

**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)
BENGALURU-560019
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**B.M.S. College of Engineering,
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 **ANKIT SINGH BHATTI (1BM22CS353)**, 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/AnkitSB19/BISLAB_1BM22CS353

Program 1

Genetic Algorithm for Optimization Problems

Algorithm:

classmate

Date _____

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24/10/24

① IMPLEMENT A GENETIC ALGORITHM TO MAXIMIZE A FUNCTION ($f(x) = x^2$)

Import numpy np

def objective_function(x):

return $x**2$

population_size = 100

mutation_rate = 0.01

crossover_rate = 0.7

num_generations = 50

x_min = -10

x_max = 10

def initialize_population(size):

return np.random.uniform(x_min, x_max, size)

def evaluate(population):

return objective_function(population)

def select(population, fitness):

selected_indices = np.random.choice(len(population))

if np.random.rand() < crossover_rate:

return population[selected_indices].argmax()

[new[selected_indices]]]

def crossover(parent1, parent2):

if np.random.rand() < crossover_rate:

return (parent1 + parent2) / 2

return parent1

```

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

def genetic_algorithm():
    population = Population(population_size)
    best_soln = None
    best_fitness = -np.inf
    for generation in range(num_generations):
        fitness = evaluate_fitness(population)
        curr_best_idx = np.argmax(fitness)
        if fitness[curr_best_idx] > best_fitness:
            best_fitness = fitness[curr_best_idx]
            best_soln = population[curr_best_idx]
    return best_fitness, best_soln

```

~~1. best_x, best_value = genetic_algorithm()
print("Best x: {} best value: {}")~~

~~2. OUTPUT:
Best x: 9.96203495
Best value: 99.2534684~~

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(population), 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:

CLASSMATE
Date _____
Page _____
7/11/24

```

PARTICLE SWARM OPTIMIZATION
import numpy as np
import random
import matplotlib.pyplot as plt

def objective_function(x):
    return x**2 + 54*x + 45.4*x**3 - 3.2*x**5

num_particles = 50
dimensions = 1
iterations = 100
w = 0.5
c1 = 1.5
c2 = 1.5

for iter in range(iterations):
    for p in range(num_particles):
        r1 = np.random.rand()
        r2 = np.random.rand()

        vel_pos[EP] = w * vel_pos[EP] + c1
        [SP] = r1 * (personal_best_pos[EP] - pos[EP])
        - pos[EP] + c2 * r2 * (global_best
        - pos[EP])

        if current_score < personal_best_scores[EP]:
            personal_best_scores[EP] = current_score
            personal_best_pos[EP] = pos[EP]

    if iteration % 10 == 0:

```

```
print("Iteration Peterating i, Global Best
score={global-best-score, 5})
```

```
print("Final Global Best Position : {global-best-pos}
print('Final Global Best Score : {global-best-score}')
```

$x = np.linspace(-10, 10, 400)$

$y = \text{objective function}(x)$

0.01 → 2.028e+02

plt.plot(x, y, label="objective function:
 $f(x) = x^2 + nx + y$ ", color='blue')

plt.legend()

plt.xlabel("x")

plt.ylabel("f(x)")

plt.show()

26.0e+00 = 26

Output:

Iteration 10: Global Best score = [9.52e-09]

Iteration 20: Global Best score = [6.91e-12]

Iteration 30: Global Best score = [4.57e-14]

Iteration 40: Global Best score = [3.05e-16]

Iteration 50: Global Best score = [1.51e-13]

Iteration 60: Global Best score = [0.]

Final Global Best Positon : [-2.]

Final Global Best Score : [0.]

