VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by

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in partial fulfillment for the award of the degree of

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in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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CERTIFICATE

This is to certify that the Lab work entitled " Bio Inspired Systems (23CS5BSBIS)" carried out by **Rahul N Raju (1BM22CS215),** 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/RahulCS215/BIS

Program 1 : Genetic Algorithm

A genetic algorithm (GA) is a search heuristic inspired by the process of natural selection and genetics. It is used to solve optimization and search problems. The algorithm simulates the process of natural evolution, where the fittest individuals are selected to reproduce and pass their genes to the next generation, leading to the gradual improvement of solutions.

Algorithm:

Algorithm :-

Step 1 :- Identify the objective fn to optimize in this case maximize $f(x) = x^2$

Step 2 :- Set the foll parameters population size, mutation rate, crossover rate, no of generation, lower bound upper bound

Step 3 :- Generate an initial ~~po~~ population within the range of -10 to 10.

Step 4 :- For each individual in population compute fitness using fitness function $f(x) = x^2$

Step 5 :- Use Roulette wheel selection to select two parents from the population

Step 6 :- For the selected parents, perform crossover with a probability of 0.8.

Step 7 :- For each offspring apply mutation with a probability of 0.8

Step 8 :- Collect the newly created offspring until the new population reaches the original population size

Step 9 :- Replace old population with new generation of individuals

Step 10 :- After final generation, evaluate fitness of the population

Code:

```
import random

# Define the fitness function
def fitness_function(x):
    return x ** 2

# Generate initial population
def generate_population(size, lower_bound, upper_bound):
    return [random.uniform(lower_bound, upper_bound) for _ in range(size)]

# Selection - select individuals based on fitness
def selection(population, fitness_values):
    total_fitness = sum(fitness_values)
    probabilities = [f / total_fitness for f in fitness_values]
    selected = random.choices(population, weights=probabilities, k=len(population))
    return selected

# Crossover - create new offspring by combining parents
def crossover(parent1, parent2, crossover_rate):
    if random.random() < crossover_rate:
        alpha = random.random()
        child1 = alpha * parent1 + (1 - alpha) * parent2
        child2 = alpha * parent2 + (1 - alpha) * parent1
        return child1, child2
    else:
        return parent1, parent2

# Mutation - introduce random variations
def mutate(individual, mutation_rate, lower_bound, upper_bound):
    if random.random() < mutation_rate:
        individual += random.uniform(-1, 1)
        individual = max(lower_bound, min(upper_bound, individual))  # Keep within bounds
    return individual

# Genetic Algorithm
def genetic_algorithm(population_size, lower_bound, upper_bound, generations, mutation_rate,
crossover_rate):
    population = generate_population(population_size, lower_bound, upper_bound)

    for generation in range(generations):
        # Evaluate fitness
        fitness_values = [fitness_function(ind) for ind in population]
```

```python
        # Selection
        selected_population = selection(population, fitness_values)

        # Crossover
        next_generation = []
        for i in range(0, len(selected_population), 2):
            parent1 = selected_population[i]
            parent2 = selected_population[i + 1 if i + 1 < len(selected_population) else 0]
            child1, child2 = crossover(parent1, parent2, crossover_rate)
            next_generation.extend([child1, child2])

        # Mutation
        population = [mutate(ind, mutation_rate, lower_bound, upper_bound) for ind in
next_generation]

        # Log best fitness of the generation
        best_fitness = max(fitness_values)
        # print(f"Generation {generation + 1}: Best Fitness = {best_fitness:.4f}")

    # Return the best fitness value from the final generation
    return max(fitness_function(ind) for ind in population)

# Parameters
population_size = 10
lower_bound = -10
upper_bound = 10
generations = 50
mutation_rate = 0.1
crossover_rate = 0.8
print("Rahul N Raju,1BM22CS215")
# Run Genetic Algorithm
best_fitness = genetic_algorithm(population_size, lower_bound, upper_bound, generations,
mutation_rate, crossover_rate)
print(f"Best fitness found: {best_fitness:.4f}")
```

Output

Clear

```
Rahul N Raju,1BM22CS215
Best fitness found: 81.2843

=== Code Execution Successful ===
```

Program 2 : Particle Swarm Optimisation for function Optimisation

Particle Swarm Optimization (PSO) is a heuristic optimization algorithm inspired by the social behavior of birds flocking or fish schooling. It is used to find optimal solutions by mimicking the collective behavior of a swarm of particles in a search space

Algorithm:

