

**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
Aug-2025 to Jan-2026**

**B.M.S. College of Engineering,
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Department of Computer Science and Engineering



CERTIFICATE

This is to certify that the Lab work entitled “ Bio Inspired Systems (23CS5BSBIS)” carried out by Skanda Mahesh (**1BM23CS332**), 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: <https://github.com/Skanda-Mahesh/Bis-lab>

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Program 1

Genetic Algorithm for Optimization Problems.

BIS lab

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How genetic algorithm work

- 1) Initialization :
- 2) Evaluation
- 3) Crossover
- 4) Termination

SL No	Initial population	Value	Fitness	$\frac{f(x)}{\sum f(x)}$		Expected Count	Actual Count
				Probability	f(x)/avg f(x)		
1	0 1 1 0 0	12	149	12.47	0.49	1	
2	1 1 0 0 1	25	625	54.11	2.164	2	
3	0 0 1 0 1	5	25	0.086	0.086	0	
4	1 0 0 1 1	19	361	1.25	1.25	1	
				11.55			

probability : $\underline{f(x) / \sum f(x)}$

Selecting Mating pool

Mating pool	Crossover point	Value	Fitness
1 0 1 1 0 0	0 1 1 0 1	13	169
2 1 1 0 0 1	1 1 0 0 0	24	576
3 1 1 0 0 1	1 1 0 1 1	27	729
4 1 0 0 1 1	1 0 0 0 1	17	289

Algorithm:

Mutation

St	After crossover mutation happens	Offspring	Actual	Fitness
01101	10000	11101	29	841
11000	00000	11000	29	578
11011	00000	11011	27	729
10001	00101	10100	20	400

Algorithm

def initial

```

    squares = (for each chrom[i], take pow2)
    sum = sum(chrom)
    expected = square(i) / arg(squares)
    actual = math.ceil(expected[i]) for i in range
    return actual
  
```

mate (chrom, actual):

```

    pool = [0 for i in range(chrom)]
    for i in range(chrom):
      if actual[i] == 0:
        for j in range(actual[i]):
          pool[i+j] = chrom[i]
  
```

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```

    for chrom[i] in range(2):
      chrom[i] = chrom[i][:-9] + bin(chrom
  
```

crossover (chrom):

```

    random = [10000, 00000, 00000, 00000]
    sel = random[i] ^ chrom[i]:
    fitness = map(**2, 16 random[i])
  
```

Code:

```

import pandas as pd
import random

def sel_indiv(df):
  return [row['Popul'] for _, row in df.iterrows() for _ in
range(int(row['ActualCnt']))]

def cross(mating_pool):
  random.shuffle(mating_pool)
  if len(mating_pool) % 2 != 0: mating_pool.append(random.choice(mating_pool))
  offspring, mating_pool_data, crossover_data = [], [], []
  for i in range(0, len(mating_pool), 2):
    p1, p2 = int(mating_pool[i]), int(mating_pool[i+1])
    bp1, bp2 = bin(p1)[2:].zfill(8), bin(p2)[2:].zfill(8)
    cp = random.randint(1, len(bp1) - 1)
    o1_binary, o2_binary = bp1[:cp] + bp2[cp:], bp2[:cp] + bp1[cp:]
    o1_decimal, o2_decimal = int(o1_binary, 2), int(o2_binary, 2)
    offspring.extend([o1_decimal, o2_decimal])
    mating_pool_data.extend([
      {'Subject No': i + 1, 'Value': p1, 'Mating Pool
(Binary)': bp1, 'Crossover Point': cp, 'Fitness': p1**2},
      {'Subject No': i + 2, 'Value': p2, 'Mating Pool
(Binary)': bp2, 'Crossover Point': cp, 'Fitness': p2**2}])
    crossover_data.append({'Parent 1': p1, 'Parent 2': p2, 'Binary Parent 1':
bp1, 'Binary Parent 2': bp2, 'Crossover Point': cp,
  
```

