VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.



LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by

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in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING in COMPUTER SCIENCE AND ENGINEERING



B.M.S. COLLEGE OF ENGINEERING
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CERTIFICATE

This is to certify that the Lab work entitled "Bio Inspired Systems (23CS5BSBIS)" carried out by **Agam Tiwari (1BM22CS023)**, 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/Agam1611/BIS-LAB-5Sem

<u>Program 1</u> Genetic Algorithm for Optimization Problems

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	· A fitness function be obtained in
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	· Cholsone to greate the next greation. · Mutation to introduce borden changes
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	and mutates themosomes to cleate new greentions raining to optimize the fitness function
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	indicating canalysise. The effectiveness of the
- 11	legithm depends on factoris like challenge and
1	nutation platobilities, population size, and to of itele

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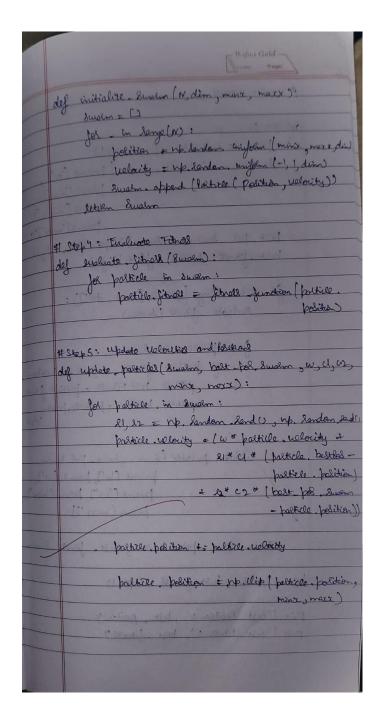
```
import numpy as np
# Objective function to maximize
def fitness function(x):
    return x**2
# Initialize parameters
population size = 50
mutation rate = 0.1
crossover rate = 0.7
num generations = 50
lower bound = -10
upper bound = 10
# Create initial population
def initialize population(size, lower, upper):
    return np.random.uniform(lower, upper, size)
# Evaluate fitness for the population
def evaluate fitness(population):
    return np.array([fitness function(x) for x in population])
# Selection using roulette wheel selection
def select parents (population, fitness):
    total fitness = np.sum(fitness)
    selection probs = fitness / total fitness
    parents indices = np.random.choice(len(population), size=2,
p=selection probs)
    return population[parents indices]
# Crossover to create offspring
def crossover(parent1, parent2):
    if np.random.rand() < crossover rate:</pre>
        return (parent1 + parent2) / 2 # Linear crossover
    return parent1
# Mutation to introduce diversity
def mutate(offspring):
    if np.random.rand() < mutation rate:</pre>
        return np.random.uniform(lower bound, upper bound)
    return offspring
# Genetic Algorithm main function
```

```
def genetic algorithm():
    # Initialize population
    population = initialize population(population size, lower bound,
upper bound)
    for generation in range (num generations):
        # Evaluate fitness of the population
        fitness = evaluate fitness(population)
        # Track the best solution
       best fitness idx = np.argmax(fitness)
       best solution = population[best fitness idx]
       best fitness value = fitness[best fitness idx]
        print(f"Generation {generation}: Best Solution = {best solution},
Fitness = {best fitness value}")
        # Create the next generation
        new population = []
        for in range (population size):
            parent1, parent2 = select parents(population, fitness)
            offspring = crossover(parent1, parent2)
            offspring = mutate(offspring)
            new population.append(offspring)
        population = np.array(new population)
    # Final evaluation
    final fitness = evaluate fitness(population)
    best fitness idx = np.argmax(final fitness)
    best solution = population[best fitness idx]
    best fitness value = final fitness[best fitness idx]
    return best solution, best fitness value
# Run the genetic algorithm
best solution, best fitness value = genetic algorithm()
print(f"Best Solution Found: x = \{best solution\}, f(x) =
{best fitness value}")
Output:
Generation 0: Best Solution = -9.967365011554792, Fitness = 99.34836527356666
Generation 1: Best Solution = -9.169251894044368, Fitness = 84.07518029643623
Generation 49: Best Solution = 9.123059138454053, Fitness = 83.23020804373002
Best Solution Found: x = 9.05670095588789, f(x) = 82.02383220438064
```