Particle Swarm Optimization

Algorithm

Initialize

Swarm size (N), problem dimensionality (D), max iteration

Assign random positions and velocities for each particle

Step 1 :- Randomly initialize, swarm population of N particles X_i (i = 1, 2, ..., n)

Step 2 :- Select hyper parameter, values w, c1 and c2

Step 3 :- For iter in range (max_iter):

for i in range (N):

(a) Compute new velocity of ith particle

swarm[i].velocity = w * swarm[i].velocity + r1 * c1 * (swarm[i].bestPos - swarm[i].position) + r2 * c2 * (best_pos_swarm - swarm[i].position)

(b) compute new position of ith particle using its new velocity

swarm[i].position += swarm[i].velocity

(c) if position is not in range [minx, maxx]
then clip it
if swarm[i].position < minx :
swarm[i].position = minx
elif swarm[i].position > maxx :
swarm[i].position = maxx
(d) Update new best of this particle and new
of swarm
if swa Incentive to scaling of Design

variables, sm[i].fitness < swarm[i]
best_fitness
swarm[i].bestFitness = swarm[i].fitness
swarm[i].bestPos = swarm[i].position
end for
end for
Step 4 :- Return best particle of swarm

Code:

```
import random

# Objective function to minimize (Example: Sphere function)
def objective_function(x):
    return sum(x_i ** 2 for x_i in x)

# Particle class to represent each particle
class Particle:
    def __init__(self, dimension, bounds):
        self.position = [random.uniform(bounds[0], bounds[1]) for _ in range(dimension)]
        self.velocity = [random.uniform(-1, 1) for _ in range(dimension)]
```

```
        self.pBest = list(self.position)
        self.pBest_fitness = objective_function(self.position)

# PSO class
class PSO:
    def __init__(self, dimension, bounds, num_particles=30, max_iterations=100):
        self.dimension = dimension
        self.bounds = bounds
        self.num_particles = num_particles
        self.max_iterations = max_iterations
        self.particles = [Particle(dimension, bounds) for _ in range(num_particles)]
        self.gBest = list(self.particles[0].position)
        self.gBest_fitness = self.particles[0].pBest_fitness
        self.w = 0.5  # Inertia weight
        self.c1 = 1.5  # Cognitive coefficient
        self.c2 = 1.5  # Social coefficient

    def optimize(self):
        for iteration in range(self.max_iterations):
            for particle in self.particles:
                fitness = objective_function(particle.position)

                # Update personal best (pBest)
                if fitness < particle.pBest_fitness:
                    particle.pBest = list(particle.position)
                    particle.pBest_fitness = fitness

                # Update global best (gBest)
                if fitness < self.gBest_fitness:
                    self.gBest = list(particle.position)
                    self.gBest_fitness = fitness

            # Update velocity and position for each particle
            for particle in self.particles:
                for i in range(self.dimension):
                    # Update velocity
                    r1, r2 = random.random(), random.random()
                    particle.velocity[i] = (self.w * particle.velocity[i]
                                            + self.c1 * r1 * (particle.pBest[i] - particle.position[i])
                                            + self.c2 * r2 * (self.gBest[i] - particle.position[i]))
                    # Update position
                    particle.position[i] += particle.velocity[i]

                    # Ensure position stays within bounds
                    particle.position[i] = max(self.bounds[0], min(particle.position[i], self.bounds[1]))

        return self.gBest, self.gBest_fitness
```

```
# Define parameters
dimension = 2  # Number of dimensions
bounds = (-10, 10)  # Search space bounds for each dimension
num_particles = 30  # Number of particles in the swarm
max_iterations = 100  # Maximum number of iterations
print('Rahul N Raju,1BM22CS215')

# Create PSO instance and optimize
pso = PSO(dimension, bounds, num_particles, max_iterations)
best_position, best_fitness = pso.optimize()

# Output the result
print(f"Best Position: {best_position}")
print(f"Best Fitness: {best_fitness}")
```

Output Clear

```
Rahul N Raju,1BM22CS215
Best Position: [1.7414933187255753e-12, -2.755332347745886e-12]
Best Fitness: 1.0624655325700673e-23

=== Code Execution Successful ===
```

Program 3 : Ant Colony Optimisation

Ants in nature deposit pheromones on their paths as they move. The intensity of the pheromone on a path influences the probability that other ants will choose that path. Over time, the pheromone trails strengthen on paths that are frequently used and weak on less frequently used ones. This behavior leads to the discovery of the shortest or optimal path between the ant colony and a food source. ACO mimics this process to solve various optimization problems, like the traveling salesman problem (TSP), vehicle routing problems, and others

