

# 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**

(Autonomous Institution under VTU)

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Bull Temple Road, Bangalore 560019

(Affiliated To Visvesvaraya Technological University, Belgaum)

**Department of Computer Science and Engineering**



## **CERTIFICATE**

This is to certify that the Lab work entitled “ Bio Inspired Systems (23CS5BSBIS)” carried out by **PADMASHREE JAIN D(1BM23CS223)** , 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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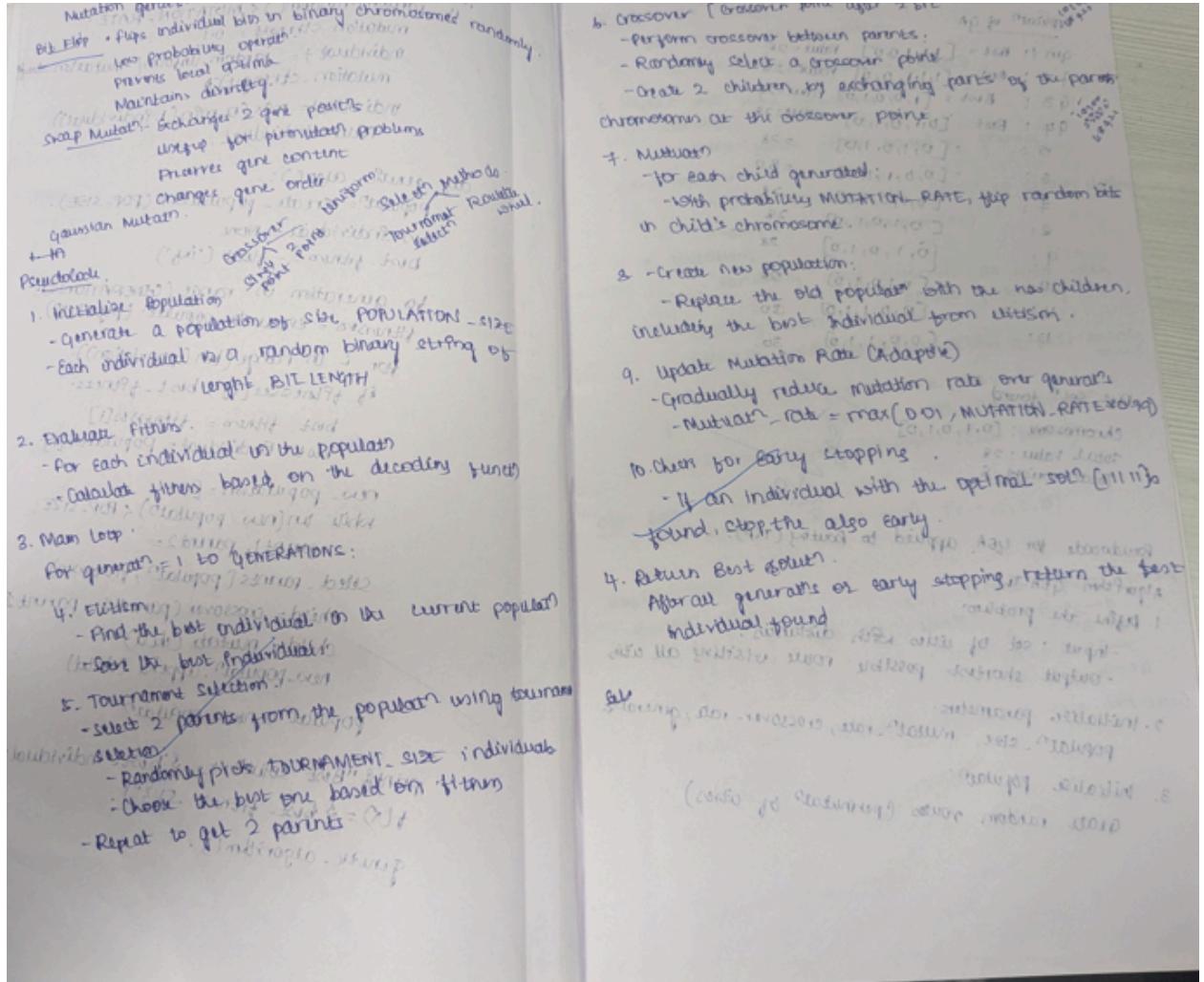
Github Link:

<https://github.com/PADMASHREE719/bio-inspired-system>

### **Program 1**

Design and implement a **genetic algorithm (Knapsack)**in Python

pseudocode  
 1. Define problem & encoding schema  
 2. Initialize population P with N random individuals  
 3. for each individual in P:  
 a. evaluate fitness  
 begin GAS  
 Input: List of  
 Genetic algorithm  
~~algo~~  
 import random  
 import math  
 def fitness(x):  
 return  $x * \sin(2\pi x) + 100$  if  $x \in [0, 1]$   
 POP\_SIZE = 10  
 MUTATION\_RATE = 0.1  
 CROSSOVER\_RATE = 0.9  
 GENERATIONS = 100  
 def create\_population(size):  
 return [random.uniform(0, 1) for i in range(size)]  
 def evaluate\_population(population):  
 return fitness(ind) for ind in population  
 def select\_parents(population, fitness):  
 def tournament():  
 i, j = random.sample(range(len(population)), 2)  
 return population[i] if fitness(i) > fitness(j)  
 return tournament(), tournament()  
 def crossover(p1, p2):  
 if random.random() < CROSSOVER\_RATE:  
 alpha = random.random()  
 return alpha \* p1 + (1 - alpha) \* p2  
 return p1  
 def mutate(individual):  
 mutation\_rate = 0.1  
 individual += random.uniform(-mutation\_rate, mutation\_rate)  
 individual = max(0, min(1, individual))  
 return individual  
 def genetic\_algorithm():
 population = create\_population(POP\_SIZE)
 best\_individual = None
 best\_fitness = float('-inf')
 for generation in range(GENERATIONS):
 fitnesses = evaluate\_population(population)
 for i in range(len(population)):
 if fitnesses[i] > best\_fitness:
 best\_fitness = fitnesses[i]
 best\_individual = population[i]
 new\_population = []
 while len(new\_population) < POP\_SIZE:
 parent1, parent2 = random.sample(population, 2)
 child = crossover(parent1, parent2)
 child = mutate(child)
 new\_population.append(child)
 population = new\_population
 print("Best solution found: ", best\_individual)
 f(x) = best\_fitness
 genetic\_algorithm()



