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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B.M.S. College of Engineering,

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(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "Bio Inspired Systems (23CS5BSBIS)" carried out by **PRATIK JANA (1BM22CS356),** 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: BIS-LAB/ at main · pratik03092003/BIS-LAB

Program 1

Genetic Algorithm for Optimization Problems

Algorithm:

Implement A genetic Algorithm to MAximize
A fn ($f(x)=x^2$)

```
import numpy np
def objective-fn (x)
        return (x**2)
population_size=100
mutation_size=0.01
crossover_rate = 0.7
num generation = 50
xmin = -10
xmax = 10

def intialize (size)
        return np.random uniform (x-min
                                  x-max
                                  size)
def evaluate (population)
        return objective-fn (population)

def select (population, fitness)
        selected_indius= np.random.choice
                         (len(population),
        size = 2, replace - False
        return population [selected_indius[
                np.argmax (fitness-indiu)
```

```
def crossover (parent, parent2)
    if np.random.rand() < crossover
                                rate
        return (parent + parent2)/2
    return parent 1

def mutate (individual):
        if np.random.rand() < mutation
                                rate
        return Individual + np.random
            uniform (-1,1)
        return Individual

def genetic_algorithm():
        population = Initialize (population_size)
        best_soln = none
        best_fitness = -np.inf
return best fitness . best_soln
```

Best x

o/p = 9.96203495

Best value 99.25534684

Code:

```
import numpy as np

# Define the objective function
def objective_function(x):
    return x**2

# Initialize parameters
population_size = 100
mutation_rate = 0.01
crossover_rate = 0.7
num_generations = 50
x_min = -10
x_max = 10

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

# Evaluate fitness
def evaluate_fitness(population):
    return objective_function(population)

# Selection (Tournament Selection)
def select(population, fitness):
    selected_indices = np.random.choice(len(poTpulation), size=2, replace=False)
    return population[selected_indices[np.argmax(fitness[selected_indices])]]

# Crossover
def crossover(parent1, parent2):
    if np.random.rand() < crossover_rate:
        return (parent1 + parent2) / 2  # Simple averaging
    return parent1

# Mutation
def mutate(individual):
    if np.random.rand() < mutation_rate:
        return individual + np.random.uniform(-1, 1)  # Random mutation
    return individual

# Genetic Algorithm
def genetic_algorithm():
    population = initialize_population(population_size)
    best_solution = None
    best_fitness = -np.inf

    for generation in range(num_generations):
```

```
        fitness = evaluate_fitness(population)

        # Track the best solution
        current_best_index = np.argmax(fitness)
        if fitness[current_best_index] > best_fitness:
            best_fitness = fitness[current_best_index]
            best_solution = population[current_best_index]

        # Create a new population
        new_population = []
        for _ in range(population_size):
            parent1 = select(population, fitness)
            parent2 = select(population, fitness)
            offspring = crossover(parent1, parent2)
            offspring = mutate(offspring)
            new_population.append(offspring)

        population = np.array(new_population)

    return best_solution, best_fitness

# Run the Genetic Algorithm
best_x, best_value = genetic_algorithm()
print(f"Best x: {best_x}, Maximum value of f(x): {best_value}")
```

```
Best x: 9.96260349526031, Maximum value of f(x): 99.25346840377296
```

Program 2

Particle Swarm Optimization for Function Optimization

Algorithm:

```
import numpy as np
import matplot.lib

def objective fn (x):
        return np.sum(x)*2+x)

Initialize parameter
  np, nD, nI, c1, c2 = 30, 2, 20, 0.5

Initialize global value
global_best_position = personal_best_position
                                (personal_best
global_best value = np.min (      -value)
                              personal_best_val)

plt.figure (figsize=(10,8))
plt.xlim (-10,10)
plt.ylim (-10,10)
plt.xlabel (x axis)
plt.ylabel (y axis)
plt.title ("PSO")
```