```

        'Offspring 1 Binary': o1_binary, 'Offspring 2 Binary': o2_binary, 'Offspring 1 Decimal': o1_decimal, 'Offspring 2 Decimal': o2_decimal)
    return offspring, pd.DataFrame(mating_pool_data), pd.DataFrame(crossover_data)

def mutate_offs(offspring, mut_rate):
    mut_offsp, mutation_data = [], []
    for i, indiv in enumerate(offspring):
        original_binary = bin(indiv)[2:].zfill(8)
        mutated_binary, mutated_indiv, mutation_happened = original_binary, indiv,
        False
        if random.random() < mut_rate:
            bin_list = list(original_binary)
            if bin_list:
                mut_point = random.randint(0, len(bin_list) - 1)
                bin_list[mut_point] = '1' if bin_list[mut_point] == '0' else '0'
                mutated_binary = ''.join(bin_list)
                mutated_indiv = int(mutated_binary, 2)
                mutation_happened = True
            mut_offsp.append(mutated_indiv)
            mutation_data.append({'Subject No': i + 1, 'Offspring Before Mutation (Binary)': original_binary,
                                  'Mutation Chromosome (Binary)': mutated_binary if
            mutation_happened else original_binary,
                                  'Offspring After Mutation (Binary)': bin(mutated_indiv)[2:].zfill(8),
                                  'X Value (Decimal)': mutated_indiv, 'Fitness': mutated_indiv**2})
    return mut_offsp, pd.DataFrame(mutation_data)

def gen_gen(popul, mut_rate, initial_popn):
    df_pop = pd.DataFrame({'Subject No': range(1, len(popul) + 1), 'Popul': popul,
                           'Initial Popn (Binary)': [bin(p)[2:].zfill(8) for p in initial_popn]})
    fit = [ind ** 2 for ind in popul]
    cumul = sum(fit)
    prob = [f / cumul for f in fit]
    perc_prob = [p * 100 for p in prob]
    exp = [len(popul) * p for p in prob]
    actual = [round(e) for e in exp]
    df_pop['Fit'], df_pop['Prob'], df_pop['Percentage Prob'],
    df_pop['ExpectCnt'], df_pop['ActualCnt'] = fit, prob, perc_prob, exp, actual
    mating_pool = sel_indiv(df_pop)
    offspring, df_mating_pool, df_crossover = cross(mating_pool)
    new_gen, df_mutation = mutate_offs(offspring, mut_rate)
    return new_gen, df_pop, df_mating_pool, df_crossover, df_mutation

popn = [12, 25, 5, 19]
initial_popn = popn[:]
curr_popul = popn[:]
best_sol, best_fit, fit_hist = None, -float('inf'), []
num_gens, mut_rate = 3, 0.01

for gen in range(num_gens):
    curr_popul, df_gen, df_mating_pool, df_crossover, df_mutation =
    gen_gen(curr_popul, mut_rate, initial_popn)
    fit_vals = [ind ** 2 for ind in curr_popul]
    best_fit_curr = max(fit_vals)
    best_ind_idx = fit_vals.index(best_fit_curr)
    best_ind_curr = curr_popul[best_ind_idx]

```

```
    if best_fit_curr > best_fit: best_fit, best_sol = best_fit_curr,
best_ind_curr
        fit_hist.append(best_fit_curr)
        print(f"Gen {gen + 1}: Best Fit = {best_fit_curr}, Best Indiv =
{best_ind_curr}, Popul = {curr_popul}")
        print("Generation Data:"); display(df_gen)
        print("Mating Pool Data:"); display(df_mating_pool)
        print("Crossover Data:"); display(df_crossover)
        print("Mutation Data:"); display(df_mutation)

print("\nGenetic Algorithm finished.")
print("Overall best solution found:", best_sol)
print("Fitness of the overall best solution:", best_fit)
```

Output :