Algorithm:

Algorithm
Initialize pheromone values $v_{i,j} = C_1, v_{i,j}, v_i / z_0$
repeat
for each ant $2 \in \{1, \ldots, n\}$
randomly choose starting city $i_0 \in S$ for and ant 2
move to starting city $i_0 \in S$ for any 2 $i \rightarrow i_0$ move
while $S \neq 0$ do
remove current city from selection set $S \rightarrow S_i \{t\}$
Choose next city i in town with probability

$$p_{ij} = \frac{z_{i,j}^{\alpha} \cdot \eta_{i,j}^{\beta}}{\sum_{h \in S} z_{in}^{\alpha} \cdot \eta_{in}^{\beta}}$$

update solution allocation $\pi_i(i) \rightarrow j$
move to new city $i \rightarrow j$
end while
finalize solution vector $\pi_l(i) \rightarrow i_0$
end for
for each solution π_l, $L \in \{1, \ldots, n\}$ do
calculate tour length $f(\pi_l) \rightarrow \sum_{i=1}^{n} d_{i\pi_l}(i)$
end for
for all (i,j) do
evaporate pheromone $z_{ij} \rightarrow (1-\rho) \cdot z_{ij}$
end for
~~determine best solution of iteration~~ $\pi^{+} = \arg\min_{9 \in [1,m]} f(\pi_l)$
if π^{+} better than current best π^{*}, i.e $f(\pi^{+}) < f(\pi^{*})$
then set $\pi^{*} \leftarrow \pi^{+}$
end if

for all $(i,j) \in \pi^+$ do
    reinforce $>ij \mapsto z_{ij} + \Delta/2$

for all $(i,j) \in \pi^*$ do
    reinforce $z_{ij} \rightarrow z_{ij} + \Delta/2$
end for
until condition for termination met

Code:

```
import numpy as np

# Parameters
NUM_CITIES = 10  # Number of cities
NUM_ANTS = 20    # Number of ants
ITERATIONS = 10 # Number of iterations
ALPHA = 1.0      # Pheromone importance
BETA = 2.0       # Heuristic importance
EVAPORATION_RATE = 0.5
Q = 100          # Pheromone deposit factor

# Distance matrix
distance_matrix = np.random.randint(1, 100, size=(NUM_CITIES, NUM_CITIES))
np.fill_diagonal(distance_matrix, 0)

# Initialize pheromone levels
pheromones = np.ones((NUM_CITIES, NUM_CITIES))

def calculate_route_length(route):
    length = 0
    for i in range(len(route) - 1):
        length += distance_matrix[route[i], route[i + 1]]
    length += distance_matrix[route[-1], route[0]]  # Return to the start city
    return length

def construct_route(start_city):
    route = [start_city]
    for _ in range(NUM_CITIES - 1):
```

```
        current_city = route[-1]
        probabilities = []
        for next_city in range(NUM_CITIES):
            if next_city not in route:
                prob = (pheromones[current_city, next_city] ** ALPHA) * \
                       ((1 / distance_matrix[current_city, next_city]) ** BETA)
                probabilities.append(prob)
            else:
                probabilities.append(0)
        probabilities = np.array(probabilities)
        probabilities /= probabilities.sum()
        next_city = np.random.choice(range(NUM_CITIES), p=probabilities)
        route.append(next_city)
    return route

def update_pheromones(pheromones, all_routes, all_lengths):
    pheromones *= (1 - EVAPORATION_RATE)  # Evaporation
    for route, length in zip(all_routes, all_lengths):
        pheromone_deposit = Q / length
        for i in range(len(route) - 1):
            pheromones[route[i], route[i + 1]] += pheromone_deposit
            pheromones[route[i + 1], route[i]] += pheromone_deposit
        # Closing the route (return to start city)
        pheromones[route[-1], route[0]] += pheromone_deposit
        pheromones[route[0], route[-1]] += pheromone_deposit

def aco():
    best_route = None
    best_length = float('inf')

    for _ in range(ITERATIONS):
        all_routes = []
        all_lengths = []

        for _ in range(NUM_ANTS):
            start_city = np.random.randint(0, NUM_CITIES)
            route = construct_route(start_city)
            route_length = calculate_route_length(route)

            all_routes.append(route)
            all_lengths.append(route_length)

            if route_length < best_length:
                best_length = route_length
                best_route = route

        update_pheromones(pheromones, all_routes, all_lengths)
```

```
    return best_route, best_length

# Run the ACO algorithm
print('Rahul N Raju,1BM22CS215')

best_route, best_length = aco()
print("Best Route:", best_route)
print("Best Length:", best_length)
```

