (nests)

def initialize-population(N, dimensions, lowerbound,
upperbound):

Random position within the bounds

#9) Evaluate Fitness (Calculate for each nest)

def evaluate-fitness(nests):

return mp.apply_async(objective-function,
nests)

#5) Generate New positions using Levy flights \rightarrow

def levy-flights(dimensions, beta = 1.5):

Return random step size using Levy distribution

step = 1/mp.digamma(1/beta) * (1/beta)

return step

Generate new positions using levy flight for each
nest.

def generate-new-solution (nest, alpha = 0.017):

Apply levy flight to generate new position

return nest + alpha * levy-flight (dimension)

#6 Bound the solution within the allowed limit

def bound-solution (solution, lower-bound, upper-bound):

return np.clip (solution, lower-bound, upper-bound)

#7 Main loop for iterations →

for iter in range (Monitor):

for i in range (N):

Generate new solution for nest i

new-nest = generate-new-solution (nests[i])

Bound the new solution

new-nest = bound-solution (new-nest,
lower-bound, upper-bound)

Evaluate the fitness of the new solution

new-fitness = objective-function
(new-nest)

If the new solution is better, replace
the old one

if new-fitness < fitness[i]:

nests[i] = new-nest

fitness[i] = new-fitness

21/11/24

Code:

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

# Objective function: 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)

# Lévy flight function for generating random steps
def levy_flight(beta=1.5, dim=2):
    sigma_u = np.power(np.math.gamma(1 + beta) * np.sin(np.pi * beta / 2) / np.math.gamma((1 + beta) / 2) / np.power(2, (beta - 1) / 2), 1 / beta)
    sigma_v = 1
    u = np.random.normal(0, sigma_u, dim)
    v = np.random.normal(0, sigma_v, dim)
    return u / np.power(np.abs(v), 1 / beta)

# Cuckoo Search Algorithm
class CuckooSearch:
    def __init__(self, func, dim, population_size, max_generations, pa=0.25, beta=1.5, lower_bound=-5, upper_bound=5):
        self.func = func          # Objective function
        self.dim = dim            # Dimension of the problem
        self.population_size = population_size # Number of nests (solutions)
        self.max_generations = max_generations # Maximum number of generations
        self.pa = pa              # Probability of alien eggs (nest replacement)
        self.beta = beta          # Lévy flight exponent
        self.lower_bound = lower_bound # Lower bound of the search space
        self.upper_bound = upper_bound # Upper bound of the search space

        # Initialize population (nests)
        self.nests = np.random.uniform(self.lower_bound, self.upper_bound, (self.population_size, self.dim))
        self.fitness = np.array([self.func(nest) for nest in self.nests]) # Fitness of each nest
        self.best_nest = self.nests[np.argmin(self.fitness)] # Best solution found
        self.best_fitness = np.min(self.fitness) # Best fitness value

    # Update nests using Lévy flights and objective function evaluations
    def generate_new_nests(self):
```



```

new_nests = []
for i in range(self.population_size):
    step = levy_flight(self.beta, self.dim)
    new_nest = self.nests[i] + step
    # Apply boundary check
    new_nest = np.clip(new_nest, self.lower_bound, self.upper_bound)
    new_nests.append(new_nest)
return np.array(new_nests)

# Main cuckoo search algorithm
def search(self):
    history = [] # To record the best fitness values over generations

    for generation in range(self.max_generations):
        # Generate new nests based on Lévy flight
        new_nests = self.generate_new_nests()
        new_fitness = np.array([self.func(nest) for nest in new_nests])

        # Replace nests with new ones if they are better
        for i in range(self.population_size):
            if new_fitness[i] < self.fitness[i] or np.random.rand() < self.pa:
                self.nests[i] = new_nests[i]
                self.fitness[i] = new_fitness[i]

        # Find the best nest in the current population
        current_best_fitness = np.min(self.fitness)
        current_best_nest = self.nests[np.argmin(self.fitness)]

        # Update the global best solution
        if current_best_fitness < self.best_fitness:
            self.best_fitness = current_best_fitness
            self.best_nest = current_best_nest