```
Genetic Algorithm finished.
Overall best solution found: 25
Fitness of the overall best solution: 625
```

Program 2

Particle Swarm Optimization for Function Optimization.

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Particle Swarm optimization

Pseudocode

- 1) $p = \text{particle init}$
 - 2) $\text{for } i = 1 \text{ till max}$
 - 3) $\text{for each particle in } p \text{ do:}$

$$F_p = f(p)$$

$$\text{if } F_p \text{ is better than } F(p_{\text{best}})$$

$$p_{\text{best}} = p$$

end if

end for
 - 5) $g_{\text{part}} = \text{best } p \text{ in } p$
 - 6) $\text{for each particle } p \text{ do:}$

$$v_p^{t+1} = v_0^t + (c_1 u_1^t) (p_t^t - p_{\text{best}}^t) +$$

$$(c_2 u_2^t) (g_{\text{part}}^t - p_t^t)$$

$$p_i^{t+1} = p_i^t + v_i^{t+1}$$
- ~~ex: $f(x, y) = x^2 + y^2$, minima = 0.3
 $c_1 = 2 + c_2 = 2$~~

Algorithm:

particles	Initial x	Initial y	Velocity	BestSol	Best F
P ₁	1	1	0 0	--	1000
P ₂	-1	1	0 0	--	1000
P ₃	0.5	-0.5	0 0	--	1000
P ₄	1	-1	0 0	--	1000
P ₅	0.25	0.25	0 0	--	1000

Iteration 2

Pos	Velocity				BestSol	Best F
	Initial x	Initial y	Vel x	Vel y		
P ₁	0.25	0.25	-0.325	0.325	1 1	2 0.125
P ₂	0.25	0.25	-0.0210	0.325	-1 1	2 0.125
P ₃	0.25	0.25	0.125	0.375	0.5 0.5	0.5 0.125
P ₄	0.25	0.25	-0.35	0.625	1 -1	1 0.125
P ₅	0.25	0.25	0	0	0.25 0.25	0.25 0.125

Output

best position 2.5, Best = 26.2500

Code:

```
import numpy as np

def polynomial(x):
    return -x**2 + 5*x + 20

num_particles = 100
lower = -10
upper = 10

positions = np.random.uniform(lower, upper, num_particles)
velocities = np.random.uniform(-1, 1, num_particles)

pbestpos = np.copy(positions)
pbestval = np.array([polynomial(p) for p in positions])

gbest_position = pbestpos[np.argmin(pbestval)]
gbestval = np.min(pbestval)

w = 0.5
c1 = 2
c2 = 2

for iteration in range(1000):
    r1 = np.random.rand(num_particles)
    r2 = np.random.rand(num_particles)

    for i in range(num_particles):
        velocities[i] = w * velocities[i] + c1 * r1[i] * (pbestpos[i] - positions[i]) + c2 * r2[i] * (gbest_position - positions[i])
        positions[i] += velocities[i]

    positions[i] = np.clip(positions[i], lower, upper)

    current = polynomial(positions[i])

    if current < pbestval[i]:
        pbestpos[i] = positions[i]
        pbestval[i] = current

    if current < gbestval:
        gbest_position = positions[i]
        gbestval = current
        #print(f"Iteration {iteration} - Best Value: {gbestval}")

print("Final solution ", gbest_position)
print("Final Best Value:", gbestval)
```

Output :
Final solution -10.0
Final Best Value: -130.0

Program 3

Ant Colony Optimization for the Traveling Salesman Problem.

Algorithm:

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Pseudocode

- 1) Initialise parameters
 - num (ants)
 - iterations (itr)
 - pheromone evaporation rate
 - pheromone evaporation factor
 - α & β values (values 1 to 5)
- 2) Calc. distance between all cities
- 3) Initialise ~~global~~ pheromone on all paths
- 4) Record best route found and length
- 5) for each iteration
 - for each ant
 - Build complete route by choosing city based on length and pheromone
 - Complete route by returning to start
 - Calculate route length, update best route if improved
 - Evaporate pheromone on all lengths
 - Add pheromone to all paths used in current routes

6) Return best route found

Output:

Input:	∞	2	2	5	7
	2	∞	9	8	2
	2	5	∞	1	3
	5	7	1	∞	2
	7	2	3	2	∞

Best path = [0, 2, 3, 9, 1] path length 9

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Code:

```
import numpy as np
import random

def initialize_pheromone(num_cities, initial_pheromone=1.0):
    return np.ones((num_cities, num_cities)) * initial_pheromone

def calculate_probabilities(pheromone, distances, visited, alpha=1, beta=2):
    pheromone = np.copy(pheromone)
    pheromone[list(visited)] = 0 # zero out visited cities

    heuristic = 1 / (distances + 1e-10) # inverse of distance
    heuristic[list(visited)] = 0

    prob = (pheromone ** alpha) * (heuristic ** beta)
    total = np.sum(prob)
    if total == 0:
        # If no options (all visited), choose randomly among unvisited
        choices = [i for i in range(len(distances)) if i not in visited]
        return choices, None
    prob = prob / total
    return range(len(distances)), prob
```

```

def select_next_city(probabilities, cities):
    if probabilities is None:
        return random.choice(cities)
    return np.random.choice(cities, p=probabilities)

def path_length(path, distances):
    length = 0
    for i in range(len(path)):
        length += distances[path[i-1]][path[i]]
    return length

def ant_colony_optimization(distances, n_ants=5, n_iterations=50, decay=0.5,
alpha=1, beta=2):
    num_cities = len(distances)
    pheromone = initialize_pheromone(num_cities)
    best_path = None
    best_length = float('inf')

    for iteration in range(n_iterations):
        all_paths = []
        for _ in range(n_ants):
            path = [0] # start at city 0
            visited = set(path)

            for _ in range(num_cities - 1):
                current_city = path[-1]
                cities, probabilities =
calculate_probabilities(pheromone[current_city], distances[current_city],
visited, alpha, beta)
                next_city = select_next_city(probabilities, cities)
                path.append(next_city)
                visited.add(next_city)

            length = path_length(path, distances)
            all_paths.append((path, length))

            if length < best_length:
                best_length = length
                best_path = path

        # Evaporate pheromone
        pheromone *= (1 - decay)

        # Deposit pheromone proportional to path quality
        for path, length in all_paths:
            deposit = 1 / length
            for i in range(len(path)):
                pheromone[path[i-1]][path[i]] += deposit

    return best_path, best_length

# Example usage
if __name__ == "__main__":
    distances = np.array([
        [np.inf, 2, 2, 5, 7],
        [2, np.inf, 4, 8, 2],
        [2, 4, np.inf, 1, 3],

```

```
[5, 8, 1, np.inf, 2],  
[7, 2, 3, 2, np.inf]  
])  
  
best_path, best_length = ant_colony_optimization(distances)  
print(f"Best path: {[int(city) for city in best_path]} with length:  
{best_length:.2f}")
```

Output :

```
Best path: [0, 1, 4, 3, 2] with length: 9.00
```

Program 4

Cuckoo Search (CS).

Algorithm:

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Step 1

Initialization

n : number of host nests x_i , ($i=1, 2, 3 \dots n$)

P_a : probability of discovering coco egg

M_{act} : Maximum number of iterations to reach optimal solution

Step 2

Generate Solutions

→ Apply Levy flight to update randomness

$$x_i^t = x_i^{t-1} + \alpha \oplus \text{Levy}(\lambda)$$

Step 3

Check Fitness

→ If $\text{Fitness}(\text{Cuckoo}) > \text{Fitness}(\text{Host})$

Then next generation

Algorithm for min stairs problem

1) Set the initial value of host to $P(0,1)$

2) for $i \leq n$:

 generate population of n hosts
 randomly apply levy flight

 choose nest = $\min(\text{Step}+1) \text{ or } (\text{Step}+2)$ cost
 place egg at said nest

 if $\text{Fitness}(\text{Step}+1) > \text{Fitness}(\text{Step}+2)$:
 solution = Step + 1.

3) Repeat for n times till the solution converges

4) Return solution.

Output Input cost = [1, 2, 1, 5, 2, 1]

Output: Minimum cost = 4.

Code:

```
import numpy as np
import math

def knapsack_fitness(solution, values, weights, capacity):
    total_weight = np.sum(solution * weights)
    if total_weight > capacity:
        return 0 # Penalize overweight solutions
    return np.sum(solution * values)

def levy_flight(Lambda, size):
    sigma = (math.gamma(1 + Lambda) * math.sin(math.pi * Lambda / 2) /
             (math.gamma((1 + Lambda) / 2) * Lambda * 2 ** ((Lambda - 1) / 2)))
    ** (1 / Lambda)
```