Output   Clear

```
Rahul N Raju,1BM22CS215
Best Route: [4, np.int64(7), np.int64(8), np.int64(9), np.int64(6), np
    .int64(2), np.int64(1), np.int64(5), np.int64(3), np.int64(0)]
Best Length: 125


=== Code Execution Successful ===
```

Program 4 : Cuckoo Search(CS)

Cuckoo Search (CS) is a nature-inspired optimization algorithm based on the brood parasitism of some cuckoo species. This behaviour involves laying eggs in the nests of other birds, leading to the optimization of survival strategies. CS uses Lévy flights to generate new solutions, promoting global search capabilities and avoiding local minima. The algorithm is widely used for solving continuous optimization problems and has applications in various domains, including engineering design, machine learning, and data mining

Algorithm:

Algorithm:-

Input:

n: No of host nests (population size)

P_a: Fraction of worse nests to be abandoned

Max Iterations: Max no of iterations

$f(x)$: Objective fn to minimize

Dimension: Dimensionality of the problem

Bounds: Lower and upper limits of the search space

Initialize:

1) Generate an initial population of n random host nests X_i (for $i = 1, 2, \ldots, n$)
2) Evaluate the fitness $f(x_i)$ for each nest.
   Determine the current best solution x^* with the best fitness $f(x^*)$

While the current iteration $t <$ Max Iterations:

Step 1: Perform Levy flight for randomly selected nest

Select a random nest X_i

Generate a new solution X' using Levy flight:

$$x' = x_i + \lambda L (x_i - x^*)$$

where L is the Levy flight step, λ is the step size

Clip x' within bounds, if necessary

Step2 :- Evaluate the fitness $f(x')$ of the new solution.

If $f(x') < f(x_i)$, replace a randomly chosen nest x_j with x'.

Step 3 :- Abandon worse nests

Identify $P_\alpha \cdot n$ worst nests and replace them with new random solutions

Step 4 :- Update the current best solution:

Identify and retain the nest with best fitness an

end while

Post-process results:

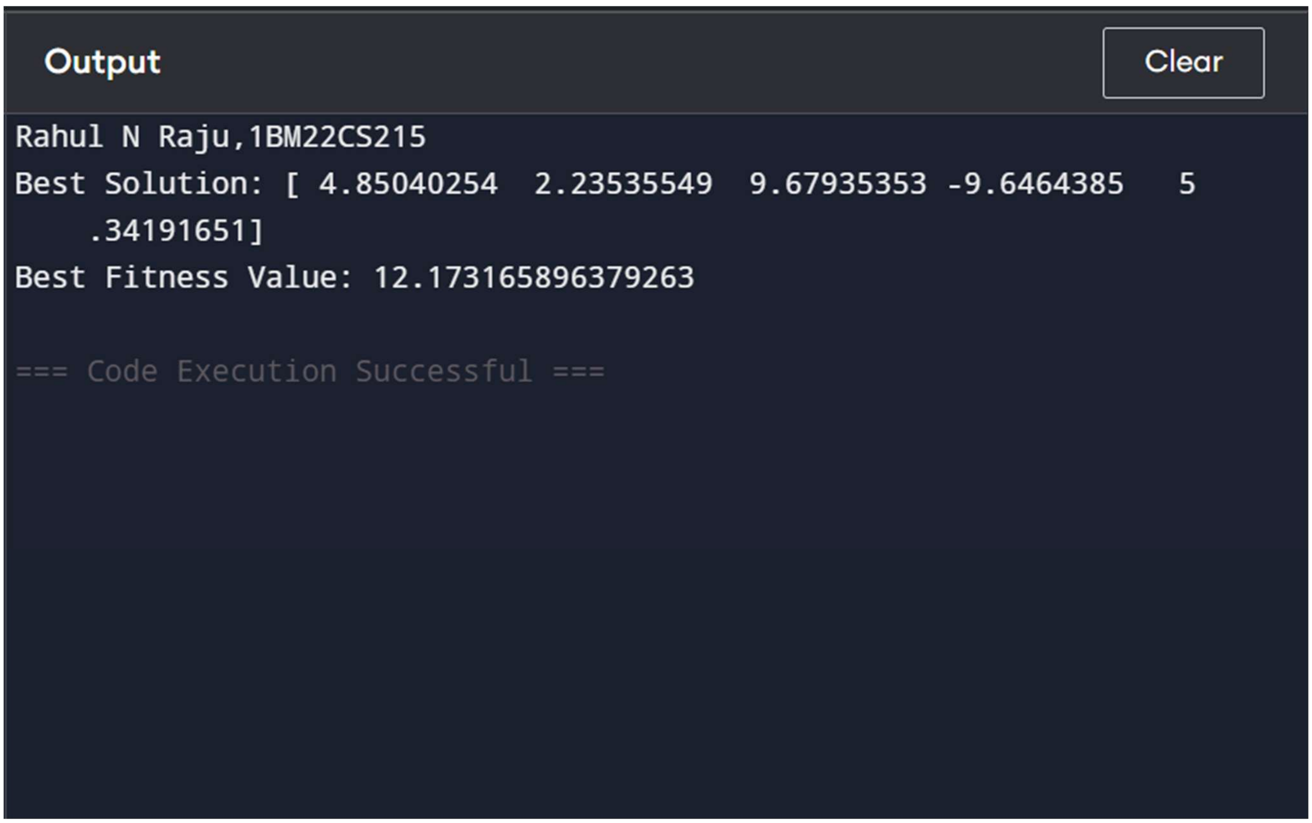
Output the best solution x^* and its fitness f(