26.0e+00 = 26

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]

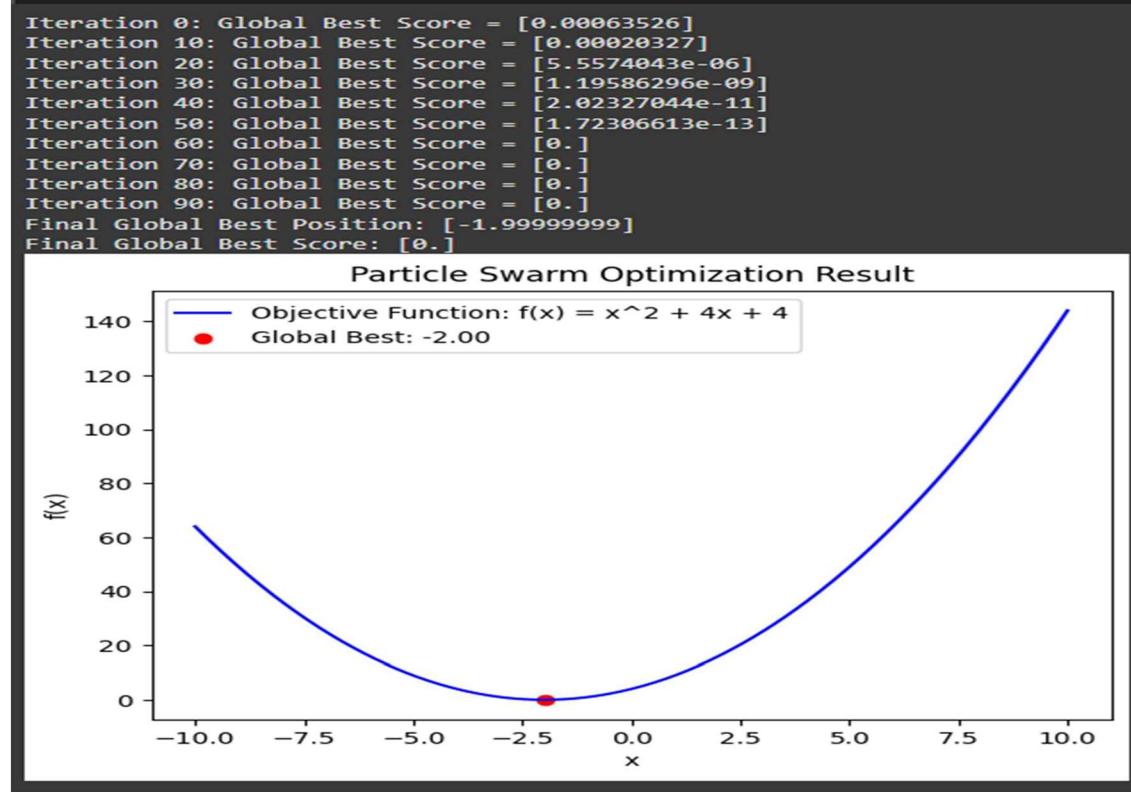
# Optionally print the global best score during the iterations
if iteration % 10 == 0:
    print(f"Iteration {iteration}: Global Best Score = {global_best_score}")

# 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()

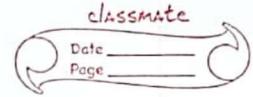
```



Program 3

Ant Colony Optimization for the Traveling Salesman Problem

Algorithm:



ANT COLONY OPTIMIZATION : (1998)our 3rd

```

import random
import math
import numpy as np
def distance(c1, c2):
    return math.sqrt((c1[0] - c2[0]) ** 2 + (c1[1] - c2[1]) ** 2)
class AntColony:
    def __init__(self, cities, num_ants, alpha):
        self.cities = cities
        self.num_cities = len(cities)
        self.num_ants = num_ants
        self.alpha = alpha
        self.distances = []
        for p in range(self.num_cities):
            for q in range(p+1, self.num_cities):
                self.distances.append(distance(self.cities[p], self.cities[q]))
        self.distances = np.array(self.distances)
    def probability(self, ant, city, visited):
        pheromone = self.pheromone[city]
        heuristic = np.array([0.0 / self.distances[city][p] if p not in visited else 0
                             for p in range(self.num_cities)])
        return pheromone * heuristic / pheromone.sum()

```

def run(self):

best_distance = float('inf')
best_tour = None

while count < self.numCities:

city = visited[-1]

prob = self.probability(city, visited)
nextCity = np.random.choice(range(0, self.numCities), p=prob)

visited.append(nextCity)

total_d += self.distances[city][nextCity]

all_tours.append(tour)

all_distances.append(total_distance)

if total_d < best_distance:

best_distance = total_d

best_tour = tour

return best_tour, best_distance

if __name__ == "__main__":

cities = [(0, 0), (1, 3), (4, 3), (6, 1), (6, 5)]

alpha = 1.0
beta = 2.0
rho = 0.1

100-1093014 143463 052009 - 121010