        # Record the best fitness for the current generation
        history.append(self.best_fitness)
        print(f"Generation {generation+1}: Best fitness = {self.best_fitness}")

    return self.best_nest, self.best_fitness, history

# Analyze the Cuckoo Search Algorithm
def analyze_cuckoo_search():
    # Set up parameters for Cuckoo Search

```

```
dim = 2
population_size = 50
max_generations = 100
cuckoo_search = CuckooSearch(func=rastrigin, dim=dim, population_size=population_size,
max_generations=max_generations)

# Run the Cuckoo Search algorithm
best_nest, best_fitness, history = cuckoo_search.search()

# Plot the convergence curve
plt.plot(history)
plt.title("Convergence Curve of Cuckoo Search Algorithm")
plt.xlabel("Generation")
plt.ylabel("Best Fitness")
plt.show()

print(f"Best solution found: {best_nest}")
print(f"Best fitness: {best_fitness}")

# Run the analysis
analyze_cuckoo_search()
```

Output:

```
Best solution found: [1.30548027 2.02026344]
Best fitness: 0.16306139523513963
```

Program 5

Grey Wolf Optimizer

Algorithm:

Gray Wolf Optimizer

Pseudo Code \rightarrow

11 Step 1: Define the Problem

Objective - Function (x) 11 Open the objective function
11 to be optimized

11 Step 2: Initialize Parameters

N = Number of wolves

max-iter = Maximum number of iterations

Dim = Number of dimensions (variables of the problem)

Lower-bound = Lower bound of the search space

Upper-bound = Upper bound of the search space

11 Step 3: Initialize Problem

for $i=1$ to N :

Wolf $[i]$.Position = Random (Lower-bound,
Upper-bound)

11 Initialize position
of wolves

Wolf $[i]$.Fitness = Objective-Function (Wolf $[i]$.Position)
11 Evaluate fitness of each wolf

11 Step 4: Sort the wolves by fitness

Sort wolves based on fitness in ascending order

Alpha Wolf = Wolf $[1]$ 11 Best fitness

Beta Wolf = Wolf $[2]$ 11 Second-Best fitness

Delta Wolf = Wolf $[3]$ 11 Third-Best fitness

11 Step 5: Main optimization loop

for iteration = 1 to max-iter:

for $i=1$ to N :

11 Step 5.1: Update position of each wolf

$A = 2 \cdot \text{Random}(0,1) - 1$ // Random vector for exploration

$C = 2 \cdot \text{Random}(0,1)$

11 Calculate Distances b/w current wolf and alpha, beta, delta wolves \rightarrow

$D_{\alpha} = \text{abs}(C \cdot \text{Alpha Wolf Position} - \text{Wolf}[i].\text{Position})$

$D_{\beta} = \text{abs}(C \cdot \text{Beta Wolf Position} - \text{Wolf}[i].\text{Position})$

$D_{\delta} = \text{abs}(C \cdot \text{Delta Wolf Position} - \text{Wolf}[i].\text{Position})$

11 Update position of current wolf

$\text{Wolf}[i].\text{Position} = \text{Wolf}[i].\text{Position} + A \cdot D_{\alpha} +$
 $D_{\beta} + D_{\delta}$

11 Ensure the new position is within bound

for $j=1$ to Dim :

If $\text{Wolf}[i].\text{Position}[j] < \text{Lower-bound}[j];$

$\text{Wolf}[i].\text{Position}[j] = \text{Lower-bound}[j]$

Else if $\text{Wolf}[i].\text{Position}[j] > \text{Upper-bound}[j];$

$\text{Wolf}[i].\text{Position}[j] = \text{Upper-bound}[j]$

11 Step 5.2 Evaluate fitness of the updated position

$\text{Wolf}[i].\text{Fitness} = \text{Objective-function}(\text{Wolf}[i].\text{Position})$

11 Step 5.3 : Sort the wolves again based on fitness

Sort wolves based on fitness in ascending order

AlphaWolf = Wolf[1]

BetaWolf = Wolf[2]

DeltaWolf = Wolf[3]

11 Step 6 : Output the Best solution

BestSolution = AlphaWolf.Position

BestFitness = AlphaWolf.Fitness

Return BestSolution, BestFitness.

o/p?
Of this
18/12/24

Code:

```
import numpy as np

def objective_function(x):
    return np.sum(x**2)

class GreyWolfOptimizer:
    def __init__(self, objective_function, n_wolves, n_variables, max_iter, lb, ub):
        self.obj_func = objective_function # Objective function
        self.n_wolves = n_wolves # Number of wolves
        self.n_variables = n_variables # Number of variables in the problem
        self.max_iter = max_iter # Maximum number of iterations
        self.lb = lb # Lower bound for the search space
        self.ub = ub # Upper bound for the search space

        self.wolves = np.random.uniform(self.lb, self.ub, (self.n_wolves, self.n_variables))

        self.alpha = np.zeros(self.n_variables)
        self.beta = np.zeros(self.n_variables)
        self.delta = np.zeros(self.n_variables)
        self.alpha_score = float("inf")
        self.beta_score = float("inf")
        self.delta_score = float("inf")

    def update_wolves(self):
        fitness = np.apply_along_axis(self.obj_func, 1, self.wolves)

        sorted_indices = np.argsort(fitness)
        self.wolves = self.wolves[sorted_indices]
        fitness = fitness[sorted_indices]

        # Update alpha, beta, and delta wolves
        self.alpha = self.wolves[0]
        self.beta = self.wolves[1]
        self.delta = self.wolves[2]
        self.alpha_score = fitness[0]
        self.beta_score = fitness[1]
        self.delta_score = fitness[2]
```

```

def optimize(self):
    for t in range(self.max_iter):
        A = 2 * np.random.random((self.n_wolves, self.n_variables)) - 1 # Random values for
        exploration
        C = 2 * np.random.random((self.n_wolves, self.n_variables)) # Random values for
        exploitation
        for i in range(self.n_wolves):
            D_alpha = np.abs(C[i] * self.alpha - self.wolves[i]) # Distance to alpha wolf
            D_beta = np.abs(C[i] * self.beta - self.wolves[i]) # Distance to beta wolf
            D_delta = np.abs(C[i] * self.delta - self.wolves[i]) # Distance to delta wolf

            self.wolves[i] = self.alpha - A[i] * D_alpha

            self.wolves[i] = np.clip(self.wolves[i], self.lb, self.ub)

        self.update_wolves()

        print(f"Iteration {t+1}/{self.max_iter}, Best Score: {self.alpha_score}")

    return self.alpha, self.alpha_score # Return the best solution found

n_wolves = 30 # Number of wolves
n_variables = 5 # Number of decision variables
max_iter = 100 # Maximum number of iterations
lb = -10 # Lower bound of the search space
ub = 10 # Upper bound of the search space

gwo = GreyWolfOptimizer(objective_function, n_wolves, n_variables, max_iter, lb, ub)
best_solution, best_score = gwo.optimize()
print("Best Solution Found:", best_solution)
print("Best Score:", best_score)

```

Output:

```

Iteration 100/100, Best Score: 1.985808550535119e-30
Best Solution Found: [-4.38373504e-17 -4.54363691e-16 -1.31663573e-15 -2.05502414e-16
 4.09828696e-17]
Best Score: 1.985808550535119e-30

```

Program 6

Parallel Cellular Algorithm

Algorithm:

Parallel Cellular Algorithms

import numpy as np
from multiprocessing import pool

def objective_function(x):

return np.sum(x**0.2)

def initialize_population(grid_size, num_cells):

return [np.random.uniform(-5, 5, grid_size)

for i in range(num_cells)]

def update_cell(cidx, population, grid_size):

row, col = divmod(cidx, int(np.sqrt(len(population))))

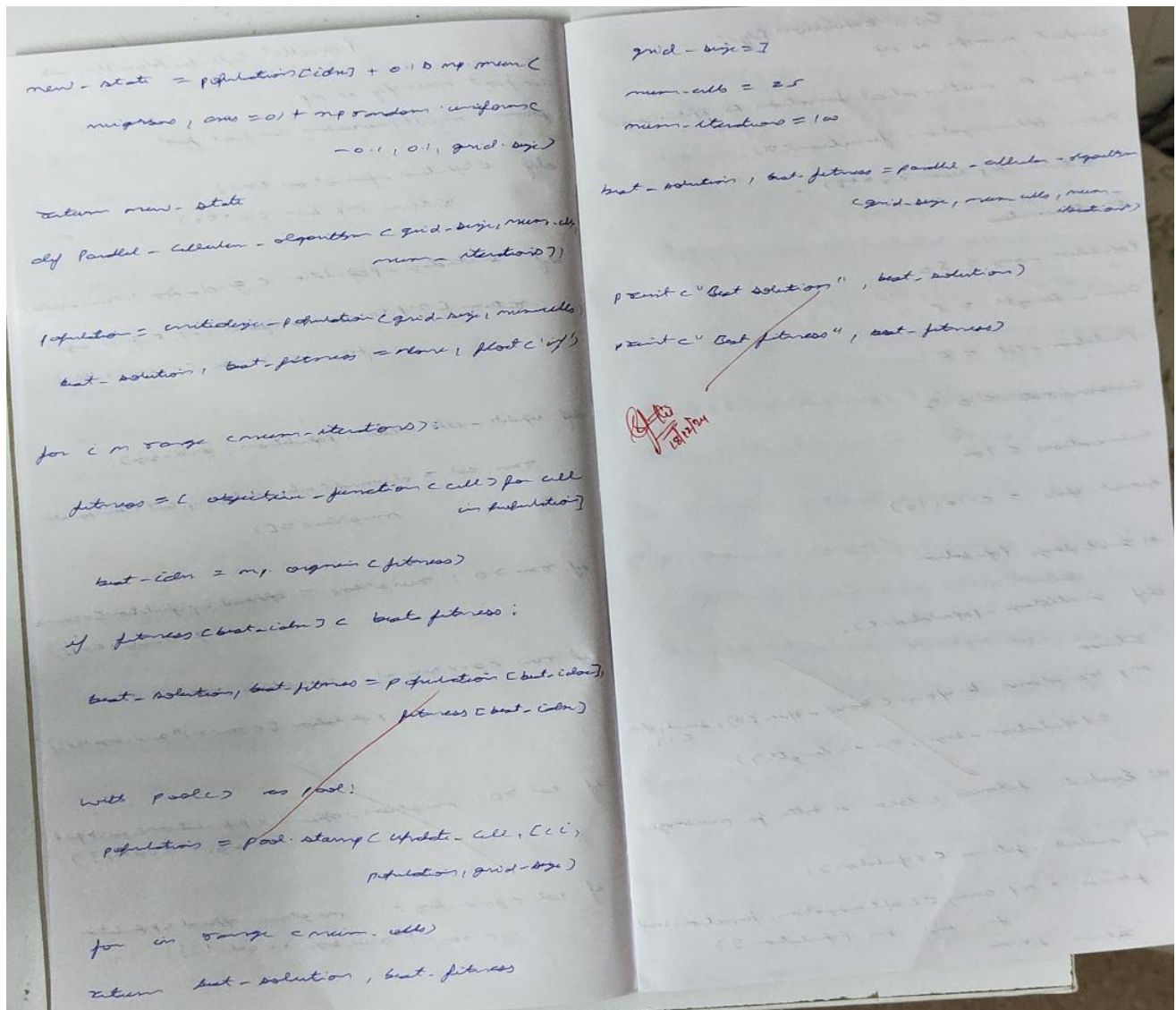
neighbors = []

if row > 0: neighbors.append(population[(row-1)*grid_size+col])

if row < grid_size-1: neighbors.append(population[(row+1)*grid_size+col])

if col > 0: neighbors.append(population[(row*grid_size+col-1)])

if col < grid_size-1: neighbors.append(population[(row*grid_size+col+1)])



Code:

```

import numpy as np
from multiprocessing import Pool
def update_cell(cell_index, grid, size):
    x, y = cell_index
    neighbors = [
        ((x-1) % size, y), ((x+1) % size, y),
        (x, (y-1) % size), (x, (y+1) % size)
    ]
    new_state = sum(grid[n[0], n[1]] for n in neighbors) % 2 # example: majority rule
    return (x, y, new_state)
def parallel_update(grid, size, num_iterations):
    pool = Pool(processes=4)
    for iteration in range(num_iterations):

```

```

print(f"Iteration {iteration + 1}:")
indices = [(x, y) for x in range(size) for y in range(size)]
result = pool.starmap(update_cell, [(i, grid, size) for i in indices])

for x, y, new_state in result:
    grid[x, y] = new_state
print(grid)
return grid
grid_size = 10
grid = np.random.randint(2, size=(grid_size, grid_size))
print("Initial state:")
print(grid)
num_iterations = 2
updated_grid = parallel_update(grid, grid_size, num_iterations)

```

Output:

```

Iteration 1:
[[1 0 0 1]
 [1 0 1 0]
 [1 0 0 1]
 [0 1 0 1]]
Iteration 2:
[[0 0 0 0]
 [0 0 0 0]
 [0 0 0 0]
 [0 0 0 0]]

```

Program 7

Gene Expression Algorithm

Algorithm:


```

Genetic Expression Algorithm
import numpy as np

# Define the mathematical function to optimize
def optimization_function(x):
    return np.mean(x**0.2)

# Parameters
population_size = 50
gene_length = 5
mutation_rate = 0.1
crossover_rate = 0.7
generations = 100
search_space = (-10, 10)

# Initialize population
def initialize_population():
    return np.random.uniform(
        search_space[0], search_space[1],
        (population_size, gene_length))

# Evaluate fitness (lower is better for minimization)
def evaluate_fitness(population):
    fitness = np.array([optimization_function(ind)
        for ind in population])
    return fitness

# Selection (Roulette wheel selection)
def select_parents(population, fitness):
    # Convert fitness to probabilities (lower fitness is better)
    inverted_fitness = 1 / (fitness + 10e-6)
    selection_prob = inverted_fitness / np.sum(inverted_fitness)

    selected_indexes = np.random.choice(
        population_size,
        size=population_size, p=selection_prob)

    return population[selected_indexes]

# Crossover = Blend Crossover
def crossover(parents):
    offspring = np.empty_like(parents)

    for i in range(0, population_size, 2):
        p1, p2 = parents[i], parents[i+1]

        if np.random.rand() < crossover_rate:
            alpha = np.random.rand()
            offspring[i] = alpha * p1 + (1-alpha) * p2
            offspring[i+1] = alpha * p2 + (1-alpha) * p1
        else:
            offspring[i], offspring[i+1] = p1, p2

    return offspring

```

```

# Selection (Roulette wheel selection)
def select_parents(population, fitness):
    # Convert fitness to probabilities (lower fitness is better)
    inverted_fitness = 1 / (fitness + 10e-6)
    selection_prob = inverted_fitness / np.sum(inverted_fitness)

    selected_indexes = np.random.choice(
        population_size,
        size=population_size, p=selection_prob)

    return population[selected_indexes]