Code:

```
import numpy as np
import math

# Objective function (example: Sphere function, you can replace it)
def objective_function(x):
    return sum(x**2)  # Minimize the sum of squares

def levy_flight(beta, d):
    sigma_u = (math.gamma(1 + beta) * math.sin(math.pi * beta / 2) /
               (math.gamma((1 + beta) / 2) * beta * 2 ** ((beta - 1) / 2)))**(1 / beta)
    u = np.random.normal(0, sigma_u, d)  # Draw from Gaussian distribution
    v = np.random.normal(0, 1, d)
    step = u / (abs(v)**(1 / beta))
    return step
```

```
# Cuckoo Search Algorithm
def cuckoo_search(n, d, alpha, pa, maxGen):
    # n: Population size, d: Dimension of the problem
    # alpha: Step size, pa: Discovery probability, maxGen: Max iterations


    nests = np.random.uniform(-10, 10, (n, d))
    fitness = np.array([objective_function(nest) for nest in nests])


    best_nest_index = np.argmin(fitness)
    best_nest = nests[best_nest_index]
    best_fitness = fitness[best_nest_index]

    beta = 1.5

    # Step 2: Iterative loop
    for gen in range(maxGen):
        for i in range(n):
            # Generate a new solution via Lévy flight
            step = levy_flight(beta, d)
            new_nest = nests[i] + alpha * step * (nests[i] - best_nest)
            new_nest = np.clip(new_nest, -10, 10)  # Keep solutions within bounds

            # Evaluate new fitness
            new_fitness = objective_function(new_nest)
            if new_fitness < fitness[i]:  # Replace with better solution
                nests[i] = new_nest
                fitness[i] = new_fitness

        # Abandon some nests with a probability pa
        for i in range(n):
            if np.random.rand() < pa:
                # Replace with new random solution
                nests[i] = np.random.uniform(-10, 10, d)
                fitness[i] = objective_function(nests[i])

        # Update the current best
        best_nest_index = np.argmin(fitness)
        if fitness[best_nest_index] < best_fitness:
            best_nest = nests[best_nest_index]
            best_fitness = fitness[best_nest_index]

        # print(f"Generation {gen+1}, Best Fitness: {best_fitness:.5f}")
```

```
    return best_nest, best_fitness

n = 25
d = 5
alpha = 0.01
pa = 0.25
maxGen = 100

print('Rahul N Raju,1BM22CS215')
best_solution, best_value = cuckoo_search(n, d, alpha, pa, maxGen)
print("Best Solution:", best_solution)
print("Best Fitness Value:", best_value)
```



Program 5 : Grey Wolf Optimiser

The Grey Wolf Optimizer (GWO) algorithm is a swarm intelligence algorithm inspired by the social hierarchy and hunting behaviour of grey wolves. It mimics the leadership structure of alpha, beta, delta, and omega wolves and their collaborative hunting strategies. The GWO algorithm uses these social hierarchies to model the optimization process, where the alpha wolves guide the search process while beta and delta wolves assist in refining the search direction. This algorithm is effective for continuous optimization problems and has applications in engineering, data analysis, and machine learning.