```
print ("Best tour: ", best_tour)
print ("Best distance: ", best_distance)
```

Output:

:(n) ~~negative~~ - 9154

~~Best tour : [0, 1, 2, 6, 5, 4, 3, 2, 7, 13]~~
~~Best DBalance : 24.772376022~~

(b) $\text{catalytic}\ \text{hydrogenation}$

1897 + ~~Concordia~~¹¹³¹¹ 23.0.47 100.000

1 (Established 1997)

3021 (Continued) 33 Examples, 336-339

(Schwartz) Sch

(1) 0.00002 0.01570103 .006807 .99 7.33

(b) $\{a\}$ is maximal in \mathcal{A} .

$$(6.8 \times 10^2) \text{ N} \times (0.7 \text{ m}) = 4.76 \times 10^2 \text{ J}$$

Q17 Answers

~~and I am not able to do a good job as~~ ~~as well as~~ ~~I can~~

(2) 3951, herbarium, 250205

John (n=2), 2-2) without methanol ($\lambda = 243 \text{ nm}$)

~~1000 + 1000 = 2000~~

Conducting research on the effects of various factors on the growth of plants.

(writing) $\theta_{\text{min}} = 30^\circ$, $\theta_{\text{max}} = 60^\circ$

Centrifugal pump addition rate

~~17~~ 18.03.2013 to return to school - 08.03.2013

Cards, and other

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:

21/11/24

CUCKOO SEARCH ALGORITHM

Import numpy as np
Import math

def sphere_function(x):

return np.sum(x**2)

def levy_flight(lamda, d):

$$\text{sigma_u} = \frac{\text{math.gamma}(1 + \text{lamda}) * \text{np.sqrt}(\text{np.pi} * \text{lamda} / 2)}{\text{math.gamma}((1 + \text{lamda}) / 2) * \text{lamda} * 2^{(1 + \text{lamda}) / 2}}$$

u = np.random.normal(0, sigma_u, d)

v = np.random.normal(0, 1, d)

step = u / np.abs(v) ** (1 / lamda)

return step

def cuckoo_search(func, n_nest, n_dim, max_iter, pa=0.25, lamda_levy=1.5):

nests = np.random.uniform(-5, 5, (n_nest, n_dim))

fitness = np.apply_along_axis(func, 1, nests)

best_nest = nests[np.argmax(fitness)]

best_fitness = np.min(fitness)

for iteration in range(max_iter):

new_nests = nests + alpha * levy_flight(lamda_levy, n_dim)

`new_nests = np.append(new_nests, -5, 5)`

`new_fitness = np.apply_along_axis(func1, 1, new_nests)`

`for p in range(n_nests):`

`: if np.random.rand() < pa:`

`: new_nests[p] = new_nests[p]`

`: new_fitness[p] = new_fitness[p]`

`n_nests = 50`

`n_dpm = 10`

`max_iter = 1000`

`pa = 0.25`

`alpha = 0.01`

`lambda_levy = 1.5`

`best_sol, best_val = nelder_mead_search(n_nests, n_dpm)`

`print("Best solution found: ", best_sol)`

`print("Best fitness value: ", best_val)`

`Output: [-1.0767, 2.064, -0.483, -1.408, -0.7945, 3.1574]`

Best fitness value: 30.96779

~~if alpha > 0.001 then do nothing else do~~

~~alpha = alpha * 0.99 + 0.01~~

~~else do nothing~~

~~do nelder mead search~~

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:

28/11/24 GREY WOLF OPTIMIZATION