Program 2

Particle Swarm Optimization for Function Optimization

23/10/24	Particle Swalm Optimization
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	6. 10/12 11.1 11.2 11.1 11.
	import nimpy as up
	#Step1: Fitness Function
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	def (itness function / position):
	def fitness function (polition): leturn pp. Sum (position + 2)
	Market Control of the same of the same of the
	# Step 2: Tritialize polarnotels
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	def initalize , polonetels ():
	palamb = 1
	'N' : 50,
	'dim': 2,
	'mex_itos': 200,
-	'mina': -lo,
-	'mar':lo
	"w": o. S. # Inaltia Weight
Legar po .	'4': 1.5, # Cognitive coefficient
	1 145 # Social Coefficient
	letur paland
10 50	sound from the season of the season
	# Steps: Tritialize felticles
528	10/41/41 some at how spice and
	-class Parkiec:
	def init (self, polition, relocity):
	Seq. position = position
	self. relocity = relocity
	self best of = boltion copy()
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V-1750	



```
import numpy as np
# Step 1: Define the Problem
def fitness function(position):
    # Example: Minimize the Sphere function
   return np.sum(position**2)
# Step 2: Initialize Parameters
def initialize parameters():
   params = {
        'N': 50,
                       # Number of particles
        'dim': 2,
                   # Dimensionality of the problem
        'max iter': 200, # Maximum number of iterations
        'minx': -10,  # Minimum bound for position
        'maxx': 10,
                      # Maximum bound for position
        'w': 0.5,
                      # Inertia weight
        'c1': 1.5,
                      # Cognitive coefficient
        'c2': 1.5
                       # Social coefficient
    }
    return params
# Step 3: Initialize Particles
class Particle:
    def init (self, position, velocity):
        self.position = position
        self.velocity = velocity
        self.bestPos = position.copy()
        self.bestFitness = float('inf')
def initialize swarm(N, dim, minx, maxx):
    swarm = []
    for in range(N):
        position = np.random.uniform(minx, maxx, dim)
       velocity = np.random.uniform(-1, 1, dim)
        swarm.append(Particle(position, velocity))
    return swarm
# Step 4: Evaluate Fitness
def evaluate fitness(swarm):
    for particle in swarm:
        particle.fitness = fitness function(particle.position)
# Step 5: Update Velocities and Positions
def update particles (swarm, best pos swarm, w, c1, c2, minx, maxx):
```

```
for particle in swarm:
        r1, r2 = np.random.rand(), np.random.rand()
        particle.velocity = (w * particle.velocity +
                             r1 * c1 * (particle.bestPos - particle.position)
                             r2 * c2 * (best pos swarm - particle.position))
        particle.position += particle.velocity
        # Clip position to be within bounds
        particle.position = np.clip(particle.position, minx, maxx)
# Step 6: Iterate
def pso():
    params = initialize parameters()
    swarm = initialize swarm(params['N'], params['dim'], params['minx'],
params['maxx'])
    best pos swarm = swarm[0].position.copy()
    best fitness swarm = float('inf')
    for in range(params['max iter']):
        evaluate fitness(swarm)
        for particle in swarm:
            if particle.fitness < particle.bestFitness:</pre>
                particle.bestFitness = particle.fitness
                particle.bestPos = particle.position.copy()
            if particle.fitness < best fitness swarm:</pre>
                best fitness swarm = particle.fitness
                best pos swarm = particle.position.copy()
        update_particles(swarm, best_pos_swarm, params['w'], params['c1'],
params['c2'], params['minx'], params['maxx'])
    # Step 7: Output the Best Solution
    return best pos swarm, best fitness swarm
best position, best fitness = pso()
print("Best Position:", best position)
print("Best Fitness:", best fitness)
Output:
Best Position: [-9.19971249e-25 1.71937901e-24]
Best Fitness: 3.802611270068504e-48
```

 $\frac{\textbf{Program 3}}{\textbf{Ant Colony Optimization for the Traveling Salesman Problem}}$