Algorithm:

```
Algorithm:-
  Initialize the population of wolves (positions)
randomly within the search space
 Define the max no of iterations (T)
 and population size (N)
Define the fitness function to evaluate solutions

Evaluate the fitness of each wolf in the population
Identify the alpha (best solution), beta (second best)
and delta (third best) wolves

For t = 1 to T:
      For each wolf i in the population:
      For each dimension d:
      A1 = 2* a * rand() - a
      C1 = 2* rand()
      D = alpha = [C1* x_alpha [d] - x_i [d]]
      X2 = x_beta [d] - A2 * D_deta
      A3 = 2* a * rand() - a
      C3 = 2* rand()
      D_delta = C3* x_delta [d] - x_1 [d]
      X3 = x_delta [d] - A3 * D_delta

      x_i [d] = (xi + x2 + x3) / 3

   end for
   end for
      a = 2 - (2* t / T)
  Update alpha, beta and delta wolves based on
  fitness
```

Code:

```
import numpy as np

def objective_function(x):
    return x ** 2  # The function to minimize

def initialize_wolves(num_wolves, search_space):
    return np.random.uniform(search_space[0], search_space[1], num_wolves)

def update_position(alpha, beta, delta, wolf, a):
    r1, r2 = np.random.rand(), np.random.rand()
    A = 2 * a * r1 - a
    C = 2 * r2
    D = abs(C * alpha - wolf)
    X1 = alpha - A * D

    r1, r2 = np.random.rand(), np.random.rand()
    A = 2 * a * r1 - a
    C = 2 * r2
    D = abs(C * beta - wolf)
    X2 = beta - A * D

    r1, r2 = np.random.rand(), np.random.rand()
    A = 2 * a * r1 - a
    C = 2 * r2
    D = abs(C * delta - wolf)
    X3 = delta - A * D

    return (X1 + X2 + X3) / 3

def grey_wolf_optimization(obj_func, num_wolves=5, max_iter=50, search_space=(-10, 10)):
    # Initialize wolves' positions
    wolves = initialize_wolves(num_wolves, search_space)
    fitness = np.array([obj_func(wolf) for wolf in wolves])

    # Identify alpha, beta, delta
    sorted_indices = np.argsort(fitness)
    alpha, beta, delta = wolves[sorted_indices[0]], wolves[sorted_indices[1]],
wolves[sorted_indices[2]]

    a = 2  # Initial value for the parameter a

    for iteration in range(max_iter):
        for i in range(num_wolves):
            wolves[i] = update_position(alpha, beta, delta, wolves[i], a)
```

```
            wolves[i] = np.clip(wolves[i], search_space[0], search_space[1])  # Ensure wolves stay within bounds

        # Recalculate fitness and update alpha, beta, delta
        fitness = np.array([obj_func(wolf) for wolf in wolves])
        sorted_indices = np.argsort(fitness)
        alpha, beta, delta = wolves[sorted_indices[0]], wolves[sorted_indices[1]], wolves[sorted_indices[2]]

        # Decrease a linearly
        a = 2 - (2 * (iteration / max_iter))

        # print(f"Iteration {iteration+1}: Alpha = {alpha}, Fitness = {obj_func(alpha)}")

    return alpha, obj_func(alpha)

# Run the algorithm
print("Rahul N Raju,1BM22CS215")
best_position, best_fitness = grey_wolf_optimization(objective_function)
print(f"Best Position: {best_position}")
print(f"Best Fitness: {best_fitness}")
```

Output Clear

```
Rahul N Raju,1BM22CS215
Best Position: 7.720946479406356e-05
Best Fitness: 5.961301453785741e-09

=== Code Execution Successful ===
```

Program 6 : Parallel Cellular Algorithms and Programs

The Parallel Cell Algorithm is a computational method used for solving problems that involve large datasets, spatial partitioning, or simulations where a domain is divided into smaller "cells" that can be processed independently or semi-independently in parallel. It is commonly applied in scientific computing, numerical simulations, and artificial intelligence, where computational efficiency is crucial.

Algorithm:

Algorithm

1. Initialization
   1) Define the grid dimensions
   2) Initialize each cell state based on the problem
   3) Define the neighborhood for each cell
   4) Define the transition rule

2. Set initial conditions

   Populate the grid with initial states for all cells

3. Parallel update

   For each time step t:

   For each c(i, j ....) in the grid (in parallel),

   1. Retrieve the current state of c(i, j ....)
   2. Retrieve the states of the neighbouring cells
   3. Apply the transition rule to compute the next state of c(i, j ....)