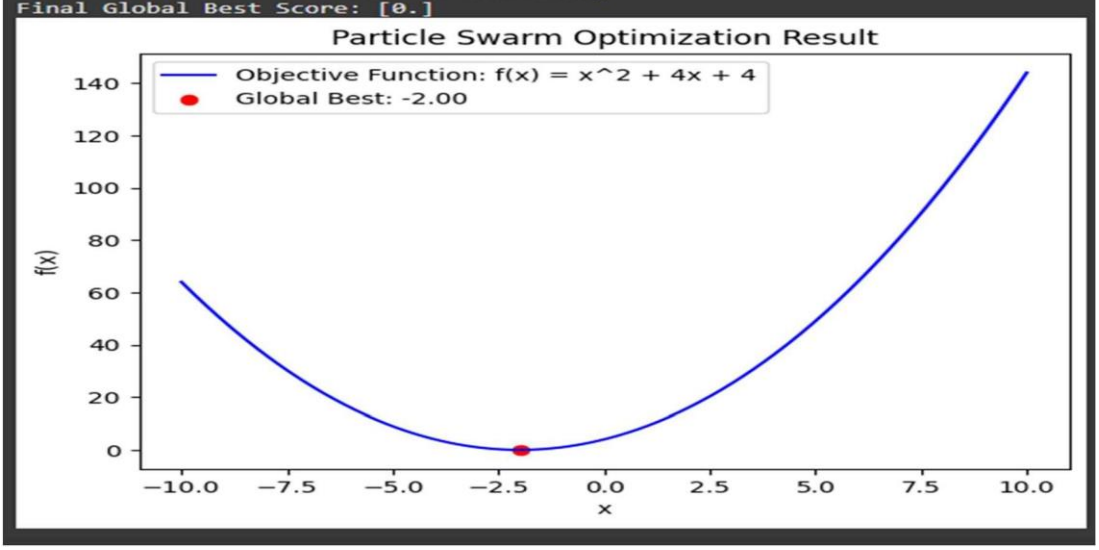
```
for i in range (num_particles)
    r1,r2 = np.random.rand(2)
    inertia = inertia_weight * particles_velocity[i]
    cognitive = c1*r1*(personal_best_pos[i] -
                                particle_pos[i])
    social = c2*r2*(gbp - pp[i])
    particles_velocity[i] = inertia + cognitive
                                    + social
    pp[i] += particles_velocity[i]

# Evaluate fitness

    fitness = objective_fn(particles_position[i])
    if fitness < personal_best_value[i]:
        personal_best_value[i] = fitness
        personal_best_position[i] = particles_
                                    position[i]

    if fitness < global_best_value:
        global_best_value = fitness
        global_best_position = particles_pos[i]

plt.show()
print (global_best_position)
print (global_best_value)
```

Code:

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

# Objective function: f(x) = x^2 + 4x + 4
def objective_function(x):
    return x**2 + 4*x + 4

# PSO parameters
num_particles = 30        # Number of particles
dimensions = 1            # Problem dimensionality (1D for this example)
iterations = 100          # Number of iterations
w = 0.5                   # Inertia weight
c1 = 1.5                  # Cognitive coefficient
c2 = 1.5                  # Social coefficient

# Initialize the particles
positions = np.random.uniform(-10, 10, size=(num_particles, dimensions))  # Random positions
velocities = np.random.uniform(-1, 1, size=(num_particles, dimensions))  # Random velocities
personal_best_positions = np.copy(positions)  # Personal best positions
personal_best_scores = np.array([objective_function(p) for p in positions])  # Personal best scores

# Global best (initially the best personal position)
global_best_position = personal_best_positions[np.argmin(personal_best_scores)]
global_best_score = np.min(personal_best_scores)

# PSO Optimization loop
for iteration in range(iterations):
    for i in range(num_particles):
        # Update velocity
        r1 = np.random.rand()
        r2 = np.random.rand()
        velocities[i] = w * velocities[i] + c1 * r1 * (personal_best_positions[i] - positions[i]) + c2 * r2 *
(global_best_position - positions[i])

        # Update position
        positions[i] = positions[i] + velocities[i]

        # Evaluate the objective function
        current_score = objective_function(positions[i])

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

        # Update global best
```

```
        if current_score < global_best_score:
            global_best_score = current_score
            global_best_position = positions[i]

    # Optionally print the global best score during the iterations
    if iteration % 10 == 0:
        print(f"Iteration {iteration}: Global Best Score = {global_best_score}")

# Final result
print(f"Final Global Best Position: {global_best_position}")
print(f"Final Global Best Score: {global_best_score}")

