

**VISVESVARAYA TECHNOLOGICAL
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“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-2025**

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CERTIFICATE

This is to certify that the Lab work entitled “Bio Inspired Systems (23CS5BSBIS)” carried out by **Prerana P Jois (1BM23CS250)**, 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/priyamthakur275/BIS__LAB.git

Program 1: Genetic Algorithm

Genetic Algorithm

Algorithm :

Genetic algo (S)

Input (r) : r → set of blocks

Output : Superstring of S

Rule : Initialization :

Initialize population, do iteration
End fitness (Σp_i)

while termination (condition not rel)

do :

Select individuals from pop.
Cross over individuals (S, P_1, P_2)
Mutate

End - fitness (S , modified individual)
 $P_{t+1} \rightarrow$ new individual

Evol. fitness (s , population):

\hookrightarrow set of blocks
population

$\forall i$ in population?

generate derived string $s(r)$
 $r \leftarrow$ all blocks from s fast
not in s

$s^r(i) \leftarrow s(i)$ from
(mutation) of $s(i)$ and,

fitness (i) \leftarrow $\frac{1}{\|s^r(i)\|^2}$

return fitness.

Cross over - individuals (s, p_1, p_2) {

New [];

import random

for i in range($P1.length$):

$p = \text{random.random}()$

if $p < 0.5$

$\text{New}[i] = P1[i];$

else if $p < 0.9$

$\text{New}[i] = P2[i];$

else

$\text{New}[i] = \text{mutate}(S)$

3

return ~~new~~ New;

~~Steps~~ Steps:

- 1) Initialize population of possible solutions.
- 2) Evaluate fitness - If ~~fitness~~ ~~is good~~ ~~the solution is~~ tells how good the solution is.
- 3) While termination not ~~reached~~ reached:

- select individuals from $P(t)$
- recombine selected individuals
- mutate some individuals
- Evaluate fitness of new individuals
- Create new population

Code :

```
import numpy as np
import random
import matplotlib.pyplot as plt

# target star constellation (fixed points)
target = np.array([
    [1,1], [2,3], [3,2], [4,4], [5,1]
])

pop_size = 30
num_stars = len(target)
generations = 100
mutation_rate = 0.1

def create_individual():
    return np.random.rand(num_stars, 2) * 6

def fitness(ind):
    return np.sum((ind - target)**2)

def selection(pop):
    scores = [(fitness(ind), ind) for ind in pop]
    scores.sort(key=lambda x: x[0])
    return scores[0][1], scores[1][1]

def crossover(p1, p2):
    cut = random.randint(1, num_stars-1)
    c1 = np.vstack((p1[:cut], p2[cut:]))
    c2 = np.vstack((p2[:cut], p1[cut:]))
    return c1, c2

def mutate(ind):
    if random.random() < mutation_rate:
        i = random.randint(0, num_stars-1)
        ind[i] = np.random.rand(2) * 6
    return ind

pop = [create_individual() for _ in range(pop_size)]
```

```
for g in range(generations):
    new_pop = []
    for _ in range(pop_size // 2):
        p1, p2 = selection(pop)
        c1, c2 = crossover(p1, p2)
        new_pop.append(mutate(c1))
        new_pop.append(mutate(c2))
    pop = new_pop

best = min(pop, key=fitness)

plt.scatter(target[:,0], target[:,1], s=80)
plt.scatter(best[:,0], best[:,1], s=80)
plt.title("Genetic Algorithm – Star Constellation Matching")
plt.legend(["Target", "Evolved"])
plt.show()
```

Program 2: Gene Expression

Optimization via Gene Expression

Input:

- population size (n)
- number of generations (g)
- mutation probability (p_m)
- crossover probability (p_c)

Transfer Probability (p_t)

Problem - specific fitness function $f(x)$

Initialization

Population \leftarrow Generate Random Chromosomes (n)

for each chromosome C in population do

 Expression \leftarrow decode (C)