   Update all cells simultaneously to their new states

4. Check stopping condition

   Terminate if a predefined condition is met

   - A fixed number of iterations completed
   - System ~~reaches~~ reaches a steady state
   - A specific pattern or result is observed

5. Output Results

   Retrieve the final grid config as the solution

Code:

```
import numpy as np
import random

# Step 1: Define the Problem (Optimization Function)
def fitness_function(position):
    """Example fitness function: Sphere function"""
    return sum(x**2 for x in position)

# Step 2: Initialize Parameters
grid_size = (10, 10)  # Grid size (10x10 cells)
dim = 2  # Dimensionality of each cell's position
minx, maxx = -10.0, 10.0  # Search space bounds
max_iterations = 50  # Number of iterations

# Step 3: Initialize Population (Random positions)
def initialize_population(grid_size, dim, minx, maxx):
    population = np.zeros((grid_size[0], grid_size[1], dim))
    for i in range(grid_size[0]):
        for j in range(grid_size[1]):
            population[i, j] = [random.uniform(minx, maxx) for _ in range(dim)]
    return population

# Step 4: Evaluate Fitness (Calculate fitness for each cell)
def evaluate_fitness(population):
    fitness_grid = np.zeros((grid_size[0], grid_size[1]))
    for i in range(grid_size[0]):
        for j in range(grid_size[1]):
            fitness_grid[i, j] = fitness_function(population[i, j])
    return fitness_grid

# Step 5: Update States (Update each cell based on its neighbors)
def get_neighbors(i, j):
    """Returns the coordinates of neighboring cells."""
    neighbors = []
    for di in [-1, 0, 1]:
        for dj in [-1, 0, 1]:
            if not (di == 0 and dj == 0):  # Exclude the cell itself
                ni, nj = (i + di) % grid_size[0], (j + dj) % grid_size[1]
                neighbors.append((ni, nj))
    return neighbors

def update_cell(population, fitness_grid, i, j, minx, maxx):
    """Update the state of a cell based on the average state of its neighbors."""
```

```
    neighbors = get_neighbors(i, j)
    best_neighbor = min(neighbors, key=lambda x: fitness_grid[x[0], x[1]])

    # Update cell position to move towards the best neighbor's position
    new_position = population[best_neighbor[0], best_neighbor[1]] + \
                   np.random.uniform(-0.1, 0.1, dim)  # Small random perturbation

    # Ensure the new position stays within bounds
    new_position = np.clip(new_position, minx, maxx)
    return new_position

# Step 6: Iterate (Repeat for a fixed number of iterations)
population = initialize_population(grid_size, dim, minx, maxx)
for iteration in range(max_iterations):
    fitness_grid = evaluate_fitness(population)

    # Update each cell in parallel (simultaneously)
    new_population = np.zeros_like(population)
    for i in range(grid_size[0]):
        for j in range(grid_size[1]):
            new_population[i, j] = update_cell(population, fitness_grid, i, j, minx, maxx)

    population = new_population

    # Print best fitness at each iteration
    best_fitness = np.min(fitness_grid)
    # print(f"Iteration {iteration + 1}, Best Fitness: {best_fitness}")

# Step 7: Output the Best Solution
best_index = np.unravel_index(np.argmin(fitness_grid), fitness_grid.shape)
best_position = population[best_index[0], best_index[1]]
best_fitness = np.min(fitness_grid)
print("Rahul N Raju,1BM22CS215")
print("Best Position Found:", best_position)
print("Best Fitness Found:", best_fitness)
```

Output Clear

```
Rahul N Raju,1BM22CS215
Best Position Found: [0.02472174 0.07560719]
Best Fitness Found: 1.7326330222717833e-05

=== Code Execution Successful ===
```

Program 7 : .Gene Expression Algorithms(GEA)

Gene Expression Algorithms (GEA) are inspired by the biological process of gene expression in living organisms. This process involves the translation of genetic information encoded in DNA into functional proteins. In GEA, solutions to optimization problems are encoded in a manner similar to genetic sequences. The algorithm evolves these solutions through selection, crossover, mutation, and gene expression to find optimal or near-optimal solutions. GEA is effective for solving complex optimization problems in various domains, including engineering, data analysis, and machine learning.