Application of GA

gen 1: Best = [1, 1, 1, 0, 0] value = 28

gen 2: Best = [1, 1, 1, 0, 0] value = 28 (no improvement)

gen 3: Best = [1, 0, 0, 1, 0] value = 28

gen 4: Best = [0, 1, 0, 1, 0] value = 28

5:     = [0, 1, 0, 1, 0] = 28

6:     = [0, 0, 1, 1, 0] = 30.

7:     = [0, 1, 0, 1, 0] value = 28

8:     = [0, 1, 0, 1, 0] value = 28

9:     = [0, 1, 0, 1, 0] value = 28

10:    = [0, 1, 0, 1, 0] value = 28

11:    = [0, 1, 0, 1, 0] value = 28

12:    = [0, 1, 0, 1, 0] value = 28

Best solution found

Chromosome: [0, 1, 0, 1, 0]

Total value: 28

Total weight: 8

### Code:

```

import random

# -----
# Problem Setup
# -----
items = [
    (2, 6), # (weight, value)
    (3, 10),
    (4, 12),
    (5, 18),
    (9, 22)
]
capacity = 10
POP_SIZE = 6 # Number of chromosomes
GENS = 15 # Number of generations
MUT_RATE = 0.1 # Mutation probability
# -----

```

```

# Helper Functions
# -----
def fitness(chromosome):
    weight, value = 0, 0
    for gene, (w, v) in zip(chromosome, items):
        if gene == 1:
            weight += w
            value += v
    if weight > capacity:
        return 0 # Invalid solution
    return value

def create_chromosome():
    return [random.randint(0, 1) for _ in range(len(items))]

def selection(pop, fits):
    # Roulette Wheel Selection
    total_fit = sum(fits)
    if total_fit == 0:
        return random.choice(pop)
    pick = random.uniform(0, total_fit)
    current = 0
    for chrom, fit in zip(pop, fits):
        current += fit
        if current >= pick:
            return chrom

def crossover(p1, p2):
    point = random.randint(1, len(items)-1)
    return p1[:point] + p2[point:], p2[:point] + p1[point:]

def mutate(chrom):
    for i in range(len(chrom)):
        if random.random() < MUT_RATE:
            chrom[i] = 1 - chrom[i] # Flip bit
    return chrom

# -----
# Genetic Algorithm
# -----
population = [create_chromosome() for _ in range(POP_SIZE)]

for gen in range(GENS):
    fitnesses = [fitness(c) for c in population]
    best_fit = max(fitnesses)
    best_chrom = population[fitnesses.index(best_fit)]

```

```

print(f'Generation {gen+1}: Best={best_chrom} Value={best_fit}')

new_population = []
while len(new_population) < POP_SIZE:
    parent1 = selection(population, fitnesses)
    parent2 = selection(population, fitnesses)
    child1, child2 = crossover(parent1, parent2)
    new_population.append(mutate(child1))
    if len(new_population) < POP_SIZE:
        new_population.append(mutate(child2))
    population = new_population

# Final Result
fitnesses = [fitness(c) for c in population]
best_fit = max(fitnesses)
best_chrom = population[fitnesses.index(best_fit)]

print("\nBest Solution Found:")
print(f"Chromosome: {best_chrom}")
print(f"Total Value: {best_fit}")
print(f"Total Weight: {sum(w for gene,(w,v) in zip(best_chrom,items) if gene)}")

```

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## **Program 2**

**gene expression** algorithm for finding Travelling salesman problem

Algorithm:

Pseudocode for GEA applied to Routing (TSP):

Algorithm GEA-TSP

1. Define the problem:

- Input : set of cities with distances,
- output: shortest possible route visiting all

2. Initialize parameters:

population\_size, mutation\_rate, crossover\_rate, gene

3. Initialise population:

create random routes (permutation of cities)

<p>4. Evaluate fitness (fitness = 1 / total distance (route))</p>																					
<p>5. Repeat until max generation</p>																					
<p>a. Selection</p>																					
<p>b. crossover</p>																					
<p>c. mutation</p>																					
<p>d. gene expression:</p> <ul style="list-style-type: none"> <li>- Ensure valid route (all cities appear exactly once)</li> </ul>																					
<p>e. Evaluate new population's fitness</p>																					
<p>f. Replace old population with new population</p>																					
<p>g. Output best solution (shortest route found)</p>																					
<p>IP: Best distance : 26.15 Best Route: [0, 1, 0, 2, 4, 5] • [0, 1, 2, 3, 0]</p>																					
<p><u>Simple example:</u></p>																					
<p>Distance Matrix:</p> <table border="1"> <tr> <th>A</th><th>B</th><th>C</th><th>D</th></tr> <tr> <th>A</th><td>0</td><td>4</td><td>13</td></tr> <tr> <th>B</th><td>4</td><td>0</td><td>10</td></tr> <tr> <th>C</th><td>13</td><td>10</td><td>0</td></tr> <tr> <th>D</th><td>0</td><td>5</td><td>6</td></tr> </table>	A	B	C	D	A	0	4	13	B	4	0	10	C	13	10	0	D	0	5	6	<p>S-1: Initial population (random)            Routes:  <math>A \rightarrow B \rightarrow C \rightarrow D \rightarrow A = 15</math>  <math>A \rightarrow C \rightarrow B \rightarrow D \rightarrow A = 17</math>  <math>A \rightarrow D \rightarrow B \rightarrow C \rightarrow A</math>  <math>A \rightarrow C \rightarrow D \rightarrow B \rightarrow A</math></p>
A	B	C	D																		
A	0	4	13																		
B	4	0	10																		
C	13	10	0																		
D	0	5	6																		
<p>Evaluate fitness (calculate the round-trip distance).</p>																					
$A \rightarrow B \rightarrow C \rightarrow D \rightarrow A = 15$																					
$A \rightarrow C \rightarrow B \rightarrow D \rightarrow A = 17$																					
<p>Shortest = 15</p>																					