 Fitness (C) $\leftarrow f$

end for

for $g = 1$ to G do

 New Population $\leftarrow \emptyset$

 while $|P| < (New Population)_{\text{len}}$ do

Paper Theory

Parent 1 \leftarrow select (Population)
Parent 2 \leftarrow select (Population),
// Greater operator

with probability p_c :
 $(\text{Child 1}, \text{Child 2}) \leftarrow \text{crossover} (\text{Parent 1}, \text{Parent 2})$

Otherwise:

Child 1 \leftarrow copy (Parent)
Child 2 \leftarrow copy (Parent)

with probability p_m :
Child 1 \leftarrow mutate (Child 1)

with probability p_m :
Child 2 \leftarrow mutate (Child 2)

With probability p_t
Child 2 \leftarrow transpose (Child 2)

// evaluate fitness

Expression 1 \leftarrow decode (Child 1)
Expression 2 \leftarrow decode (Child 2)

Code:

```
import numpy as np
import random

img = np.random.rand(100,100) # simple random image

def add(x, y): return x + y
def mul(x, y): return x * y
def sub(x, y): return x - y

ops = [add, mul, sub]
consts = [0.2, 0.5, 1.0]

def random_expr():
    return (random.choice(ops), random.choice(consts), random.choice(consts))

def apply_expr(expr, img):
    op, a, b = expr
    return np.clip(op(img * a, img * b), 0, 1)

def fitness(expr):
    new_img = apply_expr(expr, img)
    return new_img.std()

population = [random_expr() for _ in range(20)]

for gen in range(10):
    scored = sorted(population, key=fitness, reverse=True)
    population = scored[:10] # select top 10

    # mutate
    for i in range(10):
        if random.random() < 0.3:
```

```
population.append(random_expr())
print("Generation", gen, "Best fitness:", fitness(population[0]))
best = population[0]
print("\nBest evolved expression:", best)
```

Program 3: Particle Swan Optimization

particle Swarm optimization

Algo:

Input:

- Population size (N) // number of particles
- Number of iterations
- Inertia weight (w)
- Cognitive coefficient (c_1)
- Social coefficient (c_2)
- Search space bounds $[x_{\min}, x_{\max}]$
- Objective function $f(x)$ // function to optimize

Output: Best solution found (x_{best} position)

Begin:

// Step 1 : Initialization

for : each particle $p = 1$ to N do

- Position $[i] \leftarrow$ Random Value within $([x_{\min}, x_{\max}])$
- Velocity $[i] \leftarrow$ Random Value within $([x_{\max} - x_{\min}, x_{\max} - x_{\min}])$

$p_{best}[i] \leftarrow \text{Position}[i]$

$f_{fitness} - p_{best}(i) \leftarrow F(\text{Position}(i))$

End for

$g_{best} \leftarrow \text{Best position among } p_{best}$

$f_{fitness} - g_{best} \leftarrow \text{Best } f_{fitness} \text{ among } f_{fitness} - p_{best}$

// Step 2: Iteration Loop

for $i_{iter} = 1$ to MaxIter do
for each particle $i=1$ to N do
 update Velocity

$\text{Velocity}[i] \leftarrow w * \text{velocity}[i] + c_1 * \text{rand}(0) * (p_{best}[i] - \text{Position}[i])$

$+ c_2 * \text{rand}(0) * (g_{best} - \text{Position}[i])$

Update position:

gbest \leftarrow position (i)

fitness \cdot gbest \leftarrow fitness

End if

End for

Print Progress :

Print ("Iteration", iter, "Best fitness"
fitness, gbest)

End for

return best selection

return gbest

End

- Experiments in Energy optimizⁿ
- Exp. gbest, pbest, fitness fun
- How is fitness fun selected & used.

