VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB RECORD

Bio Inspired Systems (23CS5BSBIS)

Submitted by **Sanchit Kashyap(1BM23CS298)**

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING

(Autonomous Institution under VTU)

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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 **Sanchit Kashyap(1BM23CS298),** 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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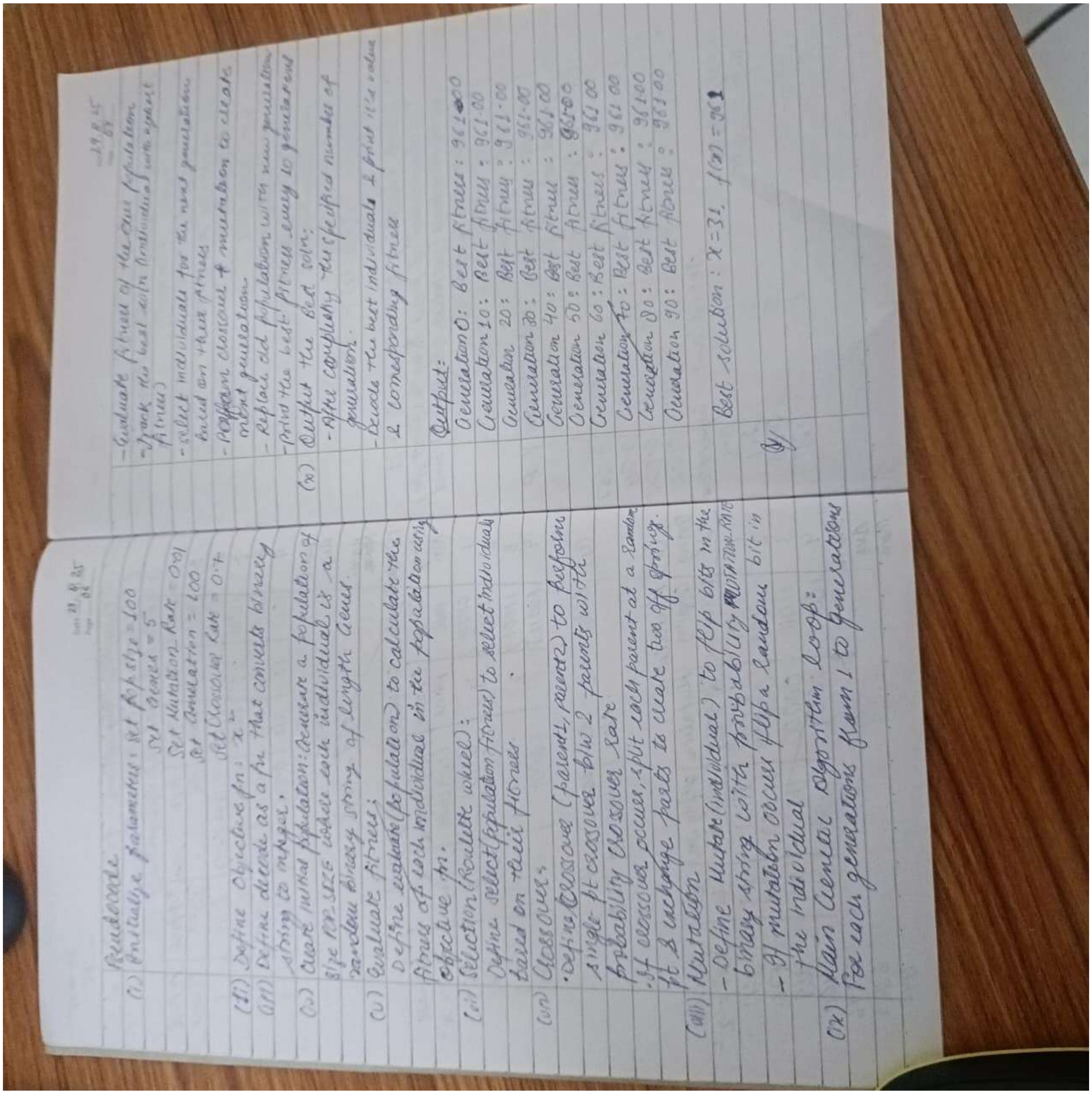
Github Link:

https://github.com/sanchit901/BIS_LAB_1BM23CS298

Program 1

Genetic Algorithm for Optimization Problems

Algorithm:



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Pseudocode

(i) Initialize parameters: Set Pop size = 100
Set Genes = 5
Set Mutation Rate = 0.01
Set Generation = 100
Set Crossover Rate = 0.7

(ii) Define Objective fn: x^2

(iii) Define decode as a fn that converts binary string to integer.

(iv) Create initial population: Generate a population of size POP_SIZE where each individual is a random binary string of length Genes.

(v) Evaluate fitness:
Define evaluate(population) to calculate the fitness of each individual in the population using objective fn.

(vi) Selection (Roulette wheel):
Define select(population fitness) to select individuals based on their fitness

(vii) Crossover:
· Define Crossover (parent1, parent2) to perform single pt crossover b/w 2 parents with probability crossover rate
· If crossover occurs, split each parent at a random pt & exchange parts to create two off spring.

(viii) Mutation
- Define Mutate (individual) to flip bits in the binary string with probability MUTATION_RATE
- If mutation occurs flip a random bit in the individual

(ix) Main Genetic Algorithm loop:
For each generations from 1 to Generations

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- Evaluate fitness of the curr population
- Track the best soln (individual with highest fitness)
- Select individuals for the next generation based on their fitness
- Perform crossover & mutation to create next generation
- Replace old population with new generation
- Print the best fitness every 10 generations

(x) Output the Best soln:
- After completing the specified number of generations.
- Decode the best individuals & print its value & corresponding fitness

Output:

Generation 0: Best fitness : 961.00
Generation 10: Best fitness : 961.00
Generation 20: Best fitness : 961.00
Generation 30: Best fitness : 961.00
Generation 40: Best fitness : 961.00
Generation 50: Best fitness : 961.00
Generation 60: Best fitness : 961.00
Generation 70: Best fitness : 961.00
Generation 80: Best fitness : 961.00
Generation 90: Best fitness : 961.00

Best solution : $x = 31$, $f(x) = 961$

Code:

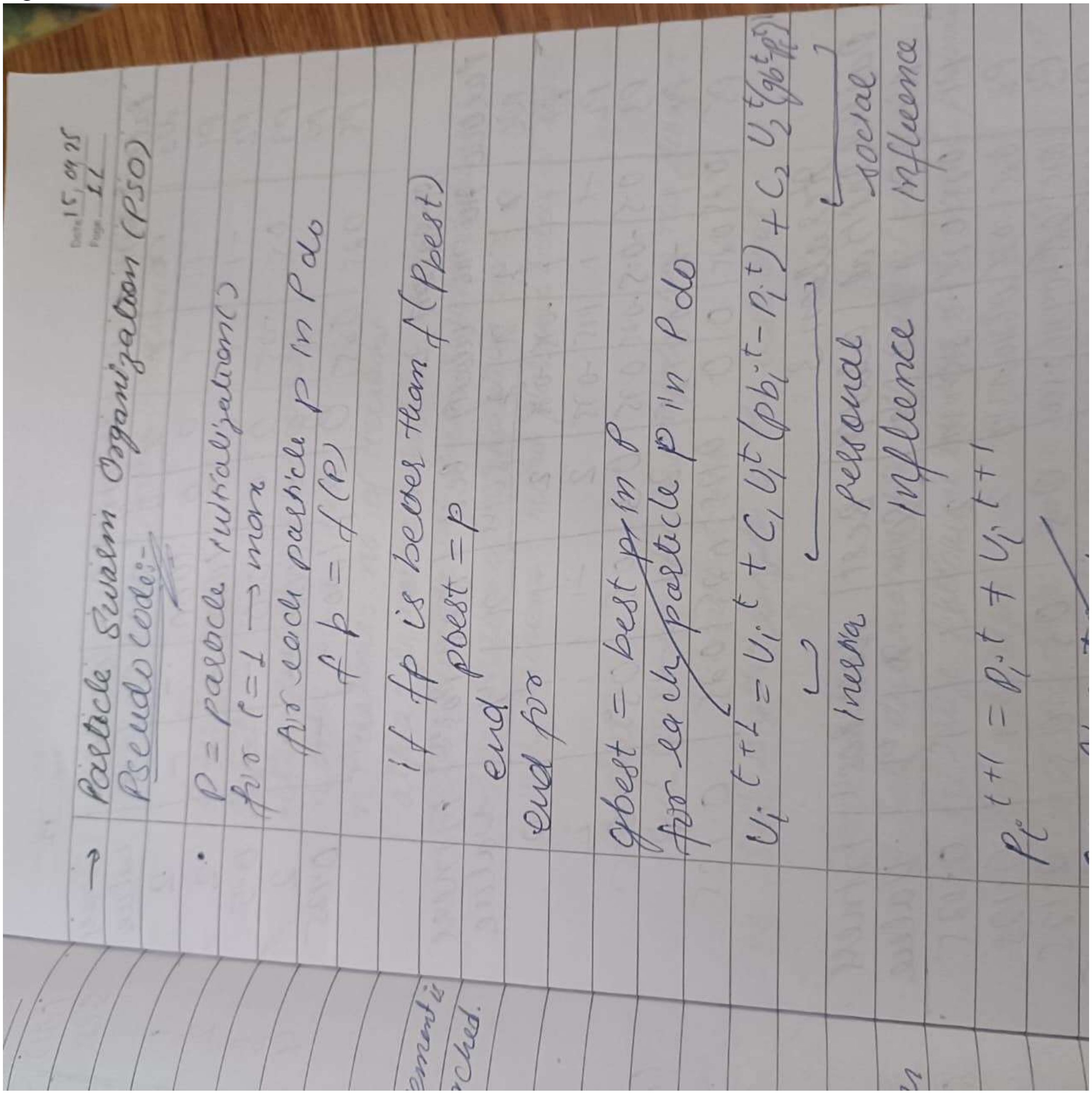
```
import numpy as np

# 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:
        return (parent1 + parent2) / 2  # Linear crossover     return
parent1

# Mutation to introduce diversity def
mutate(offspring):
    if np.random.rand() < mutation_rate:
        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

Algorithm: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Particle Swarm Organization (PSO)

Pseudo code:-

- P = particle initialization()

for i = 1 → max
  for each particle p in P do
    f_p = f(p)
    if f_p is better than f(Pbest)
      pbest = p
    end
  end for

gbest = best p in P
for each particle p in P do

$$v_i^{t+1} = \underbrace{v_i^t}_{\text{inertia}} + \underbrace{c_1 U_1^t (pb_i^t - p_i^t)}_{\text{personal influence}} + \underbrace{c_2 U_2^t (gb^t - p_i^t)}_{\text{social influence}}$$

$$p_i^{t+1} = p_i^t + v_i^{t+1}$$

Code:

```
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:
particle.bestFitness = particle.fitness
particle.bestPos = particle.position.copy()             if
particle.fitness < best_fitness_swarm:
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
```

Program 3

Ant Colony Optimization for the Traveling Salesman Problem

Algorithm:

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→ Ant Colony Optimization for the Traveling Salesman Problem

Pseudo-code:-

- Input:
  - cities: list of city coordinates
  - n_ants: no. of ants
  - n_iterations: no. of iterations
  - alpha: pheromone importance factor
  - beta: heuristic imp factor (inverse distance)
  - rho: pheromone evaporation rate
  - initial_pheromone: initial pheromone value on edges

- Output:
  - best_tour: seq. of cities representing the shortest route found
  - best_length: length of the best tour

- Procedure:
  1. Calc dist matrix b/w all pairs of cities
  2. Initialize pheromone matrix with initial_pheromone for all edges
  3. Calc heuristic matrix as inverse of dist. mat.
  4. Initialize best_length to a large no. and best_tour as empty.
  5. For iteration = 1 to n_iterations do:

     a. For each ant = 1 to n_ants do:

        i. Randomly select a start city for the ant
        ii. Initialize visited cities with start city
        iii. While there are unvisited cities do:
           - for each unvisited city, calc prob. proportional to:
             (pheromone[current_city][city] ^ alpha) *
             (heuristic[current_city][city] ^ beta)

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- Normalize the probabilities
- Select the next city based on the prob distribution
- Add the selected city to visited_cities

iv. Calc the length of the completed tour (including return to start).

b. After all ants have completed tours:
i. Evaporate pheromone on all edges:
pheromone[i][j] = (1-rho) * pheromone[i][j]

ii. For each ant:
- Deposit pheromone on edges in the ant's tour proportionality to 1/tour length:
pheromone[city_i][city_j] += Q / tour_length

c. Update best_tour and best_length if any ant found a better tour.

6. Return best_tour and best_length

Output:-

cities = (0,0), (1,5), (5,2), (6,6), (8,3), (7,7)

~~n_ants = 20~~
n_ants = 20
n_iterations = 100
alpha = 1
beta = 5
rho = 0.5
initial_pheromone = 1

Iteration 1/10, Best length: 24.2828

2/10 : 24.2828

.

.

10/10, Best length : 24.2828

Best tour found: [1, np.int64(3), np.int64(5), np.int64(2), np.int64(0)]

Best tour length: 24.282800682479206

10/10

Code:

```
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:                    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)

Algorithm:

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→ Cuckoo Search
Pseudo Code:-

```
Cuckoo_Search():
  Initialize population of n host nests (solutions)
  xi (i = 1, 2, ... n)
  Define objective fn f(x) x = (x1, x2 ... xd)^T
  Find the curr. best soln x_best among the nests

while (t < MaxGenerations OR stopping criterion
        not met), do
  for each cuckoo (i = 1 to n) do
    Generate a new soln xi_new by Levy flight from xi
    Evaluate fitness f(xi_new)
    Randomly choose a nest j among n
    if f(xi_new) < f(xj) then
       Replace xj with xi_new
    end if
  end for

  A fraction (pa) of worse nests are abandoned and
  replaced with new random solutions

  Keep the best solution (x_best) among curr. popn.
  Rank the nests and find the new x_best

  t = t + 1

End while

Return x_best as the best optimal solution
```

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Appn: Optimal Power Flow

```
Initialize population of nests (generator setting
voltages, etc.)
Evaluate power flow & cost for each nest
Find best nest

While (not stopping)
  For each nest i
    Generate new nest i_new using Lévy flight
    Run power flow, evaluate cost + penalty
    If i_new is better than a random nest j
       Replace j with i_new
    End if
  End for

  Abandon a fraction pa of worst nests and replace
  with random feasible solutions
  Rank nests, update best solution
End while

Return best nest as optimal grid settings
```