# Plotting the results for visualization
x = np.linspace(-10, 10, 400)
y = objective_function(x)

plt.plot(x, y, label="Objective Function: f(x) = x^2 + 4x + 4", color='blue')
plt.scatter(global_best_position, global_best_score, color='red', label=f"Global Best:
{global_best_position[0]:.2f}")
plt.legend()
plt.title("Particle Swarm Optimization Result")
plt.xlabel("x")
plt.ylabel("f(x)")
plt.show()
```

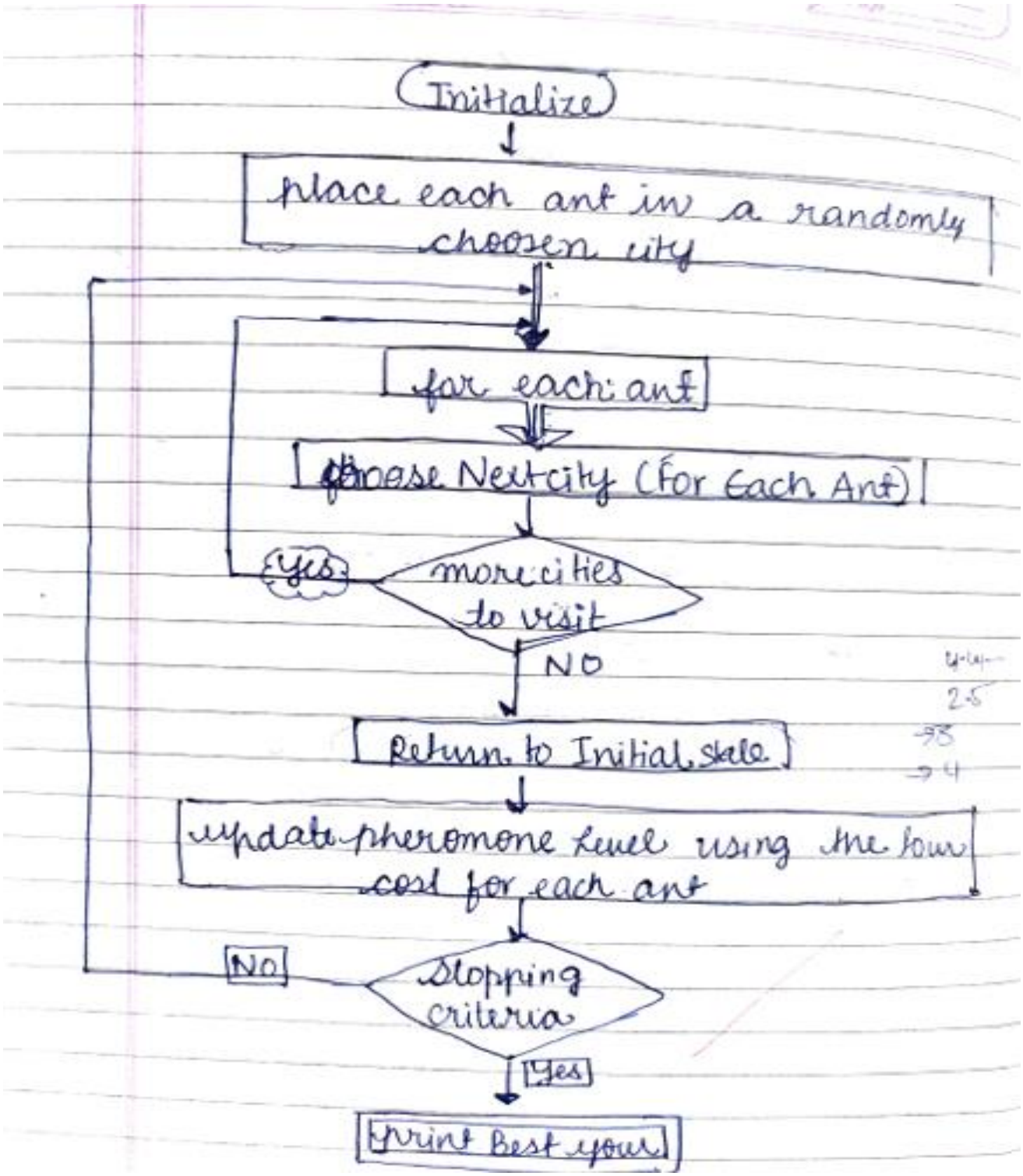
```
Iteration 0: Global Best Score = [0.00063526]
Iteration 10: Global Best Score = [0.00020327]
Iteration 20: Global Best Score = [5.5574043e-06]
Iteration 30: Global Best Score = [1.19586296e-09]
Iteration 40: Global Best Score = [2.02327044e-11]
Iteration 50: Global Best Score = [1.72306613e-13]
Iteration 60: Global Best Score = [0.]
Iteration 70: Global Best Score = [0.]
Iteration 80: Global Best Score = [0.]
Iteration 90: Global Best Score = [0.]
Final Global Best Position: [-1.99999999]
Final Global Best Score: [0.]
```



Program 3

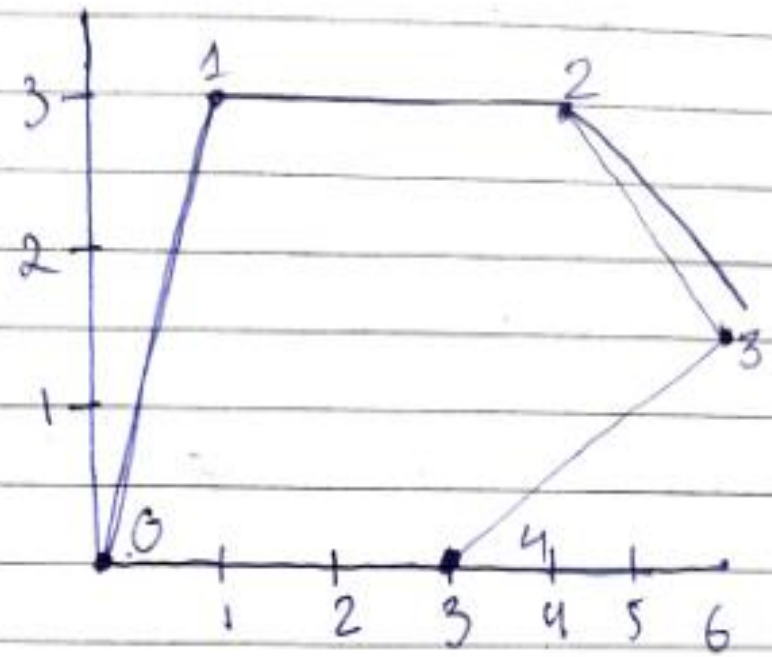
Ant Colony Optimization for the Traveling Salesman Problem

Algorithm:



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

cities = np.array([[0,0],[1,3],[4,3],[6,1],[3,0]])
num_ants, num_iteration = 5,100
alpha, beta, rho, initial_pheromone = 1.0, 2.0, 0.1, 0.0

def choose_next_city (current_city, visited):
        probs= [(pheromones [current_city][j]
                                ** alpha)
            * (1 / distance [current city][j] ** beta)


Algorithm:

best_route, best_distance = None, float ('inf')
        routs, distance = [],[]
        for in range (num_iteration):
                routes, distance_list = [], [ ]
        for _ in range (num_ants):
                route = [random.randint
        while len(route) < num cities (0, num_cities-1)]

            d = sum[distance [route[i]]
                                route [i+1]]
```

```
routes.append(route)
distance_list.append(distance)

# update pheromones
# plotting.
```