self.pop = Route 1 & R-2, sinu they're better solutions  
 "crossover":  
 P1: A → B → C → D → A  
 P2: A → C → B → D → A  
 child 1 gets slice from P1 (B, C).  
 child 1 order A, D → child 2 order A, B → A  
 ALL not from P2. child 2 order D, C → B, A → D  
 child 2 order D, C → B, A → C → B → D → A  
 crossover  
 mutation: introduce small random change  
 swap 2 cities in C → A → B → C → D → A  
 total distance stay the same.  
 Best route: A → B → C → D → A  
~~A → B → C → D → A~~  
~~(total distance stay the same)~~  
~~swap 2 cities in C → A → B → C → D → A~~  
~~[0, 1, 2, 3, 4, 5] - [2, 1, 0, 3, 4, 5]: swap 1st  
 0 & 1~~  
~~[0, 1, 2, 3, 4, 5] - [4, 5, 0, 1, 2, 3]: swap 1st~~  
~~[0, 1, 2, 3, 4, 5] - [3, 4, 5, 0, 1, 2]: swap 1st~~  
 0 & 3

### Code:

```
import random
```

#### # ---- Step 1: Problem Setup ----

```
cities = list(range(6)) # 6 cities labeled 0 to 5
```

```
distance_matrix = [  
  [0, 2, 9, 10, 7, 3],  
  [2, 0, 6, 4, 3, 8],  
  [9, 6, 0, 8, 5, 6],  
  [10, 4, 8, 0, 6, 7],  
  [7, 3, 5, 6, 0, 4],  
  [3, 8, 6, 7, 4, 0]  
]
```

#### # Parameters

```
POP_SIZE = 20
```

```
MUTATION_RATE = 0.1
```

```
GENERATIONS = 200
```

#### # ---- Step 2: Fitness Function ----

```
def total_distance(route):  
  distance = 0  
  for i in range(len(route)):  
    distance += distance_matrix[route[i]][route[(i+1) % len(route)]]
```

```

    return distance

def fitness(route):
    return 1 / total_distance(route)

# ---- Step 3: Initialize Population ----
def create_route():
    route = cities[:]
    random.shuffle(route)
    return route

def initial_population():
    return [create_route() for _ in range(POP_SIZE)]

# ---- Step 4: Selection ----
def selection(population):
    population.sort(key=total_distance)
    return population[:POP_SIZE//2] # take best half

# ---- Step 5: Crossover ---- (Order Crossover)
def crossover(parent1, parent2):
    start, end = sorted(random.sample(range(len(parent1)), 2))
    child = [None]*len(parent1)
    child[start:end] = parent1[start:end]

    fill_values = [gene for gene in parent2 if gene not in child]
    pos = 0
    for i in range(len(child)):
        if child[i] is None:
            child[i] = fill_values[pos]
            pos += 1
    return child

# ---- Step 6: Mutation ----
def mutate(route):
    if random.random() < MUTATION_RATE:
        i, j = random.sample(range(len(route)), 2)
        route[i], route[j] = route[j], route[i]
    return route

# ---- Step 7: Main Loop ----
def gene_expression_algorithm():
    population = initial_population()
    best_route = None
    best_distance = float('inf')

    for gen in range(GENERATIONS):
        selected = selection(population)

```

```

children = []
while len(children) < POP_SIZE:
    p1, p2 = random.sample(selected, 2)
    child = crossover(p1, p2)
    child = mutate(child)
    children.append(child)
population = children

# Track best
current_best = min(population, key=total_distance)
current_dist = total_distance(current_best)
if current_dist < best_distance:
    best_route = current_best
    best_distance = current_dist

if gen % 20 == 0: # log progress
    print(f"Gen {gen}: Best Distance = {best_distance}")

return best_route, best_distance

# ---- Run ----
best_route, best_distance = gene_expression_algorithm()
print("\nBest Route:", best_route)
print("Best Distance:", best_distance)

```

### **Program 3**

Find the maximum of the function  $f(x)=-x^2+y^2$  using **Particle Swarm Optimization** by iteratively updating particle positions and velocities.

Algorithm:

Particle Swarm Optimization (PSO) is based on social behavior of birds flocking or魚群 (fish schooling).  
 Objective function:  $f(x_1, x_2) = x_1^2 + x_2^2$ ,  $x_1, x_2 \in [-10, 10]$ .  
 Number of particles:  $N$ .  
 Max number of iterations: max\_iter.  
 Parameters: inertia weight  $w$ , cognitive co-efficient  $c_1$ , social coefficient  $c_2$ , max\_iter.  
 dp: maximum value  $f(x_1, x_2)$ .

Steps: 25 lines to implement PSO  
 1. Initialize the swarm

- for each particle  $i = 1, 2, \dots, N$
- Randomly initialize position  $p_{best}^{(i)} = p_i^{(i)}$  within bounds.
- Initialize velocity  $v_i = (0, 0)$ .
- Set personal best position  $p_{best} = p_i^{(i)}$ .
- Evaluate fitness  $f(p_i)$  & set as personal best value.  
↑ Max.