O/P:-

Generator 1: 259.40 MW
Generator 2: 153.22 MW
Generator 3: 87.38 MW

Total Power: 500.00 MW
Total Cost: ₹ 4303.06

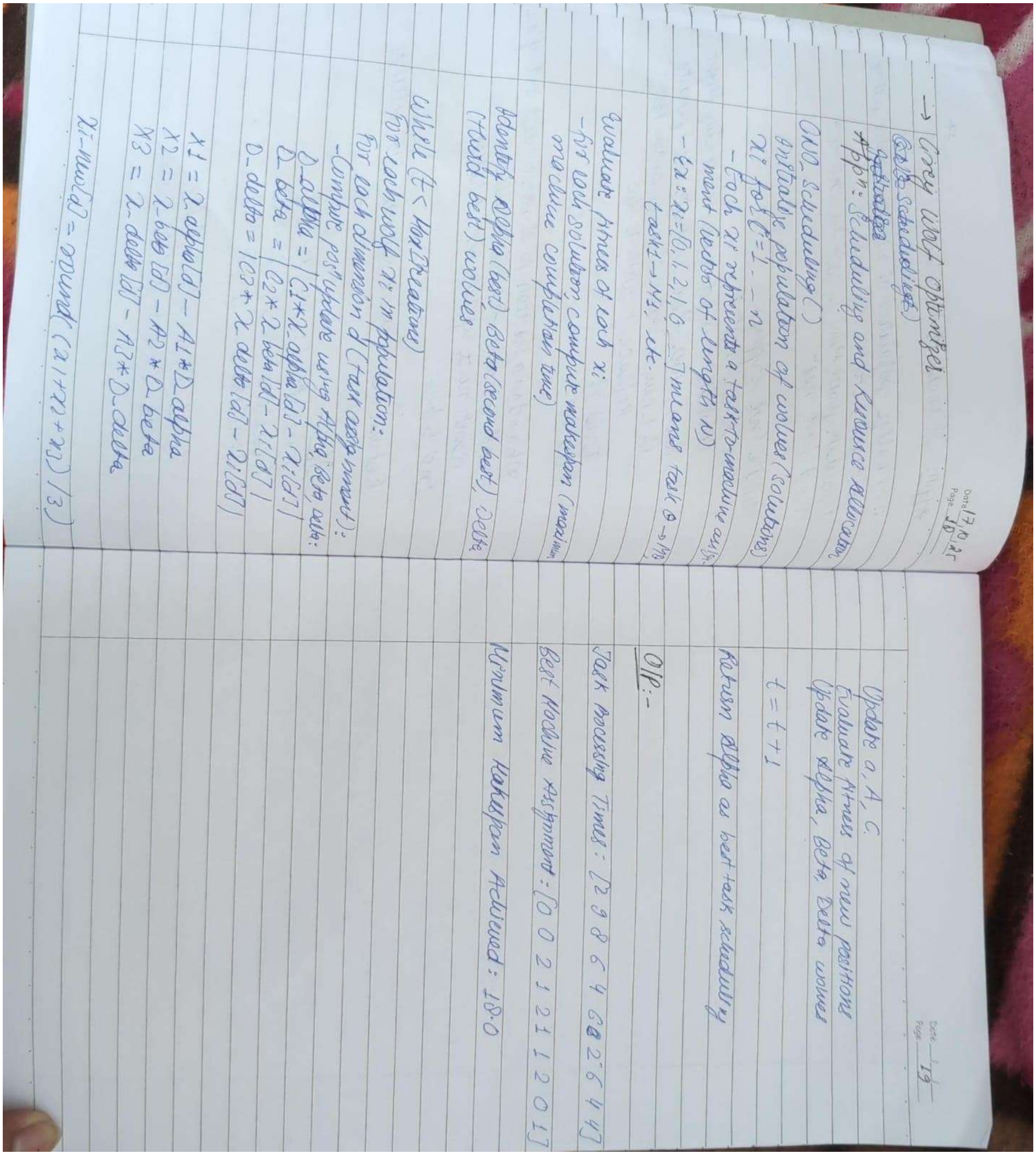
Code:

```
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]:                    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
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
```

Program 5
Grey Wolf Optimizer (GWO)

Algorithm:



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→ Grey Wolf Optimizer
(Task Scheduling)

Appⁿ: Scheduling and Resource Allocation

GWO_Scheduling()
Initialize population of wolves (solutions)
xi for i = 1 ... n
- Each xi represents a task-to-machine assignment (vector of length N)
- Ex: xi = [0, 1, 2, 1, 0 ...] means task 0 → M0, task1 → M1, etc.