Best route ACO : 15:15 unit

Code:

```
import random
import math
import numpy as np

# Calculate the Euclidean distance between two cities
def distance(city1, city2):
    return math.sqrt((city1[0] - city2[0])**2 + (city1[1] - city2[1])**2)

# Ant Colony Optimization for TSP
class AntColony:
    def _init_(self, cities, num_ants, alpha, beta, rho, iterations):
        self.cities = cities
        self.num_cities = len(cities)
        self.num_ants = num_ants
        self.alpha = alpha  # Influence of pheromone
        self.beta = beta     # Influence of distance
        self.rho = rho       # Pheromone evaporation rate
        self.iterations = iterations
        self.pheromone = np.ones((self.num_cities, self.num_cities))  # Initial pheromone
        self.distances = np.zeros((self.num_cities, self.num_cities))

        # Calculate the distance matrix for all pairs of cities
        for i in range(self.num_cities):
            for j in range(i + 1, self.num_cities):
                self.distances[i][j] = distance(self.cities[i], self.cities[j])
                self.distances[j][i] = self.distances[i][j]

    def probability(self, ant, city, visited):
        """Calculates the probability of moving to a next city."""
        pheromone = self.pheromone[city]
        heuristic = np.array([1.0 / self.distances[city][i] if i not in visited else 0 for i in
range(self.num_cities)])
        pheromone_heuristic = pheromone ** self.alpha * heuristic ** self.beta
        pheromone_heuristic[visited] = 0  # Ensure no city is visited twice

        return pheromone_heuristic / pheromone_heuristic.sum()

    def run(self):
        best_distance = float('inf')
        best_tour = None

        # Iterate for a number of iterations
        for _ in range(self.iterations):
            all_tours = []
            all_distances = []
```

```
        # Each ant constructs a solution
        for ant in range(self.num_ants):
            visited = [0]  # Start from city 0
            tour = [0]
            total_distance = 0

            # Construct the solution by visiting all cities
            while len(visited) < self.num_cities:
                city = visited[-1]
                prob = self.probability(ant, city, visited)
                next_city = np.random.choice(range(self.num_cities), p=prob)
                visited.append(next_city)
                tour.append(next_city)
                total_distance += self.distances[city][next_city]

            # Add the return to the starting city
            total_distance += self.distances[visited[-1]][visited[0]]

            # Track the best tour and distance
            all_tours.append(tour)
            all_distances.append(total_distance)

            if total_distance < best_distance:
                best_distance = total_distance
                best_tour = tour

        # Update pheromone trails
        self.pheromone *= (1 - self.rho)  # Evaporate pheromone
        for ant in range(self.num_ants):
            for i in range(self.num_cities - 1):
                city1 = all_tours[ant][i]
                city2 = all_tours[ant][i + 1]
                self.pheromone[city1][city2] += 1.0 / all_distances[ant]  # Pheromone reinforcement
                self.pheromone[city2][city1] += 1.0 / all_distances[ant]

    return best_tour, best_distance

# Example usage
if __name___== "__main__":
    # Define cities as a list of (x, y) coordinates
    cities = [(0, 0), (1, 3), (4, 3), (6, 1), (6, 5), (2, 7), (3, 4), (5, 2)]

    # Set the ACO parameters
    num_ants = 10
    alpha = 1.0    # Pheromone importance
    beta = 2.0     # Heuristic importance
    rho = 0.1      # Pheromone evaporation
```

```
iterations = 100

# Create and run the ant colony optimizer
aco = AntColony(cities, num_ants, alpha, beta, rho, iterations)
best_tour, best_distance = aco.run()

# Output the best solution found
print("Best tour:", best_tour)
print("Best distance:", best_distance)
```

```
Best tour: [0, 1, 6, 5, 4, 2, 7, 3]
Best distance: 24.772376032626727
```

Program 4

Cuckoo Search (CS)

Algorithm:

cuckoo search:

- import numpy as np
  from scipy.special import gamma,
  import random

// Rastrigin function

- def rastrigin(x)
  A=10
  return (A * len(x) + sum(x_i**2 - A*cos(2*pi*x_i)
  for (x_i) in x)