2. Determine the global best particle

- Find particle with the best max value.
- Set global best position  $g_{best} = p_{best}$ .
- Set global best fitness  $f_{best} = \max(f_{best})$ .

3. for each iteration  $t = 1$  to max\_iter:

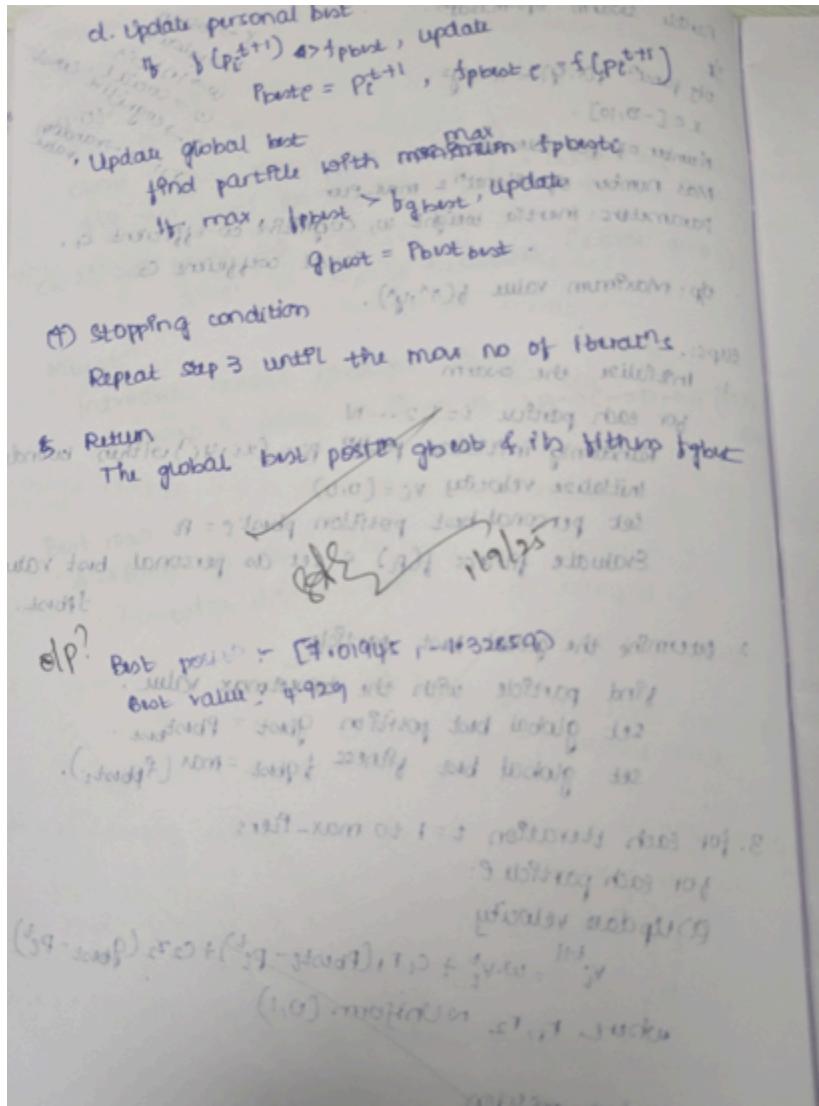
- for each particle  $i$ :
- (a) Update velocity.
$$v_i^{t+1} = w \cdot v_i^t + c_1 r_1 (p_{best} - p_i^t) + c_2 r_2 (g_{best} - p_i^t)$$

where  $r_1, r_2 \sim \text{Uniform}(0, 1)$

- (b) Update position
$$p_i^{t+1} = p_i^t + v_i^{t+1}$$

Clip  $p_i^{t+1}$  to stay within bounds.

- (c) Evaluate fitness
$$f(p_i^{t+1}) = (x_1^{t+1})^2 + (x_2^{t+1})^2$$



### Code:

```

import numpy as np

# Objective function
def f(position):
    x, y = position
    return x**2 + y**2

class Particle:
    def __init__(self, bounds):
        self.position = np.array([np.random.uniform(bounds[0][0], bounds[0][1]),
                                 np.random.uniform(bounds[1][0], bounds[1][1])])
        self.velocity = np.zeros_like(self.position)
        self.pbest_position = self.position.copy()
        self.pbest_value = float('inf')

    def update_velocity(self, gbest_position, w, c1, c2):
        r1, r2 = np.random.rand(2)

```

```

cognitive = c1 * r1 * (self.pbest_position - self.position)
social = c2 * r2 * (gbest_position - self.position)
self.velocity = w * self.velocity + cognitive + social

def update_position(self, bounds):
    self.position += self.velocity
    # Keep particle inside bounds
    for i in range(len(bounds)):
        self.position[i] = np.clip(self.position[i], bounds[i][0], bounds[i][1])

def pso(objective_function, bounds, num_particles, max_iter, w=0.5, c1=1.5,
c2=1.5):
    swarm = [Particle(bounds) for _ in range(num_particles)]
    gbest_value = float('inf')
    gbest_position = None

    for iteration in range(max_iter):
        for particle in swarm:
            fitness = objective_function(particle.position)

            # Update personal best
            if fitness < particle.pbest_value:
                particle.pbest_value = fitness
                particle.pbest_position = particle.position.copy()

            # Update global best
            if fitness < gbest_value:
                gbest_value = fitness
                gbest_position = particle.position.copy()

        # Update velocity and position for each particle
        for particle in swarm:
            particle.update_velocity(gbest_position, w, c1, c2)
            particle.update_position(bounds)

        print(f"Iteration {iteration+1}/{max_iter}, Best Fitness: {gbest_value}")

    return gbest_position, gbest_value

# Parameters
bounds = [(-10, 10), (-10, 10)] # Search space for x and y
num_particles = 30
max_iter = 50

best_pos, best_val = pso(f, bounds, num_particles, max_iter)
print(f'Best position: {best_pos}, Best value: {best_val}')

```

### Program 4

Find the shortest route visiting all cities once and returning to the start using **Ant Colony Optimization**.