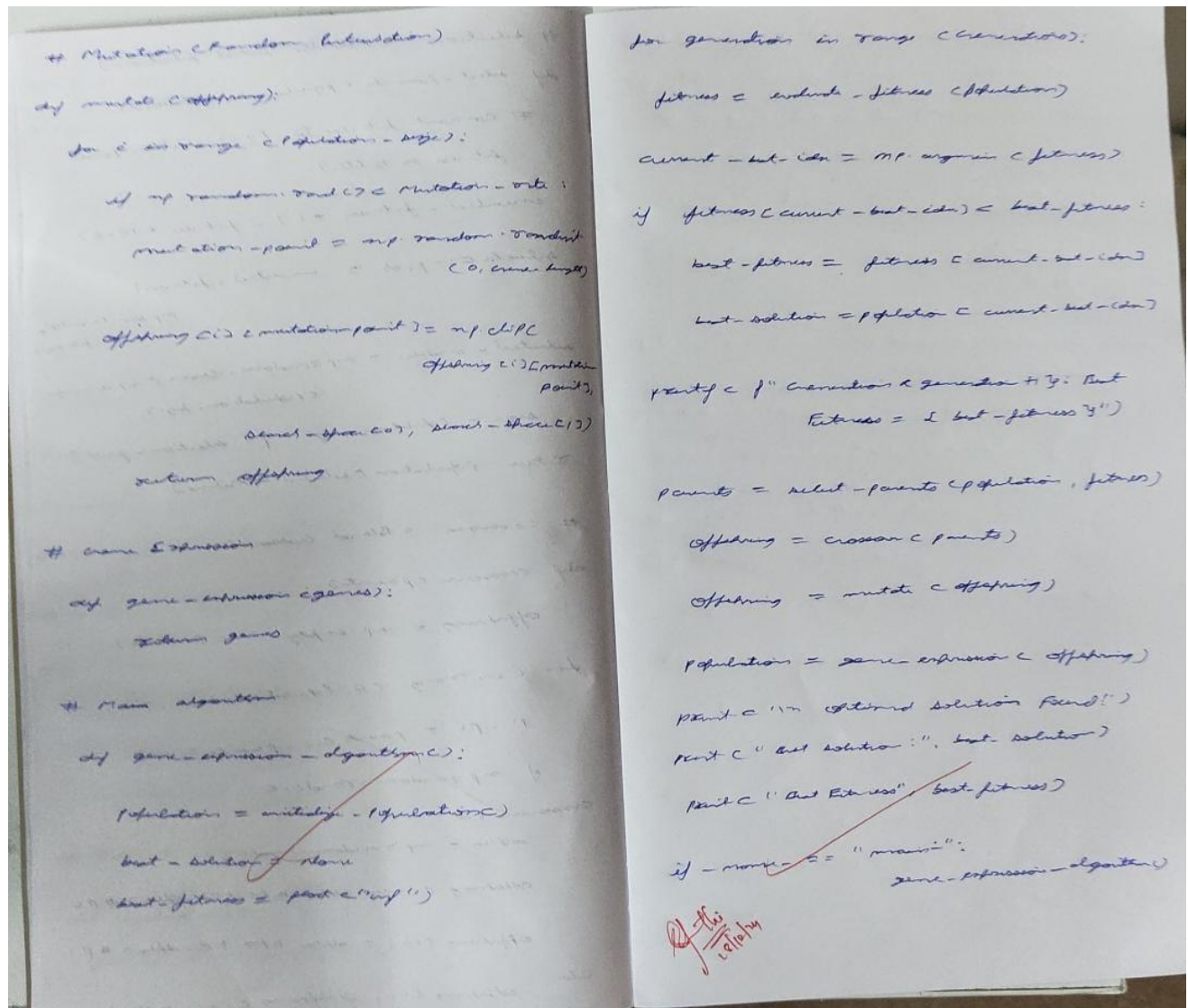
# Crossover = Blend Crossover
def crossover(parents):
    offspring = np.empty_like(parents)

    for i in range(0, population_size, 2):
        p1, p2 = parents[i], parents[i+1]

        if np.random.rand() < crossover_rate:
            alpha = np.random.rand()
            offspring[i] = alpha * p1 + (1-alpha) * p2
            offspring[i+1] = alpha * p2 + (1-alpha) * p1
        else:
            offspring[i], offspring[i+1] = p1, p2

    return offspring

```



Code:

```

import random
import numpy as np
import operator

# Function set and terminal set
FUNCTIONS = {'+': operator.add, '-': operator.sub, '*': operator.mul, '/': operator.truediv}
TERMINALS = ['x', 1, 2, 3, 4] # x and constants

def random_gene(length=10):
    """Generate a random chromosome (gene)."""
    return [random.choice(list(FUNCTIONS.keys()) + TERMINALS) for _ in range(length)]

```