  // $f(x) = A \cdot n + \sum_{i=1}^{n} (x_i^2 - A \cdot \cos(2\pi x_i))$

// create random sol

- def initialize_nest (num_nests, dim, lb, ub
  nests = np.random.uniform (Lb, up, (num_nests, dim))

  returns nest

- def levy_flight (x, alpha = 1.5, beta = 10, delta=
  sigma = (gamma(1+alpha) * np.sin(np.pi * alpha/2) /
  gamma((1+alpha)/2) * alpha * 2**((alpha-1)/2)))) ** (1/alpha)
  u = np.random.normal (0,1, len(x))
  v = np.random.uniform (0,sigma,len(x))

```
worst_nest_indices = np.argsort(fitness[-int
                    pa * num_nest):]
for idx in worst_nest_indices
nest[idx] = np.random.uniform(lb, ub, dim)
fitness[idx] = objective_fn(nest[idx])

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]

    print("Iteration:" {iteration+1}/{num_iter
                                    ns}
          "best fitness:": {best_fitness})

    return best_nest, best_fitness
```

Code:

```
import numpy as np
import math

# Sphere Function: f(x) = sum(x_i^2)
def sphere_function(x):
    return np.sum(x**2)

# Lévy Flight function
def levy_flight(Lambda, d):
    # Lévy flight step size based on power-law distribution
    sigma_u = (math.gamma(1 + Lambda) * np.sin(np.pi * Lambda / 2) /
               (math.gamma((1 + Lambda) / 2) * Lambda * 2**((Lambda - 1) / 2)))**(1 / Lambda)
    u = np.random.normal(0, sigma_u, d)
    v = np.random.normal(0, 1, d)
    step = u / np.abs(v)**(1 / Lambda)
    return step

# Initialize the Cuckoo Search Algorithm
def cuckoo_search(func, n_nests, n_dim, max_iter, pa=0.25, alpha=0.01, lambda_levy=1.5):
    # Initialize nests randomly
    nests = np.random.uniform(-5, 5, (n_nests, n_dim))  # Bound the values between -5 and 5 for the
Sphere function
    fitness = np.apply_along_axis(func, 1, nests)  # Calculate fitness of each nest

    # Keep track of the best solution found so far
    best_nest = nests[np.argmin(fitness)]
    best_fitness = np.min(fitness)

    for iteration in range(max_iter):
        # Generate new nests via Lévy flights
        new_nests = nests + alpha * levy_flight(lambda_levy, n_dim)
        # Ensure new nests are within bounds
        new_nests = np.clip(new_nests, -5, 5)

        # Evaluate new nests' fitness
        new_fitness = np.apply_along_axis(func, 1, new_nests)

        # Replace worst nests with new ones based on probability of discovery
        for i in range(n_nests):
            if np.random.rand() < pa:  # Discovery probability
                nests[i] = new_nests[i]
                fitness[i] = new_fitness[i]

        # Update the best solution if we find a better one
        if np.min(fitness) < best_fitness:
            best_fitness = np.min(fitness)
```

```
            best_nest = nests[np.argmin(fitness)]
        # Output the current iteration's best solution

    return best_nest, best_fitness

# Set algorithm parameters
n_nests = 50          # Number of nests (solutions)
n_dim = 10            # Dimensionality of the problem (number of variables)
max_iter = 100        # Number of iterations
pa = 0.25             # Probability of discovery (abandoning the worst nests)
alpha = 0.01          # Scaling factor for the Lévy flight
lambda_levy = 1.5     # Exponent for Lévy flight distribution

# Run the Cuckoo Search Algorithm to minimize the Sphere Function
best_solution, best_value = cuckoo_search(sphere_function, n_nests, n_dim, max_iter)

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

```
Best Solution Found: [ 0.02678509  0.23352996  1.6252229  -2.98750263  3.27095615 -2.01511818
  1.96138533  0.00816108  0.82788469 -0.18501841]
Best Fitness Value: 30.478578013430198
```

Program 5

Grey Wolf Optimizer (GWO)

Algorithm:

```
import numpy as np

def obj_fn(x)
    return np.sum(x**2)

def grey_w_o(obj_fn, dim, n_wolves=5
                max_itr=50, lb-10, ub+10):

    wolves - np.random.uniform(lb, ub, (n_wolves
                                        , dim))

    alpha = np.inf
    beta = np.inf
    delta = np.inf
    X_a = None
    X_b = None
    X_s = None

    for it in range(max_itr):
        fitness= np.array([objective_fn(wolf)
                    for wolf in values])

        sorted_index= np.argsor(fitness)
        X_a, X_b, X_b - wolves[sorted_index[:3]]
```

```
a = 2 - i * (2/maxitr)
new_wolves[]
for j in rang (n_wolves):
    r1, r2 = np.random.rand(dim),
        r2 = np.random.rand(dim),