```
import numpy as np
def sphere(x):
    return np.sum(x**2)

class GWO:
    def __init__(self, obj_func, dim, lb, ub):
        self.obj_func = obj_func
        self.dim = dim
        self.lb = lb
        self.ub = ub

    def update_position(self, alpha, beta, delta):
        r1 = np.random.random(self.dim)
        r2 = np.random.random(self.dim)
        d_alpha = abs((C1 * C0) * (alpha - position - self.position))
        d_beta = abs((C1 * C0) * (beta - position - self.position))
        d_delta = abs((C2 * C0) * (delta - position - self.position))

    def optimize(self):
        for t in range(self.max_iter):
            a = 2 - t * (2 / self.max_iter)
            p = np.random.uniform(-a, a, 3)
            c = np.random.uniform(0, 2, 3)
```

der P fn range (ret.pop_size);

$$\text{fnrange} = \text{self.alpha_funct} * \text{posfn}$$

~~(self.alpha_funct * self.pop_size) / (self.pop_size - 1)~~ (P)

if retfn < self.alpha_supre;

~~(self.alpha_supre + self.alpha_score) / 2~~ = fitness

else if (self.alpha_pos + self.alpha_pos) = self.f_posfn(P)

else fnrange < self.beta_score;

~~(self.pop_size - self.pop_size) / self.pop_size~~ = fnrange

else self.beta_pos = self.popfn(P)

if self.popfn(P) < self_fnrange < self_beta_score;

~~self.popfn(P) = self_fnrange~~ = fnrange

else self_beta_pos = self.popfn(P)

~~(self.popfn(P) + self_fnrange) / 2~~ = fnrange

else self_alpha_pos = self.popfn(P)

$$dRm = 10$$

$$popSize = 50$$

$$max_iter = 100$$

$$lb = -5.12$$

$$ub = +5.12$$

gwo = GWO((objfunc = sphere), dRm);, lb=lb, ub=ub

best_pos, best_score = gwo.optimize();

print("Best Soln & Best fnvalue: ", best_pos, best_score)

Output: Best Soln = [0.4866 0.21197 0.3349]

BEST fnvalue: 0.0100

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:

19/12/24

PARALLEL CELLULAR ALGORITHMS:

Code:

```
import numpy as np
from multiprocessing import pool
def rashi_gin_func(x):
    return 10 * len(x) + sum((x * x)**2 - 10 * np.log(2 * np.pi * x**2) for x
    in x)
def populate(grpd_size, dimensions, lower_bound,
upper_bound):
    return np.random.uniform(lower_bound,
upper_bound, (grpd_size, grpd_size, dimensions))
def evaluate_fitness(grpd):
    fitness = np.zeros((grpd.shape[0]),
grpd.shape[0]))
    for p in range(grpd.shape[0]):
        for g in range(grpd.shape[1]):
            fitness[p, g] = rashi_gin_
            function(grpd[p, g])
    return fitness
def parallel_cellular_algorithm(grpd_size, dimensions,
lower_bound, upper_bound):
    grpd = populate(grpd_size, dimensions,
lower_bound, upper_bound)
    for p in range(grpd_size):
        fitness = evaluate_fitness(grpd)
```

classmate

Date _____

Page _____

```
grpd = update_grpd(grpd, fitness)
pprint(f" Iteration {i+1} : Best
fitness : {fitness['mean']}")
```

```
best_ciu = np.unravel_index(np.argmax(fitness['argmin']),
(), fitness['shape'])
best_solution = grpd[best_ciu]
return best_selection, fitness['mean']
```

If `--name-- = "main":`

`CGRID_SIZE = 10`

`DIMENSIONS = 2`

`LOWER_BOUND = -5.12`

`UPPER_BOUND = 5.12`

`sol, fit = parallel_cellular_algorithm()`

`print(f"Best Solution : {best_sol}, fitness : {fit}")`

`Output :`

`Best Solution = [-0.005 0.003],
fitness : 0.22137806183.`

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:

19/12/24

OPTIMIZATION VIA GENE EXPRESSION ALGORITHM