Algorithm:

**Ant Colony Optimization (TSP)**

You are given Problem Representation.

Cities  $\rightarrow$  nodes in a graph.

Distance b/w cities  $\rightarrow$  edge weights.

Initialize parameters:

- $m$ : Number of ants.
- $\alpha(\alpha)$ : Importance of pheromone traffic.
- $\beta(\beta)$ : Importance of heuristic (1/distance).
- $\rho(\rho)$ : Evaporation rate of pheromone.
- $\tau_0$ : Initial pheromone on each edge.

Construct solutions (Tour Building):

Each ant starts at a random city.

At each step, an ant chooses the next city probabilistically.

$$P_{ij}(t) \propto [\tau_{ij}(t)]^\alpha \cdot [h_{ij}]^\beta$$

$$\sum_{k \in \text{available}} [\tau_{ik}(t)]^\alpha \cdot [h_{ik}]^\beta$$

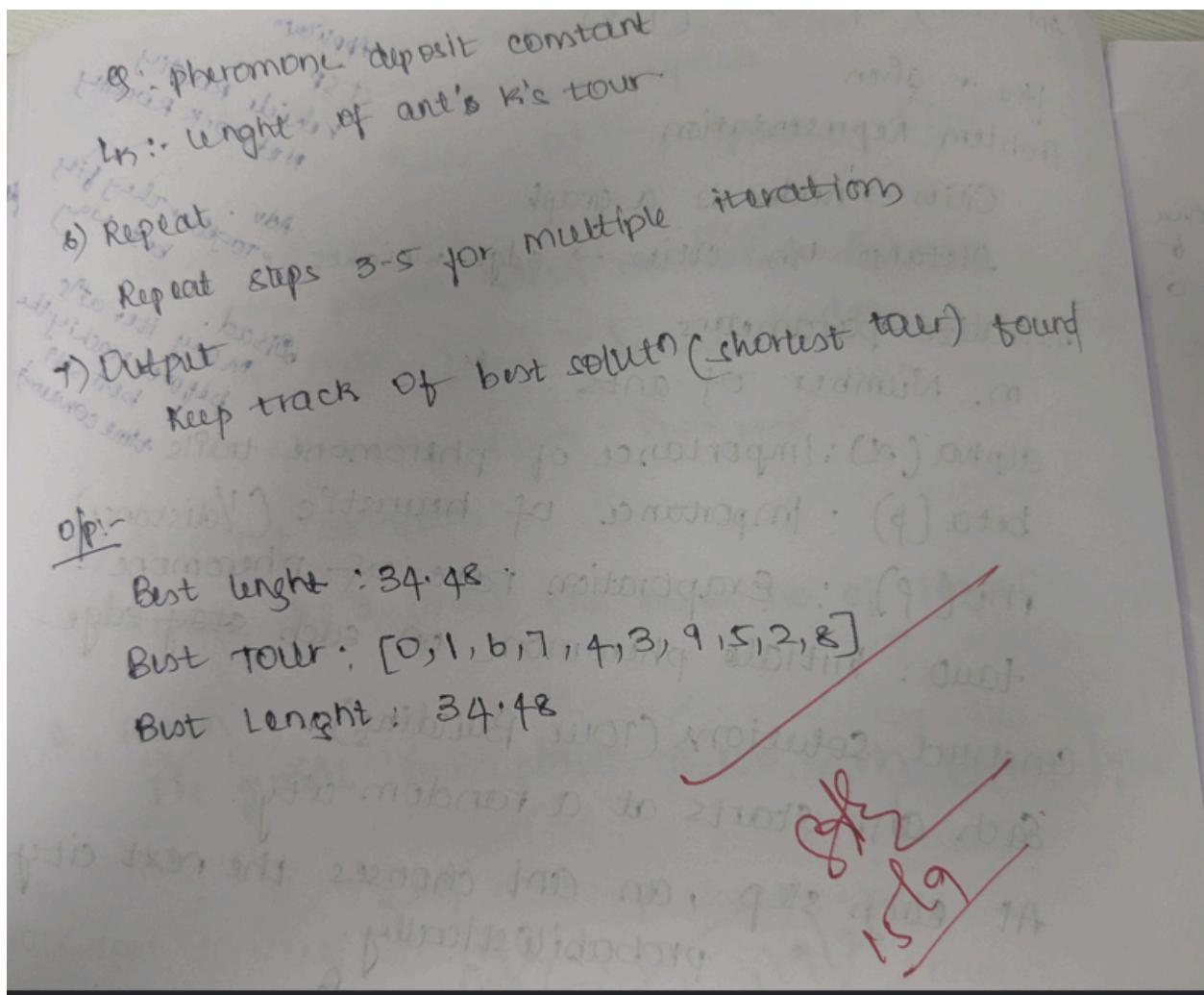
where:

- $(\tau_{ij})$ : pheromone on edge  $i-j$ .
- $h_{ij}$  =  $\frac{1}{d_{ij}}$  (inverse distance)

- ① Evaluate Solutions  
Compute total weight of each ant's tour.  
 $\tau_i(t+1) = \tau_i(t) + \Delta \tau_i$
- ② Update Pheromones ( $t+1$ )
- ③ Evaporate pheromone ( $t+1 - \rho$ )
- ④ Deposit pheromone based on ant's tours:  
 $T_{ij} \leftarrow T_{ij} + \sum_k \Delta T_{ik}$
- where  $\Delta T_{ik} = \begin{cases} 1/k & \text{if ant } k \text{ uses edge } i-j \\ 0 & \text{otherwise} \end{cases}$