    A1 = 2*a*r1 - a
    C1 = 2*r2
    D_alpha = abs(C1 * x_alpha - wolves[j])
    X1 = x_alpha - A1 * D_alpa

    r1, r2 = np.random.rand(dim),
             np.random.rand(dim)
    A2, C2 = 2*a*r1 - a, 2*r2
    D_beta = abs((2* x_b - wolves[j])
    x2 = X_beta - A2 * D_beta

    r1, r2 = np.random.rand(dim)
             np.random.rand(dim)
    A3, C3 = 2*a*r1 - a, 2*r2
    D_Delta = abs(C3 - X_delta - wolves[j])
    X3 = X_delta - A3 * D_Delta
    new_wolf = (x1+x2+x3) / 3
    new_wolves.append(np.clip(new_wolf, lb,
```

Code:

```
import numpy as np

# Define the objective function (Sphere function: sum(x^2))
def sphere(x):
    return np.sum(x**2)

# Grey Wolf Optimizer (GWO)
class GWO:
    def _init_(self, obj_func, dim, pop_size, max_iter, lb, ub):
        self.obj_func = obj_func  # Objective function to minimize
        self.dim = dim            # Number of dimensions
        self.pop_size = pop_size  # Number of wolves in the population
        self.max_iter = max_iter  # Maximum number of iterations
        self.lb = lb              # Lower bound of search space
        self.ub = ub              # Upper bound of search space

        # Initialize the wolves' positions randomly within bounds
        self.position = np.random.uniform(self.lb, self.ub, (self.pop_size, self.dim))
        self.fitness = np.array([self.obj_func(ind) for ind in self.position])  # Initial fitness of all wolves

        # Initialize the alpha, beta, and delta wolves' positions and fitness
        self.alpha_pos = np.zeros(self.dim)
        self.beta_pos = np.zeros(self.dim)
        self.delta_pos = np.zeros(self.dim)
        self.alpha_score = float('inf')  # Best score (we minimize, so start with infinity)
        self.beta_score = float('inf')
        self.delta_score = float('inf')

    def update_position(self, alpha, beta, delta, a, A, C, position):
        # Update the position of a single wolf based on the positions of alpha, beta, delta
        r1 = np.random.random(self.dim)
        r2 = np.random.random(self.dim)

        # Update position using the equation
        D_alpha = abs(C[0] * r1 - position - alpha)
        D_beta = abs(C[1] * r1 - position - beta)
        D_delta = abs(C[2] * r1 - position - delta)

        X1 = alpha - A[0] * D_alpha
        X2 = beta - A[1] * D_beta
        X3 = delta - A[2] * D_delta

        # New position is the average of the three components
        new_position = (X1 + X2 + X3) / 3
        return new_position
```

```
    def optimize(self):
        for t in range(self.max_iter):
            # Update parameters A and C based on the iteration
            a = 2 - t * (2 / self.max_iter)  # Declining over iterations
            A = np.random.uniform(-a, a, 3)
            C = np.random.uniform(0, 2, 3)

            # Evaluate fitness and update the alpha, beta, delta wolves
            for i in range(self.pop_size):
                fitness = self.obj_func(self.position[i])

                if fitness < self.alpha_score:
                    self.alpha_score = fitness
                    self.alpha_pos = self.position[i]

                elif fitness < self.beta_score:
                    self.beta_score = fitness
                    self.beta_pos = self.position[i]

                elif fitness < self.delta_score:
                    self.delta_score = fitness
                    self.delta_pos = self.position[i]

            # Update the position of each wolf in the population
            for i in range(self.pop_size):
                # Update the position of wolf i
                self.position[i] = self.update_position(self.alpha_pos, self.beta_pos, self.delta_pos, a, A, C,
self.position[i])

                # Ensure the new position stays within the bounds
                self.position[i] = np.clip(self.position[i], self.lb, self.ub)

            # Optionally print the progress
            print(f"Iteration {t+1}/{self.max_iter} - Best Fitness: {self.alpha_score}")

        return self.alpha_pos, self.alpha_score

# Set problem-specific parameters
dim = 10              # Number of dimensions (variables in the function)
pop_size = 50         # Number of wolves in the population
max_iter = 100        # Number of iterations
lb = -5.12            # Lower bound of search space
ub = 5.12             # Upper bound of search space

# Create an instance of the GWO class
gwo = GWO(obj_func=sphere, dim=dim, pop_size=pop_size, max_iter=max_iter, lb=lb, ub=ub)
```

```
# Run the optimization
best_pos, best_score = gwo.optimize()

print("\nOptimization Complete!")

print("Best Solution (Position):", best_pos)
print("Best Fitness (Value):", best_score)
```

```
Iteration 85/100 - Best Fitness: 0.010060709455679629
Iteration 86/100 - Best Fitness: 0.010060709455679629
Iteration 87/100 - Best Fitness: 0.010060709455679629
Iteration 88/100 - Best Fitness: 0.010060709455679629
Iteration 89/100 - Best Fitness: 0.010060709455679629
Iteration 90/100 - Best Fitness: 0.010060709455679629
Iteration 91/100 - Best Fitness: 0.010060709455679629
Iteration 92/100 - Best Fitness: 0.010060709455679629
Iteration 93/100 - Best Fitness: 0.010060709455679629
Iteration 94/100 - Best Fitness: 0.010060709455679629
Iteration 95/100 - Best Fitness: 0.010060709455679629
Iteration 96/100 - Best Fitness: 0.010060709455679629
Iteration 97/100 - Best Fitness: 0.010060709455679629
Iteration 98/100 - Best Fitness: 0.010060709455679629
Iteration 99/100 - Best Fitness: 0.010060709455679629
Iteration 100/100 - Best Fitness: 0.010060709455679629