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30 10 24	Ant Colony Optimization for the TSP
-	
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	import landom
	000 000
	class Actiolog;
	def init (2016, cities, num ants = 10 ; alpha = 1.0,
	bota = 20 , tho = 0.5, its lational = lool:
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	2000
	Socy. cities = cities
	Self. hum south = hum ents
	self. alpha = alpha
	Seef beta = bota
	Jelf. Sho = sho
	sey iterations = iterations
	Self num cities = len(cities)
	led, phelmore = np. and ((self, numerities,
	Self. num. cities)
	solf distance - Solf colculate - distance ()
	def Calculate - distance (Self):
	dill sell all sells
	distances - nt. selves (Seg, hum cities,
	Self num cities 1)
	fol i in large (self. num citie);
	for in lange (i+1, soff . nem citios):
	distances [i][i] = distances[i][i]
	letum distances
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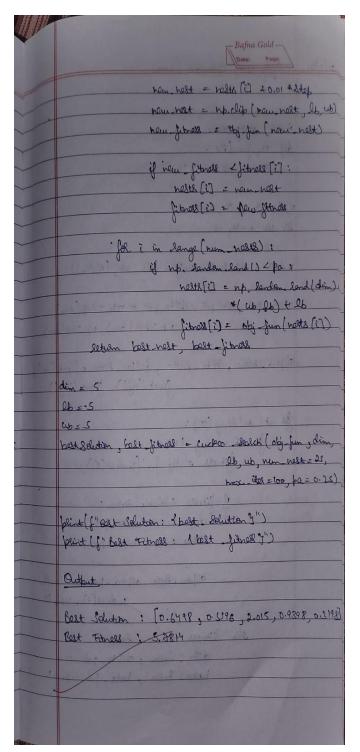
	Bafna Gold —
	def select next-city (seef cusered-city, wisited);
	for next city in large (self num cities):
11/2	if next-city not in visited:
	phalmane = salf, phelmano
	[cullent city] " sog. altho
	hewistix = (1/self distance
	[cursent_city]
	[neat_city]) ** tall bata
	plobabilities appord (pheniene & herelistic)
	e Ose:
	perhabilities, append (0)
	The second second second second
Resi	total = Sum (probabilities)
Consti	probabilities = [pl total for p in
	probabilities
- 11	Setur up lordon, chaice (large (self. hum-citie) P = probabilities)
	def constituet Solution (209):
	for in large (self. hum ants):
	the the culton, city so
	for in large (1, log . hum cities).
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-	(ausset ato wishted)
	whited appeal (reat city)
	cultont city = reat city
	white appendix
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```
import numpy as np
import random
class AntColony:
    def init (self, cities, num ants=10, alpha=1.0, beta=2.0, rho=0.5,
iterations=100):
        self.cities = cities
        self.num ants = num ants
        self.alpha = alpha
        self.beta = beta
        self.rho = rho
        self.iterations = iterations
        self.num cities = len(cities)
        self.pheromone = np.ones((self.num cities, self.num cities))
        self.distance = self.calculate distances()
    def calculate distances(self):
       distances = np.zeros((self.num cities, self.num cities))
        for i in range(self.num cities):
            for j in range(i + 1, self.num cities):
                distances[i][j] = distances[j][i] =
np.linalg.norm(np.array(self.cities[i]) - np.array(self.cities[j]))
       return distances
    def select next city(self, current city, visited):
       probabilities = []
        for next city in range(self.num cities):
            if next city not in visited:
                pheromone = self.pheromone[current city][next city] **
self.alpha
                heuristic = (1 / self.distance[current city][next city]) **
self.beta
                probabilities.append(pheromone * heuristic)
            else:
                probabilities.append(0)
        total = sum(probabilities)
        probabilities = [p / total for p in probabilities]
        return np.random.choice(range(self.num cities), p=probabilities)
    def construct solution(self):
        for in range(self.num ants):
            visited = [0]
            current city = 0
            for in range(1, self.num cities):
                next city = self.select next city(current city, visited)
                visited.append(next city)
                current city = next city
            visited.append(0) # Return to starting city
```