**TSP Applications**

- Vehicle Routing
- Network Routing
- Airline Timetabling
- Mail Delivery
- Manufacturing



### Code:

```

import numpy as np
import random
import math

# Step 1: Define the problem (set of cities with coordinates)
cities=[  

(0, 0),  

(1, 5),  

(5, 2),  

(6, 6),  

(8, 3),  

(7, 9),  

(2, 7),  

(3, 3)  

]
N = len(cities)
  
```

```

# Calculate Euclidean distance matrix
def euclidean_distance(a, b):
    return math.sqrt((a[0] - b[0]) ** 2 + (a[1] - b[1]) ** 2)

distance_matrix = [[euclidean_distance(cities[i], cities[j]) for j in range(N)] for i in range(N)]

# Step 2: Initialize Parameters
num_ants = N
max_iterations = 100
alpha = 1.0
beta = 5.0
rho = 0.5
Q = 100.0
tau_0 = 1.0

pheromone = [[tau_0 for _ in range(N)] for _ in range(N)]
heuristic = [[1 / distance_matrix[i][j] if i != j else 0 for j in range(N)] for i in range(N)]

best_tour = None
best_length = float('inf')

# Step 3, 4, 5: Iterate
for iteration in range(max_iterations):
    all_tours = []
    all_lengths = []

    for ant in range(num_ants):
        unvisited = list(range(N))
        current_city = random.choice(unvisited)
        tour = [current_city]
        unvisited.remove(current_city)

        while unvisited:
            probabilities = []
            for j in unvisited:
                tau = pheromone[current_city][j] ** alpha
                eta = heuristic[current_city][j] ** beta
                probabilities.append(tau * eta)
            total = sum(probabilities)
            probabilities = [p / total for p in probabilities]
            next_city = random.choices(unvisited, weights=probabilities, k=1)[0]
            tour.append(next_city)
            unvisited.remove(next_city)
            current_city = next_city

        all_tours.append(tour)
        all_lengths.append(len(tour))

    best_tour = min(all_tours, key=lambda tour: len(tour))
    best_length = len(best_tour)

    # Update pheromone
    for i in range(N):
        for j in range(N):
            pheromone[i][j] += Q / all_lengths[pheromone[i][j] > 0]
            pheromone[i][j] *= 1 - rho

```

```

tour_length = sum(distance_matrix[tour[i]][tour[i+1]] for i in range(N))
all_tours.append(tour)
all_lengths.append(tour_length)

if tour_length < best_length:
    best_length = tour_length
    best_tour = tour

# Step 4: Update Pheromones
# Evaporation
for i in range(N):
    for j in range(N):
        pheromone[i][j] *= (1 - rho)

# Deposit
for tour, length in zip(all_tours, all_lengths):
    for i in range(N):
        a = tour[i]
        b = tour[i+1]
        pheromone[a][b] += Q / length
        pheromone[b][a] += Q / length # because TSP is symmetric

# Step 6: Output the Best Solution
print("Best tour:", best_tour)
print("Best tour length:", round(best_length, 2))

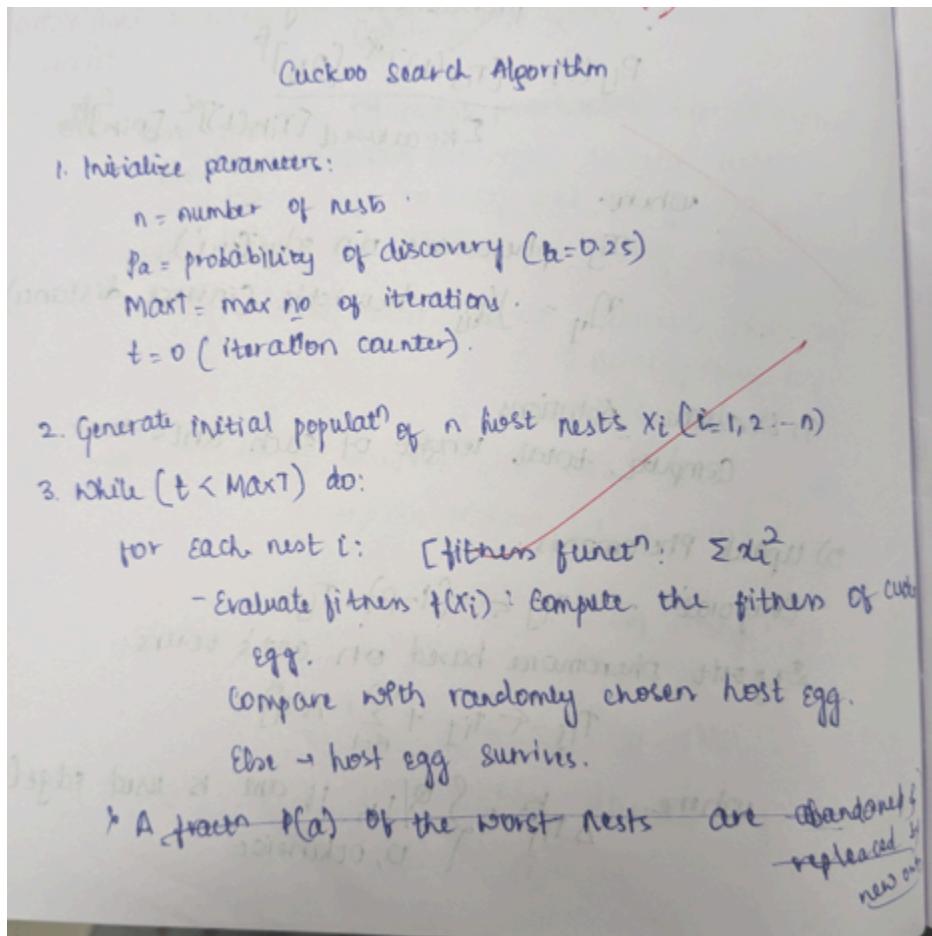
```

### Program 5

Solve the 0/1 Knapsack Problem by using **Cuckoo Search** to maximize total item value

without exceeding the weight limit.