Optimization Complete!
Best Solution (Position): [0.48660073 0.16603068 0.22455522 0.2916564  0.28708061 0.22164054
 0.45593904 0.29095408 0.33491953 0.21197124]
Best Fitness (Value): 0.010060709455679629
```

Program 6

Parallel Cellular Algorithms and Programs

Algorithm:

Lab8

(parallel cellular automation-based algorithm for optimal robot route planning grid-based environment, ensuring collision free navigation while minimizing travel distance and computational time

```
import random
import numpy as np

def initialize_grid (N,M):
np.random.choice ([0,1], size,([N,M]))

def count_live_neighbours (grid, i, j, N,M)
    return sum(
        grid[ni,nj] for ni in range (i-1, i+2)
        for nj in range (ni != i or nj != j)

def update_cell (grid, new_grid, i, j, N, M):
    Live_neighbours = count_live_neighbours
                (grid, i, j, N, M)
    if grid[i,j] == 1:
        new_grid [i, j] = 1 if live_neighbo
    else :
```

```
else:
    new_grid[i,j] = 1 if live_neighbours(grid,i,j,N,M)

def printgrid(grid)
    for row in grid :
        print(' '.join(map(str, row)))
    print()

def parallel game (N,M,steps)
    grid = initialize_grid(N,M)
        for i in range(steps)
            printgrid()
            for j in range (N)
        grid = new_grid
    print_grig(grid)

N,M = 5,5
steps = 5
final grid = 5
        = parallel of life(N,M,steps
```

Code:

```
import numpy as np
import random

# Objective function: f(x) = x^2 + 4x + 4
def objective_function(x):
    return x**2 + 4*x + 4

# Parameters
grid_size = 10              # Number of cells in the grid (1D grid here for simplicity)
num_iterations = 100        # Number of iterations
neighborhood_radius = 1     # Neighborhood range (cell's neighbors)
mutation_rate = 0.1         # Probability of mutation

# Initialize the grid: random values within a range (-10, 10)
def initialize_grid(grid_size):
    return np.random.uniform(-10, 10, grid_size)

# Fitness evaluation for each cell
def evaluate_fitness(grid):
    return np.array([objective_function(cell) for cell in grid])

# Update the state of each cell based on its neighbors
def update_states(grid, fitness, neighborhood_radius):
    new_grid = np.copy(grid)
    for i in range(grid_size):
        # Get the neighbors (with wraparound at boundaries)
        left = (i - neighborhood_radius) % grid_size
        right = (i + neighborhood_radius) % grid_size

        # Ensure that the indices are valid
        if left <= right:
            neighbors = grid[left:right+1]
            fitness_neighbors = fitness[left:right+1]
        else:
            # Handle wraparound correctly
            neighbors = np.concatenate([grid[left:], grid[:right+1]])
            fitness_neighbors = np.concatenate([fitness[left:], fitness[:right+1]])

        # Update rule: take the average of neighbors if their fitness is better
        best_neighbor = neighbors[np.argmin(fitness_neighbors)]
        # Update rule: Apply smaller mutation
        new_grid[i] = best_neighbor + random.uniform(-mutation_rate / 10, mutation_rate / 10) #
Reduced mutation impact

    return new_grid
```

```
# Main Cellular Algorithm Function
def parallel_cellular_algorithm():
    # Initialize grid
    grid = initialize_grid(grid_size)

    best_solution = None
    best_fitness = float('inf')

    # Iterate through generations
    for iteration in range(num_iterations):
        fitness = evaluate_fitness(grid)

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

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

        # Output the best solution at regular intervals
        if iteration % 10 == 0:
            print(f"Iteration {iteration}: Best Fitness = {best_fitness}")

    return best_solution, best_fitness

# Run the Parallel Cellular Algorithm
best_solution, best_fitness = parallel_cellular_algorithm()

# Output the final best solution
print(f"Final Best Solution: {best_solution}")
print(f"Final Best Fitness: {best_fitness}")
```

```
Iteration 0: Best Fitness = 0.008102765732833639
Iteration 10: Best Fitness = 0.0006178173275515064
Iteration 20: Best Fitness = 8.999472633774985e-08
Iteration 30: Best Fitness = 2.5049349261507814e-09
Iteration 40: Best Fitness = 2.5049349261507814e-09
Iteration 50: Best Fitness = 7.945333280190425e-11
Iteration 60: Best Fitness = 7.945333280190425e-11
Iteration 70: Best Fitness = 7.945333280190425e-11
Iteration 80: Best Fitness = 7.945333280190425e-11
Iteration 90: Best Fitness = 7.945333280190425e-11
Final Best Solution: -1.9999910863479302
Final Best Fitness: 7.945333280190425e-11
```

Program 7

Optimization via Gene Expression Algorithms

Algorithm:

Lab 9 :- BisLab:-