Evaluate fitness of each xi
- for each solution, compute makespan (maximum machine completion time)

Identify Alpha (best), Beta (second best), Delta (third best) wolves

While (t < MaxIterations)
For each wolf xi in population:
For each dimension d (task assignment):
- Compute pos" update using Alpha, Beta, Delta:
D_alpha = |C1 * X_alpha[d] - Xi[d]|
D_beta = |C2 * X_beta[d] - Xi[d]|
D_delta = |C3 * X_delta[d] - Xi[d]|

X1 = X_alpha[d] - A1 * D_alpha
X2 = X_beta[d] - A2 * D_beta
X3 = X_delta[d] - A3 * D_delta

Xi_new[d] = round((X1 + X2 + X3) / 3)

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Update a, A, C.
Evaluate fitness of new positions
Update Alpha, Beta, Delta wolves

t = t + 1

Return Alpha as best task scheduling

O/P:-

Task Processing Times: [2 9 8 6 4 6 2 6 4 4]

Best Machine Assignment: [0 0 2 1 2 1 1 2 0 1]

Minimum Makespan Achieved: 18.0

Code:

```
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:
            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:
            delta_score, delta_pos = beta_score, beta_pos.copy()
beta_score, beta_pos = fitness, wolves[i].copy()         elif
fitness < delta_score:
            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 :
```

```
Best Solution: [-1.28434275  1.94786008  0.82301541 -1.85113457 -2.08806377
3.74582237
  0.84065243  0.8938704  -1.22271966 -0.29007149]
Best Score: 31.023829961456407
```

Program 6

Parallel Cellular Algorithms and Programs

Algorithm:

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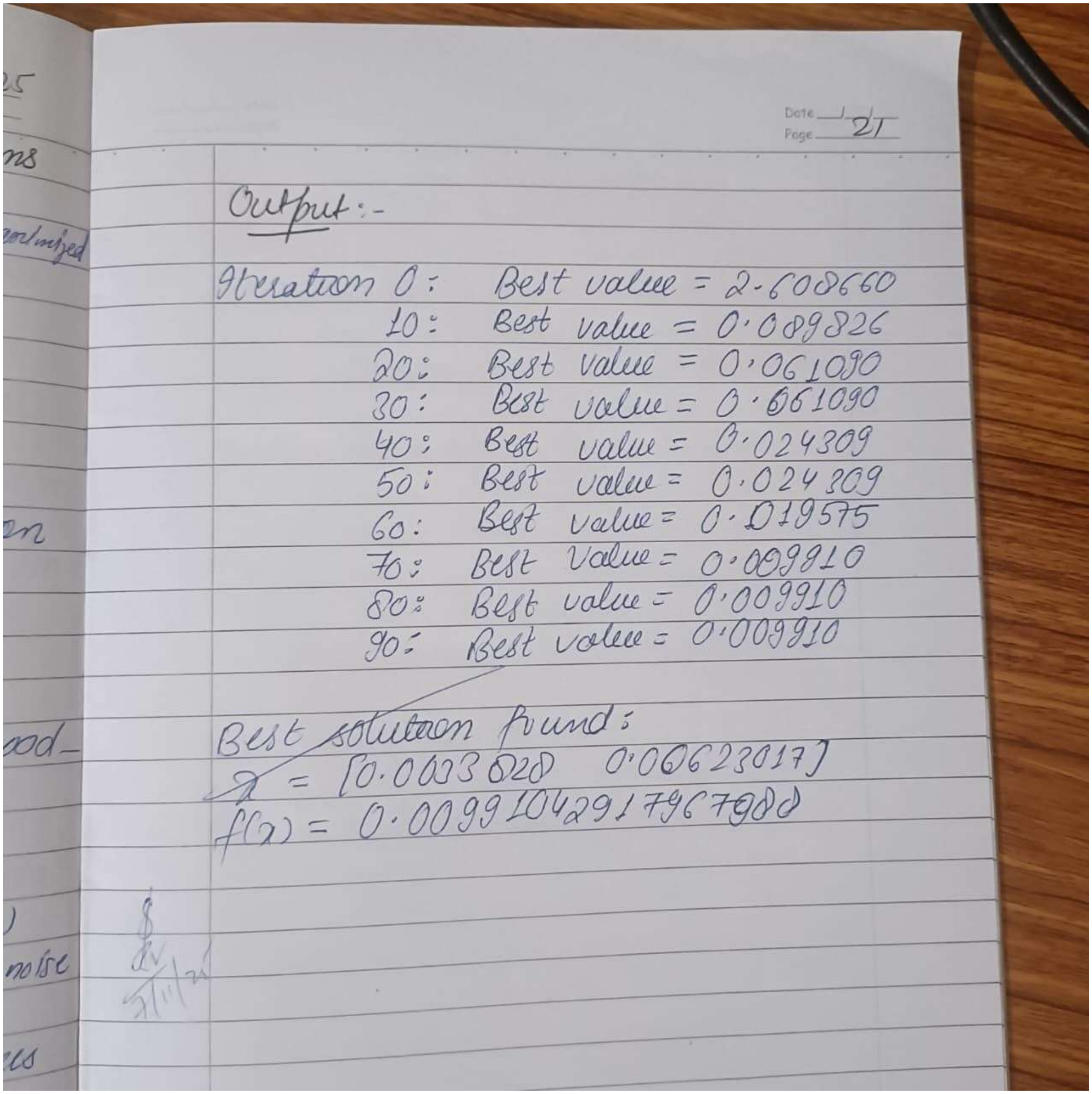
→ Parallel Cellular Algorithms and Programs