Algorithm:



Generate a new cuckoo solution using Levy flight:  
 $x_{\text{new}} = x_i + \alpha \text{Levy}(\lambda)$   
 Initialize a single current solution  
 $\alpha = 0.01$ ; Step size scaling factor.  
 $\text{Levy}(\lambda)$ : Random step size from Levy distribution  
 → this balances big jumps & small local moves.  
 Evaluate fitness( $f(x_{\text{new}})$ ).  
 Choose a random nest  $j$ :  
 If  $f(x_{\text{new}}) > f(x_j)$  then  
 Replace  $x_j$  with  $x_{\text{new}}$ .  
 End For  
 After each iteration, rank the nests  
 Abandon a fraction  $\rho$  of worst nests:  
 - Replace them with new random solutions.  
 Keep the best solutions.  
 Rank nests & identify the best solution so far  
 $t=t+1$   
 4. End while.  
 5. Return the best soln(nest).  
  
~~Levy flight function is used to improve chances of finding the global optimum.~~  
 Q/P: [X-98.01-97] [X-97.1523012e-46]  
 Best solution: [1.0602491e-45]  
 Final best fitness 1.72368145

### Code:

```

import random
import numpy as np

# Step 1: Define the Knapsack Problem
# Sample data: values and weights of items
values = [60, 100, 120, 80, 30]
weights = [10, 20, 30, 15, 5]
max_weight = 50
num_items = len(values)

# Fitness function: maximize value while staying under weight limit
def fitness(nest):
    total_value = 0
  
```

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total_weight = 0
for i in range(num_items):
    if nest[i] == 1:
        total_value += values[i]

total_weight += weights[i]
if total_weight > max_weight:
    return 0 # Penalty for exceeding capacity
return total_value

# Step 2: Initialize Parameters
num_nests = 25
max_iterations = 100
discovery_rate = 0.25 # Probability of discovering a nest
alpha = 1.0 # Step size for Lévy flights

# Step 3: Initialize Population
def initialize_population():
    return [[random.randint(0, 1) for _ in range(num_items)] for _ in range(num_nests)]

population = initialize_population()

# Step 4: Evaluate Fitness
fitness_values = [fitness(nest) for nest in population]

# Step 5: Generate New Solutions using Lévy flights (simple binary flipping)
def levy_flight(nest):
    new_nest = nest.copy()
    for i in range(num_items):
        if random.random() < 0.3: # 30% chance to flip each bit
            new_nest[i] = 1 - new_nest[i]
    return new_nest

# Step 6: Replace worst nests
def abandon_worst_nests(population, fitness_values):
    num_abandon = int(discovery_rate * num_nests)
    worst_indices = np.argsort(fitness_values)[:num_abandon]

    for idx in worst_indices:
        population[idx] = [random.randint(0, 1) for _ in range(num_items)]
    return population

# Step 7: Main Loop
best_nest = None
best_fitness = -1

for iteration in range(max_iterations):
    for i in range(num_nests):

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# Generate a new solution by Lévy flight
new_nest = levy_flight(population[i])
new_fitness = fitness(new_nest)

# Greedy selection

if new_fitness > fitness_values[i]:
    population[i] = new_nest
    fitness_values[i] = new_fitness

# Track the global best
if new_fitness > best_fitness:
    best_fitness = new_fitness
    best_nest = new_nest.copy()

# Abandon a fraction of the worst nests
population = abandon_worst_nests(population, fitness_values)
fitness_values = [fitness(nest) for nest in population]

# Step 8: Output the Best Solution
print("Best Solution (Item Inclusion):", best_nest)
print("Best Total Value:", best_fitness)
print("Total Weight:",
      sum(weights[i] for i in range(num_items) if best_nest[i] == 1))

```

**Program 6**

Optimize the assignment of cars to parking slots to minimize total walking distance using **Grey Wolf Optimization**, simulating the social hierarchy and hunting behavior of grey wolves to iteratively improve solutions.

Algorithm:



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population.append(wolf)
return population

# Fitness function: total walking distance for assigned slots
def fitness(wolf):
    total_distance = 0
    for car_index, slot_index in enumerate(wolf):
        total_distance += slot_distances[slot_index] # Distance of car's assigned slot
    return total_distance

# Update position of wolf based on alpha, beta, delta (GWO update mechanism)
def update_position(wolf, alpha, beta, delta, a):
    # Generate a new wolf position by exploring around alpha, beta, delta wolves
    new_wolf = wolf.copy()

    for i in range(len(wolf)):
        r1 = np.random.rand()
        r2 = np.random.rand()

        # Move the wolf toward the alpha, beta, or delta
        if r1 < 0.33:
            new_wolf[i] = alpha[i] # Move toward alpha wolf
        elif r1 < 0.66:
            new_wolf[i] = beta[i] # Move toward beta wolf
        else:
            new_wolf[i] = delta[i] # Move toward delta wolf

    # Ensure new_wolf is a valid permutation (no duplicates)
    new_wolf = np.unique(new_wolf)
    if len(new_wolf) < len(wolf):
        # if duplicates occur, randomly swap elements to maintain uniqueness
        missing_values = list(set(range(len(wolf))) - set(new_wolf))
        np.random.shuffle(missing_values)
        new_wolf = np.append(new_wolf, missing_values)

    # Now we randomly swap some elements to increase diversity and exploration
    swap_indices = np.random.choice(len(wolf), 2, replace=False)
    new_wolf[swap_indices[0]], new_wolf[swap_indices[1]] = new_wolf[swap_indices[1]], new_wolf[swap_indices[0]]

    return new_wolf

# Main GWO loop for parking slot allocation
def gwo_parking_allocation():
    # Initialize wolves (population)
    population = initialize_population(num_wolves, num_slots)