```

def decode_chromosome(chromosome, x):
    """Decode chromosome into a functional expression tree (phenotype)."""
    stack = []
    for gene in chromosome:
        if gene in FUNCTIONS: # If it's a function, pop arguments and apply
            if len(stack) < 2: # Avoid errors if stack has fewer than 2 elements
                stack.append(0)
                continue
            b = stack.pop()
            a = stack.pop()
            try:
                result = FUNCTIONS[gene](a, b)
            except ZeroDivisionError:
                result = 1 # Avoid division by zero
            stack.append(result)
        elif gene == 'x':
            stack.append(x)
        else:
            stack.append(gene)
    return stack[0] if stack else 0 # Return top of stack as output

```

```

def fitness_function(chromosome, target_function, x_values):
    """Calculate fitness based on Mean Squared Error."""
    predictions = [decode_chromosome(chromosome, x) for x in x_values]
    targets = [target_function(x) for x in x_values]
    mse = np.mean([(p - t) ** 2 for p, t in zip(predictions, targets)])
    return mse

```

```

def selection(population, fitnesses):
    """Select individuals based on fitness (roulette wheel selection)."""
    total_fitness = sum(1 / (f + 1e-6) for f in fitnesses) # Avoid division by zero
    probabilities = [(1 / (f + 1e-6)) / total_fitness for f in fitnesses]
    return population[np.random.choice(len(population), p=probabilities)]

```

```

def mutate(chromosome, mutation_rate=0.1):
    """Apply mutation to a chromosome."""
    new_chromosome = chromosome[:]
    for i in range(len(new_chromosome)):
        if random.random() < mutation_rate:

```

```

        new_chromosome[i] = random.choice(list(FUNCTIONS.keys()) + TERMINALS)
    return new_chromosome

```

```

def crossover(parent1, parent2):
    """Perform one-point crossover between two parents."""
    point = random.randint(1, len(parent1) - 1)
    child1 = parent1[:point] + parent2[point:]
    child2 = parent2[:point] + parent1[point:]
    return child1, child2

```

```

def gene_expression_algorithm(target_function, x_values, population_size=10, generations=20):
    """Main Gene Expression Algorithm."""
    # Initialize random population
    population = [random_gene() for _ in range(population_size)]

    print("Initial Population:")
    for i, chrom in enumerate(population):
        print(f"Chromosome {i}: {chrom}")

    for generation in range(generations):
        print(f"\nGeneration {generation + 1}:")
        # Calculate fitness for each individual
        fitnesses = [fitness_function(chrom, target_function, x_values) for chrom in population]
        for i, (chrom, fit) in enumerate(zip(population, fitnesses)):
            print(f"Chromosome {i}: {chrom}, Fitness: {fit:.4f}")

        # Select the next generation
        new_population = []
        for _ in range(population_size // 2):
            parent1 = selection(population, fitnesses)
            parent2 = selection(population, fitnesses)
            child1, child2 = crossover(parent1, parent2)
            child1 = mutate(child1)
            child2 = mutate(child2)
            new_population.extend([child1, child2])
        population = new_population

    # Final results
    print("\nFinal Population and Fitness:")
    fitnesses = [fitness_function(chrom, target_function, x_values) for chrom in population]

```

```

for i, (chrom, fit) in enumerate(zip(population, fitnesses)):
    print(f"Chromosome {i}: {chrom}, Fitness: {fit:.4f}")

best_index = np.argmin(fitnesses)
print("\nBest Solution:")
print(f"Chromosome: {population[best_index]}, Fitness: {fitnesses[best_index]:.4f}")

# Target function for regression
def target_function(x):
    return x**2 + 2*x + 1 # Example:  $f(x) = x^2 + 2x + 1$ 

# Input values
x_values = np.linspace(-10, 10, 20)

# Run the algorithm
gene_expression_algorithm(target_function, x_values, population_size=10, generations=10)

```

Output:

```

Best Solution:
Chromosome: [1, 3, '+', 2, 1, 4, '*', '*', '*', 3], Fitness: 1259.2067
<ipython-input-3-6df17022c257>:25: RuntimeWarning: divide by zero encountered in scalar divide
    result = FUNCTIONS[gene](a, b)

```