```
yield visited
    def update pheromones(self, solutions):
        self.pheromone *= (1 - self.rho) # Evaporation
        for solution in solutions:
            length = self.calculate tour length(solution)
            pheromone deposit = 1 / length
            for i in range(len(solution) - 1):
                self.pheromone[solution[i]][solution[i + 1]] +=
pheromone deposit
    def calculate tour length(self, solution):
        return sum(self.distance[solution[i]][solution[i + 1]] for i in
range(len(solution) - 1))
    def run(self):
        best solution = None
        best length = float('inf')
        for in range(self.iterations):
            solutions = list(self.construct solution())
            self.update pheromones(solutions)
            for solution in solutions:
                length = self.calculate tour length(solution)
                if length < best length:</pre>
                    best length = length
                    best solution = solution
        return best solution, best length
cities = [(0, 0), (1, 2), (2, 1), (4, 4), (2, 4)]
aco = AntColony(cities)
best route, best distance = aco.run()
print("Best Route:", best route)
print("Best Distance:", best distance)
Output :
Best Route: [0, 1, 4, 3, 2, 0]
Best Distance: 12.313755207963359
```

Program 4 Cuckoo Search (CS)

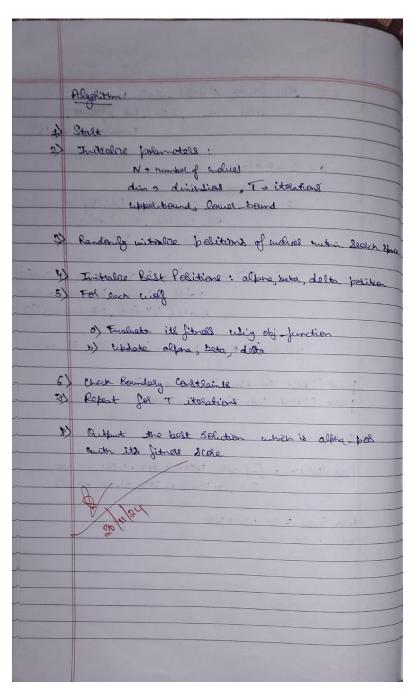
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01.1	A . O AO a b
20/11/24	Cuckoo Soelch Algolithm
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	impost number as no
	impost numby as no
	myste math
	def objective function (a):
	letur np. Sum (x ** 2)
	131/3
	def lang-Right (beta = 1.5, Size = 1):
	signa . U - (moth genne (1+ beta) * hp. sin(
1000	np. pi * bota 12)/
111111111111111111111111111111111111111	
	math. gemma ((14 bots) 1/2) 3 bots &
	(2 ** ((beta-1) 2))) ** (1/beta)
	U = np. Sandon nomal (0, signa U, size)
	V = np. landom, notnel (0, 1, Size)
	Itap = U (np. abs(v) * (1 beta))
	Sotuen Step
	def cucker deach (obj-fun, dim, lb, ub, num, nests
	=25 max ites =100 , pa=0.25):
	nests = np. landon land (num nests, dim)
	* (ub-lb)+lb
	filmes = np. apply, along axis objective.
	function, 1, helts)
	bost-nest-ide = np. arguin (filmels)
	both nost = nosts [bosts nost ida]
	best fithers = fithers [best_nest ida]
	los delation in lenge (mor itse).
	for storation in large (max, itse):
	for it in large (num nosts): Step = lawy flight (Size = dim)
	sup = lung fright (Sile = dim)
18 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	