Code:

```
import numpy as np

def energy(x):
    return 0.5*x**2 + 10*np.sin(x) + 20

n=20
w=0.6
c1=1.4
c2=1.4
it=40

x=np.random.uniform(-10,10,n)
v=np.zeros(n)
p=x.copy()
pv=np.array([energy(i) for i in x])
g=p[np.argmin(pv)]
gv=min(pv)

for _ in range(it):
    r1=np.random.rand(n)
    r2=np.random.rand(n)
    v=w*v + c1*r1*(p-x) + c2*r2*(g-x)
    x=x+v
    vals=np.array([energy(i) for i in x])
    b=vals<pv
    p[b]=x[b]
    pv[b]=vals[b]
    if min(vals)<gv:
        g=x[np.argmin(vals)]
        gv=min(vals)

print("Best value:", g)
print("Min energy:", gv)
```

Program 4: Ant Colony Optimization

Paper theory

Ant Colony Optimization
for the Travelling Salesman Problem

Algorithm:

Initialize pheromone values τ on all solution components.

Set parameters α (pheromone influence), β (heuristic influence), evaporation rate γ , number of ants m .

while stopping criteria not met:

for each ant k in 1 to m :

initialize ~~solution~~ on ~~empty~~ station ~~s_K~~

while solution ~~s_K~~ is incomplete:

Select next solution component c

based ~~on~~ on probability proportional to:

$$[\tau(c)]^\alpha \cdot [h(c)]^\beta$$

where ~~is~~ $h(c)$ is the heuristic desirability of component c .

add component c to ~~s_K~~
solution s_K

Evaluate the quality of solution S_k

for each solution Component c :

evaporate pheromone

$$T(c) = (1-\rho)^{\alpha} T(c)$$

for each ant K :

deposit pheromone or components

in solution S_k

$$T(c) = T(c) + \Delta T_k(c)$$

amount $\Delta T_k(c)$ depends on quality
of "solution" S_k

returns the best solution found

* α - Pheromone influence

β - Heuristic influence

ρ - Evaporation rate

m - number of ants

Paper theory

$\Delta T_k(c) \rightarrow$ Reward Signal ("that goods")
future ants towards better solution

$\Delta T \rightarrow$ Change in pheromone

Ants
Pheromone
Management

X P

X S

o 30/10

Code:

```
import numpy as np
import random

dist=np.array([
    [0,12,10,19,8],
    [12,0,3,7,2],
    [10,3,0,6,20],
    [19,7,6,0,4],
    [8,2,20,4,0]
])

n=dist.shape[0]
ants=20
alpha=1
beta=2
rho=0.5
Q=100
iters=40
pher=np.ones((n,n))

def tour_len(t):
    s=0
    for i in range(n-1):
        s+=dist[t[i],t[i+1]]
    s+=dist[t[-1],t[0]]
    return s

best=None
best_len=1e9

for it in range(1,iters+1):
    all_tours=[]
    for k in range(ants):
        t=[random.randint(0,n-1)]
        for _ in range(n-1):
            c=t[-1]
            probs=[]
            for j in range(n):
```

```

if j not in t:
    p=(pher[c,j]**alpha)*((1/dist[c,j])**beta)
    probs.append((j,p))
s=sum([p for _,p in probs])
r=random.random()*s
tot=0
for j,p in probs:
    tot+=p
    if tot>=r:
        t.append(j)
        break
all_tours.append(t)

for t in all_tours:
    L=tour_len(t)
    if L<best_len:
        best=t
        best_len=L

pher=(1-rho)*pher
for t in all_tours:
    L=tour_len(t)
    for i in range(n-1):
        a,b=t[i],t[i+1]
        pher[a,b]+=Q/L
        pher[b,a]+=Q/L
    a,b=t[-1],t[0]
    pher[a,b]+=Q/L
    pher[b,a]+=Q/L

print("Iteration",it,"| Best:",best_len)

print("Final Best Path:",best)
print("Final Best Length:",best_len)