```

u = np.random.normal(0, sigma, size)
v = np.random.normal(0, 1, size)
step = u / (np.abs(v) ** (1 / Lambda))
return step

def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def cuckoo_search_knapsack(values, weights, capacity, n_nests=25, miter=100,
pa=0.25):

    n_items = len(values)
    nests = np.random.randint(0, 2, size=(n_nests, n_items))
    fitness = np.array([knapsack_fitness(n, values, weights, capacity) for n in
nests])

    best_idx = np.argmax(fitness)
    best_solution = nests[best_idx].copy()
    best_fitness = fitness[best_idx]

    Lambda = 1.5 # Levy flight exponent

    for iteration in range(miter):
        for i in range(n_nests):
            step = levy_flight(Lambda, n_items)
            current = nests[i].astype(float)
            new_solution_cont = current + step
            probs = sigmoid(new_solution_cont)
            new_solution_bin = (probs > 0.5).astype(int)

            new_fitness = knapsack_fitness(new_solution_bin, values, weights,
capacity)

            # Greedy selection
            if new_fitness > fitness[i]:
                nests[i] = new_solution_bin
                fitness[i] = new_fitness

                if new_fitness > best_fitness:
                    best_fitness = new_fitness
                    best_solution = new_solution_bin.copy()

        # Abandon worst nests with probability pa
        n_abandon = int(pa * n_nests)
        if n_abandon > 0:
            abandon_indices = np.random.choice(n_nests, n_abandon, replace=False)
            for idx in abandon_indices:
                nests[idx] = np.random.randint(0, 2, n_items)
                fitness[idx] = knapsack_fitness(nests[idx], values, weights,
capacity)

        # Update global best after abandonment
        current_best_idx = np.argmax(fitness)
        if fitness[current_best_idx] > best_fitness:

```

```

        best_fitness = fitness[current_best_idx]
        best_solution = nests[current_best_idx].copy()

    # Print progress: every 10 iterations and first iteration
    if iteration == 0 or (iteration + 1) % 10 == 0:
        print(f"Iteration {iteration + 1}/{miter}, Best Fitness: {best_fitness}")

    return best_solution, best_fitness

if __name__ == "__main__":
    # Example knapsack problem
    values = np.array([60, 100, 120, 80, 30])
    weights = np.array([10, 20, 30, 40, 50])
    capacity = 100

    best_sol, best_val = cuckoo_search_knapsack(values, weights, capacity,
n_nests=30, miter=100, pa=0.25)

    print("\nBest solution found:")
    print(best_sol)
    print("Total value:", best_val)
    print("Total weight:", np.sum(best_sol * weights))

```

Output :

```

Iteration 1/100, Best Fitness: 280
Iteration 10/100, Best Fitness: 360
Iteration 20/100, Best Fitness: 360
Iteration 30/100, Best Fitness: 360
Iteration 40/100, Best Fitness: 360
Iteration 50/100, Best Fitness: 360
Iteration 60/100, Best Fitness: 360
Iteration 70/100, Best Fitness: 360
Iteration 80/100, Best Fitness: 360
Iteration 90/100, Best Fitness: 360
Iteration 100/100, Best Fitness: 360

```

```

Best solution found:
[1 1 1 1 0]
Total value: 360
Total weight: 100

```

Program 5

Grey Wolf Optimizer (GWO).

Algorithm:

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Grey Wolf Optimizer

→ Representation: values are candidate solutions

→ Wolves move the search space, as some lone into a solution, they become alpha, Beta, delta and omega.

→ After α, β, γ , δ, ω are identified their position are used to identify and calculate amongst others.

→ They simulate encircling prey to get solution

→ Check the optimality of the solution, return the alpha position.

Pseudocode

1) Generate random position in a position array
2) best cost = infinity
3) for i in maximum iteration:
 for wolf in each position:
 cost = step(stare, wolf)
 if cost < best cost:
 best cost = cost

Code:

```
import numpy as np

def sphere(x):
    return np.sum(x**2)

class GreyWolfOptimizer:
    def __init__(self, obj_func, n_wolves, dim, max_iter, lb=-10, ub=10):
        self.obj_func = obj_func
        self.n_wolves = n_wolves
        self.dim = dim
        self.max_iter = max_iter
        self.lb = lb
        self.ub = ub

        self.positions = np.random.uniform(self.lb, self.ub, (self.n_wolves,
self.dim))

        self.alpha_pos = np.zeros(self.dim)
        self.alpha_score = float('inf')

        self.beta_pos = np.zeros(self.dim)
        self.beta_score = float('inf')

        self.delta_pos = np.zeros(self.dim)
        self.delta_score = float('inf')

    def optimize(self):
        for iter in range(self.max_iter):
            for i in range(self.n_wolves):
                self.positions[i] = np.clip(self.positions[i], self.lb, self.ub)

            fitness = self.obj_func(self.positions)

            if fitness < self.alpha_score:
                self.alpha_score = fitness
                self.alpha_pos = self.positions[i].copy()
            elif fitness < self.beta_score:
                self.beta_score = fitness
                self.beta_pos = self.positions[i].copy()
            elif fitness < self.delta_score:
                self.delta_score = fitness
                self.delta_pos = self.positions[i].copy()

            a = 2 - iter * (2 / self.max_iter)

            for i in range(self.n_wolves):
                for j in range(self.dim):
                    r1 = np.random.rand()
                    r2 = np.random.rand()
                    A1 = 2 * a * r1 - a
                    C1 = 2 * r2
                    D_alpha = abs(C1 * self.alpha_pos[j] - self.positions[i, j])
```

```

        X1 = self.alpha_pos[j] - A1 * D_alpha

        r1 = np.random.rand()
        r2 = np.random.rand()
        A2 = 2 * a * r1 - a
        C2 = 2 * r2
        D_beta = abs(C2 * self.beta_pos[j] - self.positions[i, j])
        X2 = self.beta_pos[j] - A2 * D_beta

        r1 = np.random.rand()
        r2 = np.random.rand()
        A3 = 2 * a * r1 - a
        C3 = 2 * r2
        D_delta = abs(C3 * self.delta_pos[j] - self.positions[i, j])
        X3 = self.delta_pos[j] - A3 * D_delta

        self.positions[i, j] = (X1 + X2 + X3) / 3

    return self.alpha_pos, self.alpha_score

if __name__ == "__main__":
    n_wolves = int(input("Enter number of wolves: "))
    dim = int(input("Enter number of dimensions: "))
    max_iter = int(input("Enter max iterations: "))

    gwo = GreyWolfOptimizer(obj_func=sphere, n_wolves=n_wolves, dim=dim,
max_iter=max_iter)
    best_pos, best_score = gwo.optimize()

    print(f"Best Position: {best_pos}")
    print(f"Best Score: {best_score}")

```

Output :
Best Position: [-0.84143788 0.86909036 0.62871764 -0.69388586 -0.30850344]
Best Score: 2.435273584330572

Program 6

Parallel Cellular Algorithms and Programs.

Algorithm:

Lab-6 Parallel Execution

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→ Used with optimisation problem with either discrete or continuous problems.

→ The a f(G) optimisation formula applies a Σ (array) on a group of cells

$$\begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 0 & 1 & 1 \end{bmatrix} \leftarrow \text{grid}$$
 group ↑ neighbors

Over many iterations, the grid values converge to a optimal, and again the f(G) is the resultant

function parallel execution :

```

def grid = [ ] of initialisation
group = no. of cells in grouping
  
```

Code:

```

import numpy as np

# Initialize
grid = np.random.uniform(low=-10, high=10, size=(10, 10))
num_iterations = 100

# Define fitness function
def fitness_function(x):
    return x**2 - 4*x + 4

# Iterate
for iteration in range(num_iterations):
    new_grid = np.zeros_like(grid)
    for r in range(grid.shape[0]):
        for c in range(grid.shape[1]):
            neighbor_values = []
            for dr in [-1, 0, 1]:
                for dc in [-1, 0, 1]:
                    nr = (r + dr) % grid.shape[0]
  
```