```
import numpy as np
import math
# Objective function to optimize (example: Sphere function)
def objective function(x):
    return np.sum(x**2)
# Lévy Flight distribution
def levy flight(beta=1.5, size=1):
    sigma u = (math.gamma(1 + beta) * np.sin(np.pi * beta / 2) /
               math.gamma((1 + beta) / 2) * beta * (2 ** ((beta - 1) /
2)))**(1 / beta)
    u = np.random.normal(0, sigma_u, size)
    v = np.random.normal(0, 1, size)
    step = u / (np.abs(v) ** (1 / beta))
    return step
# Cuckoo Search Algorithm
def cuckoo search (objective function, dim, lower bound, upper bound,
num nests=25, max iter=100, pa=0.25):
    # Initialize nests with random solutions within bounds
    nests = np.random.rand(num nests, dim) * (upper bound - lower bound) +
lower bound
    fitness = np.apply along axis(objective function, 1, nests)
    # Initialize the best solution
    best nest idx = np.argmin(fitness)
    best nest = nests[best nest idx]
    best fitness = fitness[best nest idx]
    # Iterate for a fixed number of generations or until convergence
    for iteration in range (max iter):
        for i in range(num nests):
            # Generate a new solution using Lévy flight
            step = levy flight(size=dim)
            new nest = nests[i] + 0.01 * step
            new_nest = np.clip(new nest, lower bound, upper bound)
            # Evaluate the new solution
            new fitness = objective function(new nest)
            # If the new solution is better, replace the old solution
            if new fitness < fitness[i]:</pre>
                nests[i] = new nest
                fitness[i] = new fitness
```

```
# Abandon the worst nests
        for i in range(num nests):
            if np.random.rand() < pa: # Probability to abandon</pre>
                nests[i] = np.random.rand(dim) * (upper bound - lower bound)
+ lower bound
                fitness[i] = objective function(nests[i])
        # Find the current best nest
       best nest idx = np.argmin(fitness)
        best nest = nests[best nest idx]
       best fitness = fitness[best nest idx]
        # print(f"Iteration {iteration+1}, Best Fitness: {best fitness}")
   return best nest, best fitness
# Example usage of Cuckoo Search
# Define the problem dimensions and bounds
dim = 5 # Dimension of the solution space
lower_bound = -5 # Lower bound of the search space
upper bound = 5 # Upper bound of the search space
# Run Cuckoo Search
best solution, best fitness = cuckoo search(objective function, dim,
lower bound, upper bound, num nests=25, max iter=100, pa=0.25)
print(f"Best Solution: {best solution}")
print(f"Best Fitness: {best fitness}")
Output :
Best Solution: [0.64982748 0.55961241 2.01501756 0.93987275 0.31984962]
Best Fitness: 5.78140211553397
```

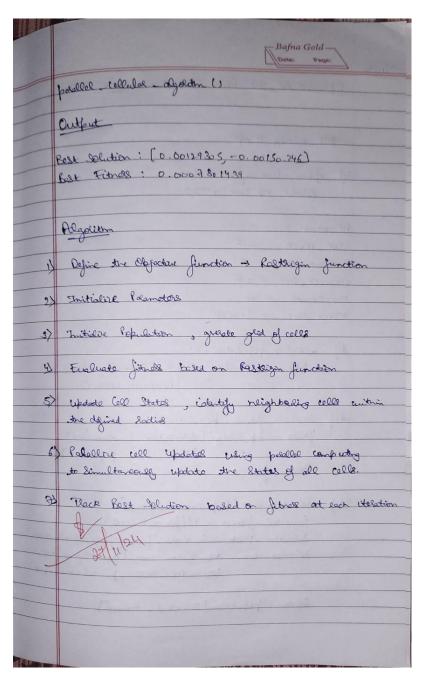
<u>Program 5</u> Grey Wolf Optimizer (GWO)