Algorithm:

Gene Expression Algorithm

* Algorithm

1) Initialization

Define constants and parameters:

Set population size P, no of generation G, mutation rate M, crossover rate C and max tree depth D.

Define the function set F (eg. +, *, /) and terminal set T

Initialize the population

Generate P random individuals, each represented by a mathematical expression of depth upto 'D'.

2) Evaluate fitness

① For each individual in the population:

Replace the variable x in the individual's expression with a specific value. (eg:- x = 3).

② Evaluate the mathematical expression to calculate fitness

③ If the expression is invalid, assign a high fitness value.

3) Selection

① Identify the best individual in the population

② Store or output the best individual's fitness for the current generation

4) Generate new population, with crossover and mutation

5) Find best individual & its fitness.

Code :

```
import random
import operator
import math

# Constants for the genetic algorithm
POPULATION_SIZE = 100
GENERATIONS = 5
MUTATION_RATE = 0.1
CROSSOVER_RATE = 0.7
MAX_TREE_DEPTH = 5
FUNCTIONS = ['+', '*', '/']
TERMINALS = ['x', '1', '2', '3']

# Class to represent an individual in the population
class Individual:
    def __init__(self, expression):
        self.expression = expression
        self.fitness = float('inf')

    # Function to evaluate the fitness of an individual
    def evaluate_fitness(self, x_value):
        try:
            expr = self.expression.replace('x', str(x_value))
            # Using eval to evaluate the expression
            self.fitness = eval(expr)
        except Exception as e:
            self.fitness = float('inf')

# Function to generate a random individual
def generate_random_individual():
    expression = generate_random_expression(MAX_TREE_DEPTH)
    return Individual(expression)

# Function to generate a random expression (tree-like structure)
def generate_random_expression(depth):
    if depth == 0 or random.random() < 0.3:
        # Return a terminal (e.g., x or constants)
        return random.choice(TERMINALS)
    else:
        # Return a function with two subexpressions
        function = random.choice(FUNCTIONS)
        left = generate_random_expression(depth - 1)
        right = generate_random_expression(depth - 1)
        return f"({left} {function} {right})"
```

```
# Function to perform crossover between two individuals
def crossover(parent1, parent2):
    # For simplicity, we just swap subexpressions between two individuals
    expr1, expr2 = parent1.expression, parent2.expression
    split1 = random.choice(expr1.split())
    split2 = random.choice(expr2.split())
    offspring_expr = expr1.replace(split1, split2, 1)
    return Individual(offspring_expr)

# Function to mutate an individual
def mutate(individual):
    if random.random() < MUTATION_RATE:
        # Replace a random part of the expression with a new one
        mutated_expr = individual.expression
        split_expr = mutated_expr.split()
        mutated_expr = mutated_expr.replace(random.choice(split_expr),
generate_random_expression(MAX_TREE_DEPTH), 1)
        individual.expression = mutated_expr

# Function to select the best individual
def select_best_individual(population, x_value):
    best_individual = min(population, key=lambda ind: ind.fitness)
    best_individual.evaluate_fitness(x_value)
    return best_individual

# Main function to run the GEP algorithm
def run_gep_algorithm():
    population = [generate_random_individual() for _ in range(POPULATION_SIZE)]

    for generation in range(GENERATIONS):
        # Evaluate fitness for each individual
        for individual in population:
            individual.evaluate_fitness(3)  # Example with x=3

        # Select the best individual
        best_individual = select_best_individual(population, 3)

        # Print the fitness of the best individual in each generation
        print(f"Generation {generation + 1}: Best fitness = {best_individual.fitness}")

        # Create a new population using crossover and mutation
        new_population = []
        while len(new_population) < POPULATION_SIZE:
            if random.random() < CROSSOVER_RATE:
                parent1 = random.choice(population)
                parent2 = random.choice(population)
```

```
            offspring = crossover(parent1, parent2)
            new_population.append(offspring)
        else:
            individual = random.choice(population)
            mutate(individual)
            new_population.append(individual)

    population = new_population

# Run the algorithm
if __name__ == "__main__":
    print("Rahul N Raju,1BM22CS215")
    run_gep_algorithm()
```

Output Clear

```
Rahul N Raju,1BM22CS215
Generation 1: Best fitness = 0.011904761904761904
Generation 2: Best fitness = 0.2608695652173913
Generation 3: Best fitness = 0.14285714285714285
Generation 4: Best fitness = 0.14285714285714285
Generation 5: Best fitness = 0.029556650246305417

=== Code Execution Successful ===
```