```

        nc = (c + dc) % grid.shape[1]
        neighbor_values.append(grid[nr, nc])
    # Update to average of neighbor values (per algorithm spec)
    new_grid[r, c] = np.mean(neighbor_values)
grid = new_grid.copy()

# Find best solution
fitness_values = fitness_function(grid)
best_fitness_overall = np.min(fitness_values)
best_x_overall = grid[np.unravel_index(np.argmin(fitness_values), grid.shape)]

# Verbose Output
print("== Parallel Cellular Algorithm Results ==")
print(f"Total iterations performed: {num_iterations}")
print(f"Best x value found: {best_x_overall:.6f}")
print(f"Corresponding fitness (minimum f(x)): {best_fitness_overall:.6f}")
print("Algorithm converged toward x ≈ 2, where f(x) = 0 (expected optimum).")

```

Output :

```

Total iterations performed: 100
Best x value found: 0.317779
Corresponding fitness (minimum f(x)): 2.829867
Algorithm converged toward x ≈ 2, where f(x) = 0 (expected optimum).

```

Program 7

Optimization via Gene Expression Algorithms.

Algorithm:

Lab - 7		PAGE NO DATE / /																														
<u>Gene expression algorithm</u>																																
<u>Step 1:</u> Fitness function $f(x) = x^2$ Encoding Technique: 0 to 31 Use Chromosomes of fixed length (genotype)																																
<u>Step 2:</u> Initial population																																
<table border="1"> <thead> <tr> <th>Sno</th> <th>Genotype</th> <th>Phenotype</th> <th>Value</th> <th>Fitness</th> <th>p</th> </tr> </thead> <tbody> <tr> <td>1.</td> <td>x_2x</td> <td>x</td> <td>12</td> <td>144</td> <td>0.1247</td> </tr> <tr> <td>2.</td> <td>$+xx$</td> <td>$2x$</td> <td>25</td> <td>625</td> <td>0.5411</td> </tr> <tr> <td>3.</td> <td>x</td> <td>x</td> <td>5</td> <td>25</td> <td>0.0216</td> </tr> <tr> <td>4.</td> <td>$-xx$</td> <td>$x-2$</td> <td>19</td> <td>361</td> <td>0.3125</td> </tr> </tbody> </table>		Sno	Genotype	Phenotype	Value	Fitness	p	1.	x_2x	x	12	144	0.1247	2.	$+xx$	$2x$	25	625	0.5411	3.	x	x	5	25	0.0216	4.	$-xx$	$x-2$	19	361	0.3125	
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Sum : 1155 avg : 288.75 max : 625																																
Actual Expected 1 0.5 2 2.1 0 0.08 1 1.25																																
																																
<u>Step 3: Selection of mating pool</u>																																
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4	$+x2$	None	$+x2$	x_+																												

x value	Fitness (x)
29	341
24	576
27	929
20	400

Step 6: Gene expression & evaluation.

Decode each genotype \rightarrow Phenotype
calculate fitness

$$\sum f(x) = 2546 \quad \text{Avg: } 636.5 \quad \text{Max: } 341$$

Step 7 Store till convergence

Pseudocode

Output

- 1) Define function
 - 2) Create population
 - 3) Create mating pool
 - 4) Mutation after mating
 - 5) Gene expression and evaluate
 - 6) Store and output best value
- For 1000 iteration,
 $x: 26.37$
 $f(x) = 695.45$

Code:

```
import random
import math
def fitness_function(x):
    return x * math.sin(10 * math.pi * x) + 2
POPULATION_SIZE = 6
```