```
import numpy as np
# Objective function (example: Sphere function)
def objective function(x):
   return np.sum (x**2)
N, dim, T = 30, 10, 100 # Number of wolves, dimensions, iterations
lower bound, upper bound = -10, 10
wolves = np.random.uniform(lower bound, upper bound, (N, dim))
alpha pos, beta pos, delta pos = np.zeros(dim), np.zeros(dim), np.zeros(dim)
alpha score, beta score, delta score = float('inf'), float('inf'),
float('inf')
for t in range(T):
   for i in range(N):
       fitness = objective function(wolves[i]) # Evaluate fitness
       if fitness < alpha score:</pre>
           delta score, delta pos = beta score, beta pos.copy()
           beta score, beta pos = alpha score, alpha pos.copy()
           alpha score, alpha pos = fitness, wolves[i].copy()
       elif fitness < beta score:</pre>
           delta score, delta pos = beta score, beta pos.copy()
           beta score, beta pos = fitness, wolves[i].copy()
       elif fitness < delta score:</pre>
           delta score, delta pos = fitness, wolves[i].copy()
   a = 2 - t * (2 / T)
   for i in range(N):
       r1, r2 = np.random.rand(dim), np.random.rand(dim)
       A, C = 2 * a * r1 - a, 2 * r2
       wolves[i] += A * (abs(C * alpha pos - wolves[i]) +
                         abs(C * beta pos - wolves[i]) +
                         abs(C * delta pos - wolves[i]))
       wolves[i] = np.clip(wolves[i], lower bound, upper bound)
print("Best Solution:", alpha pos)
print("Best Score:", alpha score)
Output:
3.74582237
 0.84065243  0.8938704  -1.22271966  -0.290071491
Best Score: 31.023829961456407
```

Program 6

Parallel Cellular Algorithms and Programs

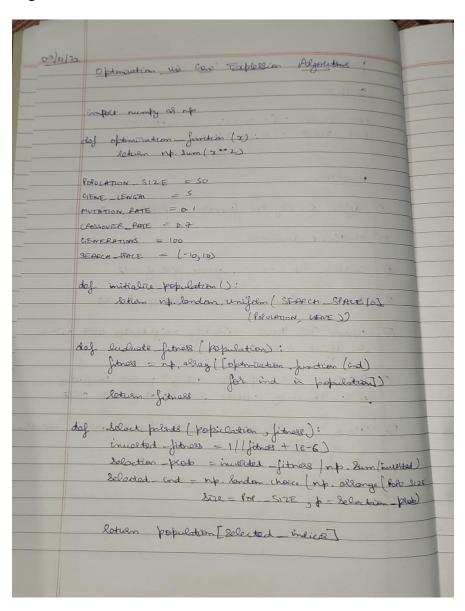


```
import numpy as np
import random
import concurrent.futures
def rastrigin(x):
   A = 10
   return A * len(x) + sum([(xi ** 2 - A * np.cos(2 * np.pi * xi)) for xi in
x])
GRID SIZE = (10, 10)
DIM = 2
RADIUS = 1
ITER = 100
BEST = None
def init grid(size, dim):
    return [[np.random.uniform(-5.12, 5.12, size=(dim,)) for in
range(size[1])] for in range(size[0])]
def fitness(cell):
   return rastrigin(cell)
def update state(grid, i, j, radius):
    curr = grid[i][j]
    fitness curr = fitness(curr)
    neighbors = [grid[ni][nj] for dx in range(-radius, radius+1) for dy in
range(-radius, radius+1)
                 if 0 \le (ni := i+dx) \le len(grid) and 0 \le (nj := j+dy) \le len(grid)
len(grid[0]) and (dx or dy)]
    if neighbors:
        best neigh = min(neighbors, key=fitness)
        return curr + 0.1 * (best_neigh - curr)
    return curr
def run iteration(grid, radius):
    new grid = [[None for in range(len(grid[0]))] for in
range(len(grid))]
    with concurrent.futures.ThreadPoolExecutor() as ex:
        futures = [ex.submit(update state, grid, i, j, radius) for i in
range(len(grid)) for j in range(len(grid[0]))]
        for idx, future in enumerate(futures):
            i, j = divmod(idx, len(grid[0]))
            new grid[i][j] = future.result()
return new grid
```

```
def track best(grid):
    global BEST
    best cell, best fitness = None, float('inf')
    for row in grid:
        for cell in row:
            f = fitness(cell)
            if f < best fitness:</pre>
                best fitness = f
                best cell = cell
    if BEST is None or best fitness < fitness(BEST):</pre>
        BEST = best cell
def parallel cellular algorithm():
    global BEST
    grid = init grid(GRID SIZE, DIM)
    for _ in range(ITER):
        grid = run iteration(grid, RADIUS)
        track best(grid)
        print(f"Best Fitness: {fitness(BEST)}")
    print("Best Solution:", BEST)
    print("Best Fitness:", fitness(BEST))
parallel_cellular_algorithm()
Output :
Best Fitness: 2.4309484366586602
Best Fitness: 2.4309484366586602
Best Fitness: 0.0007801439196555293
Best Fitness: 0.0007801439196555293
Best Fitness: 0.0007801439196555293
Best Solution: [ 0.00129305 -0.00150346]
Best Fitness: 0.0007801439196555293
```

Program 7

Optimization via Gene Expression Algorithms