```

Program 5: Cuckoo Search Algorithm

Paper Theory

Cuckoo Search Algorithm

Initialize population (nests):

for $i=1$ to n :

 Initalize rest i with a random
 x_i in solution x_i within search bounds

~~optimize traffic right~~ Evaluate fitness $f_i = f(x_i)$

~~evaluate fitness~~ ~~$f_i = f(x_i) / f_p$~~

 Find for

(2) find the current best solutions:

$x_{best} = \text{nest with minimum (or}$
 $\text{maximum) fitness value}$

(3) repeat until stopping criteria (maxIter
or convergence):

for $t=1$ to maxIter:

 for each cuckoo ($j=1$ to r):

 Generate a new solution

~~x_j new = by Levy flight!~~

x_j new = $x_j + d^t \text{ Levy}(t)$

Code:

```
import numpy as np
import random

def cost(x):
    return 0.5*x**2 + 20*np.sin(x) + 30

n=20
lb=-10
ub=10
pa=0.25
iters=40

nest=np.random.uniform(lb,ub,n)
fitness=np.array([cost(x) for x in nest])

def levy():
    u=np.random.normal(0,1)
    v=np.random.normal(0,1)
    s=u/abs(v)**0.5
    return s

best=nest[np.argmin(fitness)]
best_val=min(fitness)

for it in range(1,iters+1):
    for i in range(n):
        step=levy()
        new=nest[i]+step*(nest[i]-best)
        new=np.clip(new,lb,ub)
        if cost(new)<fitness[i]:
            nest[i]=new
            fitness[i]=cost(new)

    for i in range(n):
        if random.random()<pa:
            j=random.randint(0,n-1)
            k=random.randint(0,n-1)
            new=nest[i]+random.random()*(nest[j]-nest[k])
```

```
new=np.clip(new,lb,ub)
if cost(new)<fitness[i]:
    nest[i]=new
    fitness[i]=cost(new)

best=nest[np.argmin(fitness)]
best_val=min(fitness)
print("Iteration",it,"| Best:",best_val)

print("Final Best Traffic Load:",best)
print("Final Congestion Cost:",best_val)
```

Program 6: Grey wolf Optimization

Grey Wolf Optimization

Initialize population of grey wolves
 $x_i \quad (i=1, 2, 3 \dots N)$

Initialize a, A, C
Evaluate fitness of each wolf

Identify alpha (best), beta (2nd best),
delta (3rd best)

$t = 0$
while $t < \text{max iterations}$
 $a = 2 * (1 - t / \text{max iterations})$

for each wolf $i = 1 \dots N$:
 $s_i = \text{rand}(0, 1)$

$A_1 = 2 * a + r_1 - a$
 ~~$C_1 = 2 * r_2$~~

$\alpha = \text{abs}(C_1 * s_i * \alpha - x_i)$
 $x_i = x_i - \alpha * A_1 * D_{\alpha}$

$r_1 = \text{rand}(0, 1);$

Paper Theory

$$r_2 = \text{rand}(0, 1)$$

$$A_2 = 2 * a + r_1 - a$$

$$C_2 = 2 * r_2$$

$$\begin{aligned} D_{\text{beta}} &= \text{abs}(C_2 + x_{\text{beta}} - r_2) \\ x_2 &= x_{\text{beta}} - A_2 + D_{\text{beta}} \end{aligned}$$

$$r_1 = \text{rand}(0, 1)$$

$$r_2 = \text{rand}(0, 1)$$

$$A_3 = 2 * a + r_1 - a$$

$$C_3 = 2 * r_2$$

$$D_{\text{delta}} = \text{abs}(C_3 + x_{\text{delta}} - r_2)$$

$$x_3 = x_{\text{delta}} - A_3 + D_{\text{delta}}$$

$$x_{\text{new}} = (x_1 + x_2 + x_3) / 3$$

$$x_{\text{new}} = \text{clip to bounds}(x_{\text{new}}, \text{lower bound}, \text{upper bound})$$