```
import numpy as np
import random
def objective_function(x):
    return x[0]**2 + 4*x[1] + 4*x[2]
population_size = 30
num_genes = 10
mutation_rate = 0.05
crossover_rate = 0.7
NUM_GENERATION = 100

def initialize_population(population_size, num_genes):
    return np.random.uniform(-10, 10, population_size * num_genes)

def evaluate_fitness(population):
    return np.array([objective_function(individual) for individual in population])

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

def crossover(parent1, parent2):
    if random.random() < crossover_rate:
        return (parent1 + parent2) / 2
    return parent1
```

def gene_expression_algorithm():

population = initialize_population(pop_size, num_gen
-es)

best_sln = None

best_fitness = float('inf')

for generation in range(num_generation):

fitness = evaluate_fitness(population)

current_best_idx = np.argmax(fitness)

If fitness[current_best_idx] < best_fitness:

best_fitness = fitness[current_best_idx]

best_sln = population[current_best_
idx]

newpop = []

for p in range(pop_size):

parent1 = select(population, fitness)

parent2 = select(population, fitness)

offspring = crossover(parent1, parent2)

offspring = mutate(offspring)

newpop.append(offspring)

population = np.array(new_population)

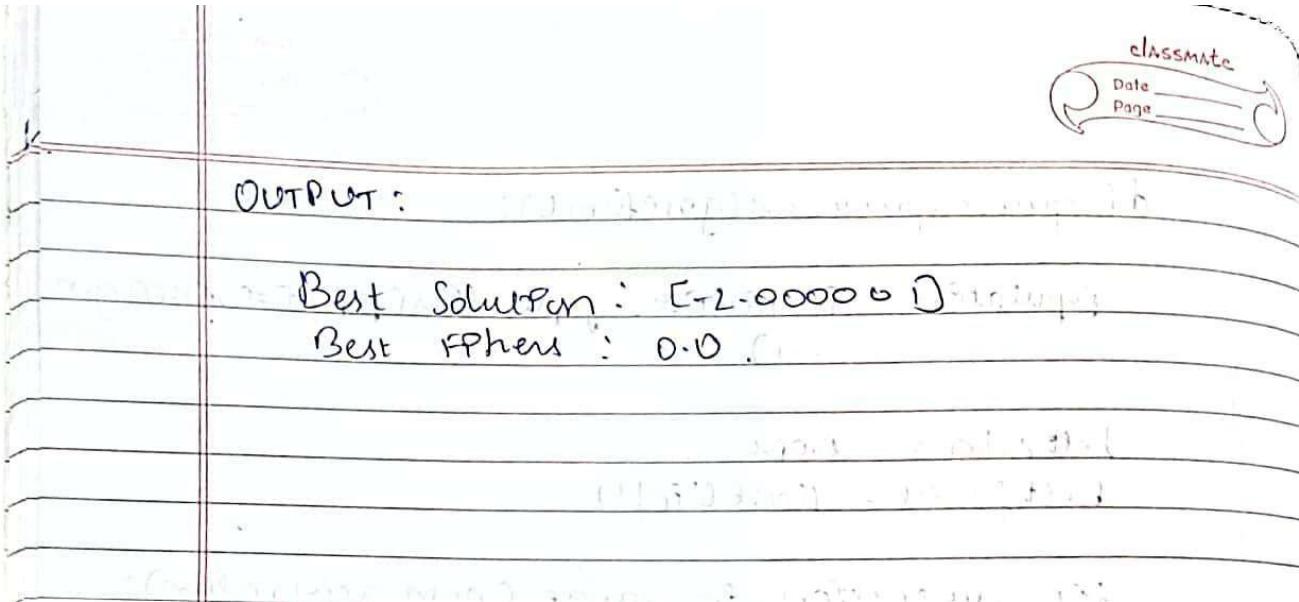
population = gene_expression(population)

return best_sln, best_fitness

best_sln, best_fitness = gene_expression_algorithm()

print("Best solution : {} ".format(best_sln))

print("Best fitness : {} ".format(best_fitness))



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

```