(i) Define objective fn f(x) to be minimized or maximized
(ii) Set algorithm parameters:
- grid size
- num_iterations
- neighborhood_type
- alpha (diffusion coefficient)
- mutation_rate

(iii) Initialize each cell with a random position x_i in the search space
(iv) Evaluate fitness f(x_i) for each cell
(v) for each iteration t = 1 to num iterations:
  for each cell i in the grid:
  - Get neighbor cells based on neighborhood_type
  - Find best neighbor soln x_best
  - Update cell's solution:
    x_i new = x_i + alpha * (x_best - x_i) + mutation_rate * random noise

  Evaluate f(x_i new) for all cells
  Replace x_i with x_i_new if it improves fitness
  Track global best solution
(vi) Output best solution found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Output:-

Iteration 0: Best value = 2.608660
10: Best value = 0.089826
20: Best value = 0.061090
30: Best value = 0.061090
40: Best value = 0.024309
50: Best value = 0.024309
60: Best value = 0.019575
70: Best value = 0.009910
80: Best value = 0.009910
90: Best value = 0.009910

Best solution found:
x = [0.0033028 0.00623017]
f(x) = 0.00991042917967980

Code:

```
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 <= (ni := i+dx) < len(grid) and 0 <= (nj
:= j+dy) < 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:
```