end ~~for~~ for

Evaluate fitness $f(x_{\text{new}})$ for all wolves
(using x_{new})

update alpha, beta, delta based on new fitness values

$$t = t + 1$$

Code:

```
import numpy as np
import time

# Objective function (Sphere)
def f(x):
    return np.sum(x**2)

# Grey Wolf Optimizer
def GWO(dim=10, search_agents=20, max_iter=100):
    lb, ub = -10, 10
    positions = np.random.uniform(lb, ub, (search_agents, dim))

    # α, β, δ wolves
    Alpha_pos = np.zeros(dim)
    Beta_pos = np.zeros(dim)
    Delta_pos = np.zeros(dim)

    Alpha_score = float("inf")
    Beta_score = float("inf")
    Delta_score = float("inf")

    early_stop = int(max_iter * 0.6) # incomplete execution (stop at 60%)

    for t in range(max_iter):
        for i in range(search_agents):
            positions[i] = np.clip(positions[i], lb, ub)
            fitness = f(positions[i])

            if fitness < Alpha_score:
                Alpha_score = fitness
                Alpha_pos = positions[i].copy()

            elif fitness < Beta_score:
                Beta_score = fitness
                Beta_pos = positions[i].copy()

            elif fitness < Delta_score:
                Delta_score = fitness
```

```

Delta_pos = positions[i].copy()

a = 2 - t * (2 / max_iter)

for i in range(search_agents):
    for j in range(dim):
        r1, r2 = np.random.rand(), np.random.rand()
        A1 = 2 * a * r1 - a
        C1 = 2 * r2
        D_alpha = abs(C1 * Alpha_pos[j] - positions[i][j])
        X1 = Alpha_pos[j] - A1 * D_alpha

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

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

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

# Late execution simulation
time.sleep(0.15)

print(f"Iter {t+1} | Alpha Score: {Alpha_score:.6f}")

# Stop early (incomplete execution)
if t == early_stop:
    print("\n    Early stopping triggered (incomplete execution)\n")
    break

return Alpha_pos, Alpha_score

# Run GWO

```

```
best_pos, best_score = GWO(dim=10, search_agents=20, max_iter=100)
print("\nBest Found Position:", best_pos)
print("Best Score:", best_score)
```

Program 7: Parallel Cellular Algorithm

paper theory

Parallel Cellular Algorithm

Algorithm :

Begin

Initialize each cell s_i in grid with

Step 1 : Define objective function $f(s)$

Step 2 : Initialize parameters

number of cells $\leq N$

set initial temperature T

Define grid Structure and neighbourhood pattern

Step 3 : Initialize population

for each cell i from 1 to N do

Initialize all state s_i with

a random

Solution

END FOR

Step 4 : Evaluate fitness

for each cell i for 1 to N do

$f_{eval}(i) \leftarrow f(\text{cell. state}(i))$

END FOR

```

Iteration ← 0
for each cell  $i$  from 1 to  $N$  do
    PARALLEL
        Identify Neighbor Set ( $i$ )
        new-state( $i$ ) ← update Rule [cell-state( $i$ )]
        neighbor set ( $i$ )
    END for
    States (Synchronous update)
    for each cell  $i$  from 1 to  $N$  do
        cell-state( $i$ ) ← new-state( $i$ )
        fitness( $i$ ) ← f (cell-state( $i$ ))
    END for
    Iteration ← Iterations
END WHILE
Output cell-state( $K$ ) as Best Solution
END

```

Pointing &
No Solution

Code:

```
import numpy as np

n=12
m=3
tasks=np.random.randint(5,25,n)
routes=[0]*m
assign=[[ ] for _ in range(m)]

for t in tasks:
    r=np.argmin(routes)
    routes[r]+=t
    assign[r].append(t)

print("Tasks:",tasks)
print("Route Loads:",routes)
print("Assignments:",assign)
print("Final Makespan:",max(routes))
```