```

```

# Variables to keep track of the best solutions
alpha = None
beta = None
delta = None

alpha_score = float('inf')
beta_score = float('inf')
delta_score = float('inf')

# GWO main loop (iterations)
for iteration in range(max_iter):
    # Evaluate the fitness of each wolf in the population
    fitness_scores = []
    for wolf in population:
        score = fitness(wolf)
        fitness_scores.append(score)

    # Update alpha, beta, delta based on fitness
    if score < alpha_score:
        delta_score, delta = beta_score, beta
        beta_score, beta = alpha_score, alpha
        alpha_score, alpha = score, wolf
    elif score < beta_score:
        delta_score, delta = beta_score, beta
        beta_score, beta = score, wolf
    elif score < delta_score:
        delta_score, delta = score, wolf

    # Update positions of wolves based on best wolves (alpha, beta, delta)
    new_population = []
    for wolf in population:
        # Adjust the exploration factor "a" to control the step size over iterations a = 2
        - iteration * (2 / max_iter)
        new_wolf = update_position(wolf, alpha, beta, delta, a)
        new_population.append(new_wolf)
    population = new_population

    # Print progress
    print(f"Iteration {iteration+1}: Best total walking distance = {alpha_score}")
    # Final best result
    print("\nBest Assignment of Cars to Slots (car i -> slot number):")
    print(alpha)
    print("Slot distances:", slot_distances[alpha])
    print("Total walking distance:", alpha_score)

# Run the optimizer
gwo_parking_allocation()

```



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C = [
    [8, 6, 10], # Task 1 costs
    [7, 5, 9], # Task 2 costs
    [9, 8, 4] # Task 3 costs
]

num_tasks = len(C)
num_resources = len(C[0])

# -----
# PCA Parameters
# -----
M, N = 3, 3      # Grid size
max_iter = 5     # Number of iterations
p_mut = 0.1       # Mutation probability

# -----
# Helper Functions
# -----
def compute_cost(allocation):
    """Compute total cost for a given allocation."""
    return sum(C[i][allocation[i]] for i in range(num_tasks))

def random_allocation():
    """Generate a random valid allocation (permutation)."""
    alloc = list(range(num_resources))
    random.shuffle(alloc)
    return alloc

def random_swap(alloc):
    """Randomly swap two tasks' resource assignments."""
    a = alloc[:]
    i, j = random.sample(range(num_tasks), 2)
    a[i], a[j] = a[j], a[i]
    return a

def swap_first_difference(a, b):
    """Move a slightly toward b by swapping the first differing task."""
    a = a[:]
    for i in range(num_tasks):
        if a[i] != b[i]:
            # Find index where b[i] currently exists in a
            j = a.index(b[i])
            a[i], a[j] = a[j], a[i]
            break
    return a

def get_neighbors(grid, x, y):

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"""Return Moore neighborhood of (x,y)."""
neighbors = []
for dx in [-1, 0, 1]:
    for dy in [-1, 0, 1]:
        if dx == 0 and dy == 0:
            continue
        nx, ny = x + dx, y + dy
        if 0 <= nx < M and 0 <= ny < N:
            neighbors.append(grid[nx][ny])
return neighbors

# -----
# Initialize grid
# -----
grid = []
for i in range(M):
    row = []
    for j in range(N):
        alloc = random_allocation()
        cost = compute_cost(alloc)
        row.append({"alloc": alloc, "cost": cost})
    grid.append(row)

# Track global best
best_cell = min((grid[i][j] for i in range(M) for j in range(N)), key=lambda c: c["cost"])
best_alloc = best_cell["alloc"][:]
best_cost = best_cell["cost"]

# -----
# Main PCA Loop
# -----
for iteration in range(1, max_iter + 1):
    new_grid = [[cell.copy() for cell in row] for row in grid]

    for i in range(M):
        for j in range(N):
            cell = grid[i][j]
            neighbors = get_neighbors(grid, i, j)

            # Find best neighbor (tie-break randomly)
            min_cost = min(n["cost"] for n in neighbors)
            best_neighbors = [n for n in neighbors if n["cost"] == min_cost]
            chosen = random.choice(best_neighbors)

            # Move slightly toward best neighbor
            candidate = swap_first_difference(cell["alloc"], chosen["alloc"])
            candidate_cost = compute_cost(candidate)

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# Mutation
if random.random() < p_mut:
    candidate = random_swap(candidate)
    candidate_cost = compute_cost(candidate)

# Accept if better
if candidate_cost < cell["cost"]:
    new_grid[i][j] = {"alloc": candidate, "cost": candidate_cost}

# Update grid
grid = new_grid

# Update global best
current_best = min((grid[i][j] for i in range(M) for j in range(N)), key=lambda c: c["cost"])
if current_best["cost"] < best_cost:
    best_cost = current_best["cost"]
    best_alloc = current_best["alloc"]

# Print iteration summary
print(f"\nIteration {iteration}:")
for r in range(M):
    for c in range(N):
        print(grid[r][c]["alloc"], ">", grid[r][c]["cost"], end=" ")
    print()
print("Best so far:", best_alloc, "Cost:", best_cost)

# -----
# Final Result
# -----
print("\nFinal Best Allocation:", best_alloc)
print("Minimum Total Cost:", best_cost)

```