```
import random
# Def knapsack problem (objective fn)
def knapsnack problem (objective fn)
def knapsack_fitness (items, capacity, solution)
    total_wieght = sums[items[i][0] for i in
        range (len(solution) if solution[i]==1])
    total_value = sum[items[i][1] for i in range
        len(solution)) if solution[i]==1

# If total weight exceeds the capacity return
if total_wieght > capacity
        return 0
return total value

# gene expression algorithm (GEA)
    def_init_(self population size, numitems mut
        rate, crossover_rate, generation, cap
        items)
        self population_size = population size
        self num_items = num_items
        self mutation rate = mutation_rate
        self crossover rate = crossover_rate
        self capacity_rate = capacity
```

```
self population = []

# Initialize population with random sol (binary
representation

def initialize_population(self):

    self.population = [[random.randint(0,1) for _ in
    range(self.population_size)]

# Evaluate fitness of population
def evaluate_fitness(self):
    return [knapsack_fitness(self.items,
            self.capacity, individual) for
    individual in self.population

# Select individuals based on fitness (roulette wheel
                                        selection)

def selection(self):
    fitness_values = self.evaluate_fitness()
    total_fitness == 0: # Avoid division by zero
    return random.choices(self.population, k=
                          self.population_size)
```

```
# crossover.
def crossover(self, parent 1, parent 2):
    if random.random() < self.crossover_rate:
        crossover_point = random.randint(
                                1, self.num_items - 1)
    return individual


# evolve population over generation
def evolve(self):
    self.initialize_population()
    best_solution = None
    best_fitness = 0
    for gen in range(self.generations):
        # selection
            selected = self.selection()

# get user Input for gea parameter
def get_user_input
print ("Enter population size)
    best_solution, fitness = gea.evolve()
print(best solution)
```

Code:

```
import numpy as np
import random

# Objective function: f(x) = x^2 + 4x + 4
def objective_function(x):
    return x**2 + 4*x + 4

# GEA parameters
population_size = 30          # Number of genetic sequences (solutions)
num_genes = 1                 # Number of genes in each sequence (1D optimization in this case)
mutation_rate = 0.05          # Probability of mutation
crossover_rate = 0.7          # Probability of crossover
num_generations = 100         # Number of generations

# Initialize Population: Generate random genetic sequences (chromosomes)
def initialize_population(population_size, num_genes):
    return np.random.uniform(-10, 10, (population_size, num_genes))

# Fitness Evaluation: Evaluate fitness of each sequence
def evaluate_fitness(population):
    return np.array([objective_function(individual[0]) for individual in population])

# Selection: Tournament Selection
def select(population, fitness):
    selected_indices = np.random.choice(len(population), size=2, replace=False)
    return population[selected_indices[np.argmin(fitness[selected_indices])]]

# Crossover: Single-point crossover
def crossover(parent1, parent2):
```

```
    if random.random() < crossover_rate:
        # Random crossover point (for 1D, just average)
        return (parent1 + parent2) / 2
    return parent1

# Mutation: Introduce small random changes
def mutate(individual):
    if random.random() < mutation_rate:
        return individual + np.random.uniform(-1, 1)
    return individual

# Gene Expression: Translate genetic sequence to a functional solution
def gene_expression(population):
    return population

# Main GEA Function: Optimization Loop
def gene_expression_algorithm():
    # Initialize population
    population = initialize_population(population_size, num_genes)

    best_solution = None
    best_fitness = float('inf')

    # Track the best solution through generations
    for generation in range(num_generations):
        fitness = evaluate_fitness(population)

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

        # Create a new population
        new_population = []
        for _ in range(population_size):
            parent1 = select(population, fitness)
            parent2 = select(population, fitness)
            offspring = crossover(parent1, parent2)
            offspring = mutate(offspring)
            new_population.append(offspring)

        population = np.array(new_population)

        # Gene expression (translation of genetic sequence to solutions)
        population = gene_expression(population)
```

```
        # Output the best solution at regular intervals
        if generation % 10 == 0:
            print(f"Generation {generation}: Best Fitness = {best_fitness}")
    return best_solution, best_fitness

# Run the GEA
best_solution, best_fitness = gene_expression_algorithm()

# Output final best solution
print(f"Final Best Solution: {best_solution}")
print(f"Final Best Fitness: {best_fitness}")
```

```
Generation 0: Best Fitness = 4.302998488681217
Generation 10: Best Fitness = 1.8683297042798586e-07
Generation 20: Best Fitness = 2.078337502098293e-13
Generation 30: Best Fitness = 0.0
Generation 40: Best Fitness = 0.0
Generation 50: Best Fitness = 0.0
Generation 60: Best Fitness = 0.0
Generation 70: Best Fitness = 0.0
Generation 80: Best Fitness = 0.0
Generation 90: Best Fitness = 0.0
Final Best Solution: [-2.00000001]
Final Best Fitness: 0.0
```