```
import numpy as np
# Define the mathematical function to optimize (example: minimize f(x) = x^2)
def optimization function(x):
    return np.sum(x**2) # Modify this for other functions to optimize
# Parameters
POPULATION SIZE = 50 # Number of individuals
GENE LENGTH = 5 # Number of genes (dimensions of the problem)
MUTATION RATE = 0.1 # Probability of mutation
CROSSOVER RATE = 0.7 # Probability of crossover
GENERATIONS = 100 # Number of generations
SEARCH SPACE = (-10, 10) # Range of values for genes
# Initialize Population
def initialize population():
    return np.random.uniform(SEARCH SPACE[0], SEARCH SPACE[1],
(POPULATION SIZE, GENE LENGTH))
# Evaluate Fitness (lower is better for minimization)
def evaluate fitness(population):
    fitness = np.array([optimization function(ind) for ind in population])
   return fitness
# Selection (Roulette Wheel Selection)
def select parents (population, fitness):
    # Convert fitness to probabilities (lower fitness is better)
    inverted fitness = 1 / (fitness + 1e-6) # Avoid division by zero
    selection prob = inverted fitness / np.sum(inverted fitness)
    selected indices = np.random.choice(np.arange(POPULATION SIZE),
size=POPULATION SIZE, p=selection prob)
    return population[selected indices]
# Crossover (Blend Crossover)
def crossover(parents):
    offspring = np.empty like(parents)
    for i in range(0, POPULATION SIZE, 2):
       p1, p2 = parents[i], parents[i+1]
        if np.random.rand() < CROSSOVER RATE:</pre>
            alpha = np.random.rand() # Blending factor
            offspring[i] = alpha * p1 + (1 - alpha) * p2
            offspring[i+1] = alpha * p2 + (1 - alpha) * p1
       else:
            offspring[i], offspring[i+1] = p1, p2
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return offspring
# Mutation (Random Perturbation)
def mutate(offspring):
   for i in range (POPULATION SIZE):
        if np.random.rand() < MUTATION RATE:</pre>
            mutation point = np.random.randint(0, GENE LENGTH)
            offspring[i][mutation point] += np.random.uniform(-1, 1)
            # Keep within search space
            offspring[i][mutation point] =
np.clip(offspring[i][mutation point], SEARCH_SPACE[0], SEARCH_SPACE[1])
    return offspring
# Gene Expression (Translate Genetic Code into Solutions)
def gene expression(genes):
    # In this simple example, the genes directly represent the solution
   return genes
# Main Algorithm
def gene expression algorithm():
    # Initialize population
    population = initialize population()
   best solution = None
   best fitness = float('inf')
    # Iterate through generations
    for generation in range (GENERATIONS):
        # Evaluate fitness
        fitness = evaluate fitness(population)
        # Track the best solution
        current best idx = np.argmin(fitness)
        if fitness[current best idx] < best fitness:</pre>
            best_fitness = fitness[current_best_idx]
            best solution = population[current best idx]
        print(f"Generation {generation+1}: Best Fitness = {best fitness}")
        # Selection
        parents = select parents(population, fitness)
        # Crossover
        offspring = crossover(parents)
        # Mutation
        offspring = mutate(offspring)
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# Gene Expression (not needed explicitly as genes represent
solutions)
       population = gene expression(offspring)
   print("\nOptimal Solution Found:")
   print("Best Solution:", best_solution)
   print("Best Fitness:", best fitness)
# Run the algorithm
if name == " main ":
   gene expression algorithm()
Output :
Generation 1: Best Fitness = 16.545885126119284
Generation 2: Best Fitness = 11.641082640808637
Generation 99: Best Fitness = 0.02233046748484963
Generation 100: Best Fitness = 0.02233046748484963
Optimal Solution Found:
Best Solution: [ 0.07226226 -0.11854791 0.03245473 -0.01236219 0.04299877]
Best Fitness: 0.02233046748484963
```