```

GENE_LENGTH = 10
MUTATION_RATE = 0.05
CROSSOVER_RATE = 0.8
GENERATIONS = 20
DOMAIN = (-1, 2)

def random_gene():
    return random.uniform(DOMAIN[0], DOMAIN[1])

def create_chromosome():
    return [random_gene() for _ in range(GENE_LENGTH)]

def initialize_population(size):
    return [create_chromosome() for _ in range(size)]

def evaluate_population(population):
    return [fitness_function(express_gene(chrom)) for chrom in population]

def express_gene(chromosome):
    return sum(chromosome) / len(chromosome)

def select(population, fitnesses):
    total_fitness = sum(fitnesses)
    pick = random.uniform(0, total_fitness)
    current = 0
    for individual, fitness in zip(population, fitnesses):
        current += fitness
        if current > pick:
            return individual
    return random.choice(population)

def crossover(parent1, parent2):
    if random.random() < CROSSOVER_RATE:
        point = random.randint(1, GENE_LENGTH - 1)
        child1 = parent1[:point] + parent2[point:]
        child2 = parent2[:point] + parent1[point:]
        return child1, child2
    return parent1[:], parent2[:]

def mutate(chromosome):
    new_chromosome = []
    for gene in chromosome:
        if random.random() < MUTATION_RATE:
            new_chromosome.append(random_gene())
        else:
            new_chromosome.append(gene)
    return new_chromosome

def gene_expression_algorithm():
    population = initialize_population(POPULATION_SIZE)
    best_solution = None
    best_fitness = float("-inf")
    for generation in range(GENERATIONS):
        fitnesses = evaluate_population(population)

        for i, chrom in enumerate(population):
            if fitnesses[i] > best_fitness:
                best_fitness = fitnesses[i]

```

```

        best_solution = chrom[:]

    print(f"Generation {generation+1}: Best Fitness = {best_fitness:.4f},
Best x = {express_gene(best_solution):.4f}")

    new_population = []
    while len(new_population) < POPULATION_SIZE:
        parent1 = select(population, fitnesses)
        parent2 = select(population, fitnesses)
        offspring1, offspring2 = crossover(parent1, parent2)
        offspring1 = mutate(offspring1)
        offspring2 = mutate(offspring2)
        new_population.extend([offspring1, offspring2])

    population = new_population[:POPULATION_SIZE]

    print("\nBest solution found:")
    print(f"Genes: {best_solution}")
    x_value = express_gene(best_solution)
    print(f"x = {x_value:.4f}")
    print(f"f(x) = {fitness_function(x_value):.4f}")

if __name__ == "__main__":
    gene_expression_algorithm()

```

Output :

```

Generation 1: Best Fitness = 2.3125, Best x = 0.4262
Generation 2: Best Fitness = 2.3125, Best x = 0.4262
Generation 3: Best Fitness = 2.3125, Best x = 0.4262
Generation 4: Best Fitness = 2.3125, Best x = 0.4262
Generation 5: Best Fitness = 2.3125, Best x = 0.4262
Generation 6: Best Fitness = 2.3125, Best x = 0.4262
Generation 7: Best Fitness = 2.3125, Best x = 0.4262
Generation 8: Best Fitness = 2.4233, Best x = 0.6237
Generation 9: Best Fitness = 2.4233, Best x = 0.6237
Generation 10: Best Fitness = 2.4233, Best x = 0.6237
Generation 11: Best Fitness = 2.4233, Best x = 0.6237
Generation 12: Best Fitness = 2.4233, Best x = 0.6237
Generation 13: Best Fitness = 2.4233, Best x = 0.6237
Generation 14: Best Fitness = 2.4233, Best x = 0.6237
Generation 15: Best Fitness = 2.4233, Best x = 0.6237
Generation 16: Best Fitness = 2.4233, Best x = 0.6237
Generation 17: Best Fitness = 2.4395, Best x = 0.4594
Generation 18: Best Fitness = 2.4395, Best x = 0.4594
Generation 19: Best Fitness = 2.4395, Best x = 0.4594
Generation 20: Best Fitness = 2.4395, Best x = 0.4594

```

```

Best solution found:
Genes: [0.6948405045559576, -0.647173288232043, -0.3013499383055478, 1.6316275489
10124, 0.9271637073163099, 0.0324867196364278, -0.3565755055362756, 1.52263966083
97925, 1.0654293190513275, 0.024805208657060707]
x = 0.4594
f(x) = 2.4395

```