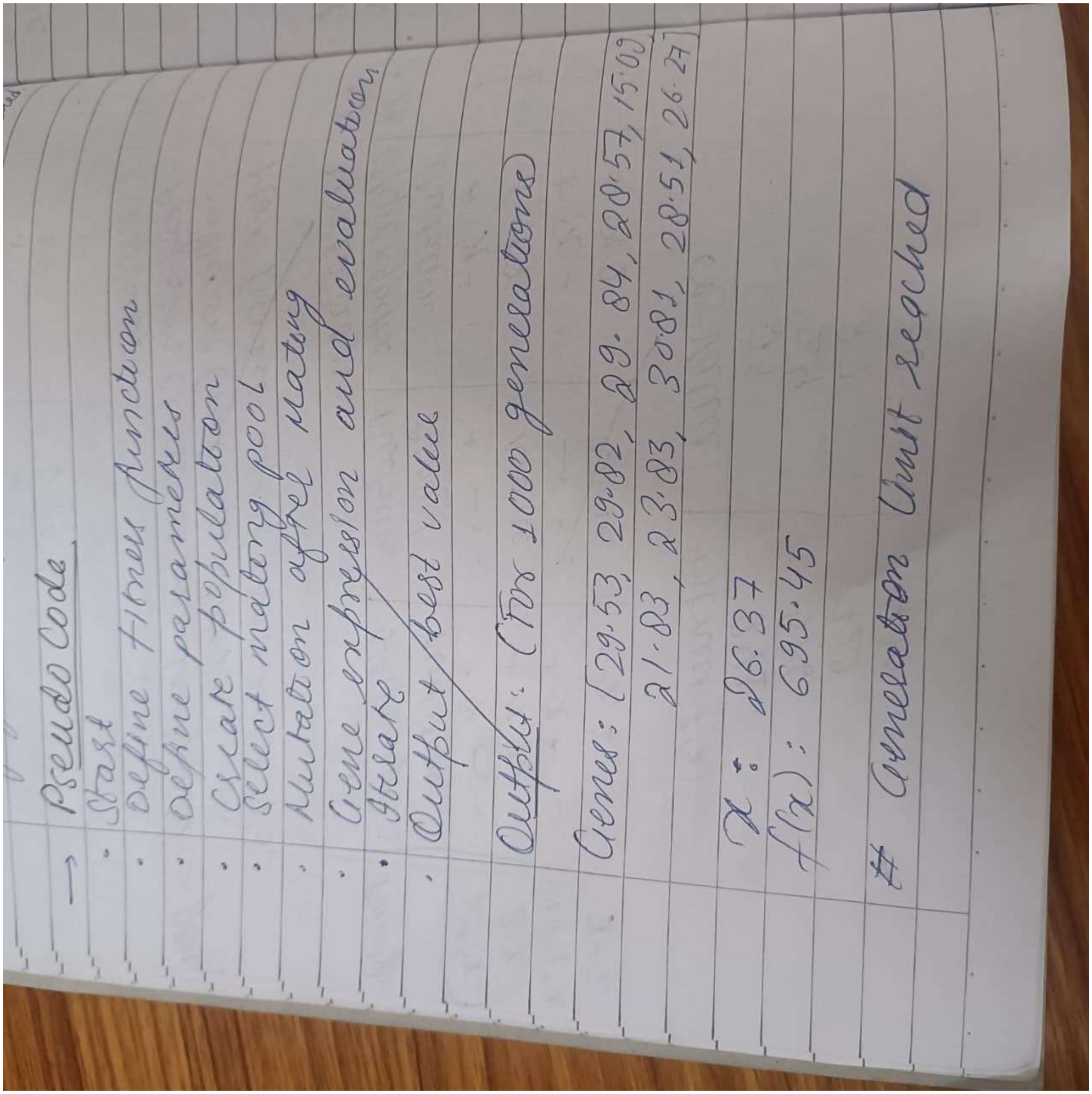
```
        for cell in row:
            f = fitness(cell)             if f <
best_fitness:                best_fitness = f
best_cell = cell      if BEST is None or best_fitness
< fitness(BEST):
        BEST = best_cell
 def parallel_cellular_algorithm():     global
BEST     grid = init_grid(GRID_SIZE, 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

Algorithm:



→ Pseudo Code

- Start
- Define fitness function
- Define parameters
- Create population
- Select mating pool
- Mutation after mating
- Gene expression and evaluation
- Iterate
- Output best value

Output: (For 1000 generations)

Genes: [29.53, 29.82, 29.84, 28.57, 15.00, 21.83, 23.83, 30.81, 28.51, 26.27]

x : 26.37
f(x) : 695.45

Generation limit reached

Code:

```
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:
            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
return offspring
```

```
# Mutation (Random Perturbation) def
mutate(offspring):     for i in
range(POPULATION_SIZE):         if
np.random.rand() < MUTATION_RATE:
            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:
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)
```

```
        # 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
```