AI for Water Resources and Hydrology:

Optimal Reservoir Operation & Inflow Forecasting using Genetic Algorithms & Neural Networks considering Climate Change

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Acknowledgement: ***Prof M Janga Reddy***, IIT Bombay

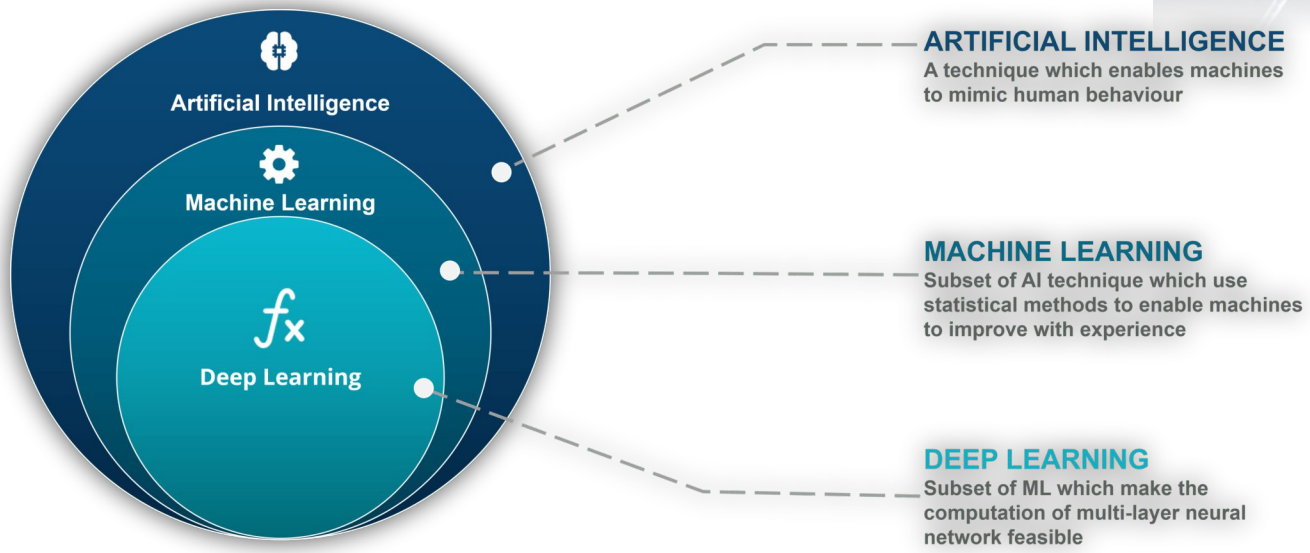
Outline

- Optimization Methods
- Genetic Algorithms (GA)
  - Introduction
  - GA for optimization
  - Case Studies for single and multi-objective Reservoir Operation
- Artificial Neural Networks for inflow forecasting considering climate change
  - ANN
  - PSO NN
  - ANFIS
- Conclusions & Future scope

Deep Learning



Source: Harvard University

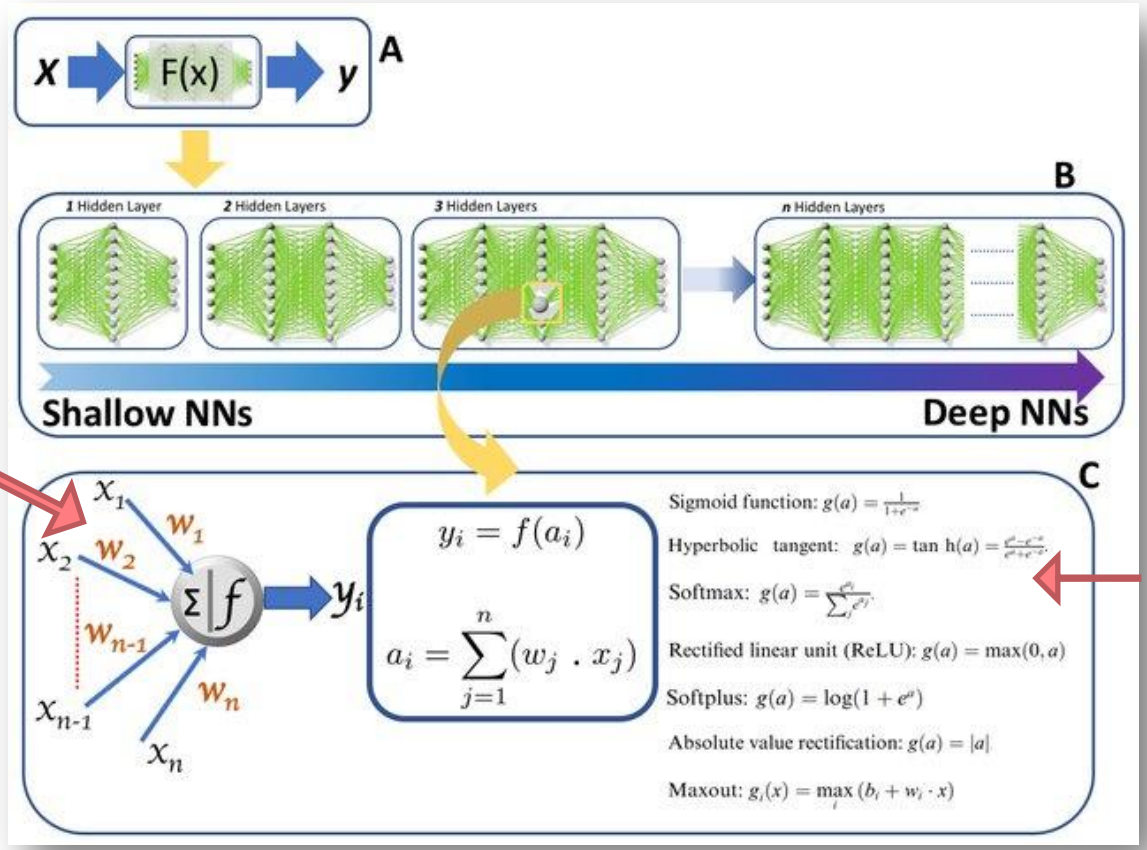


Source: Edureka

- **Deep Learning** is a computer algorithm that mimics the network of neurons in a brain.
- It is a subset of machine learning based on artificial neural networks.
- It is called deep learning because it makes use of deep neural networks.
- This learning can be supervised, semi-supervised or unsupervised.

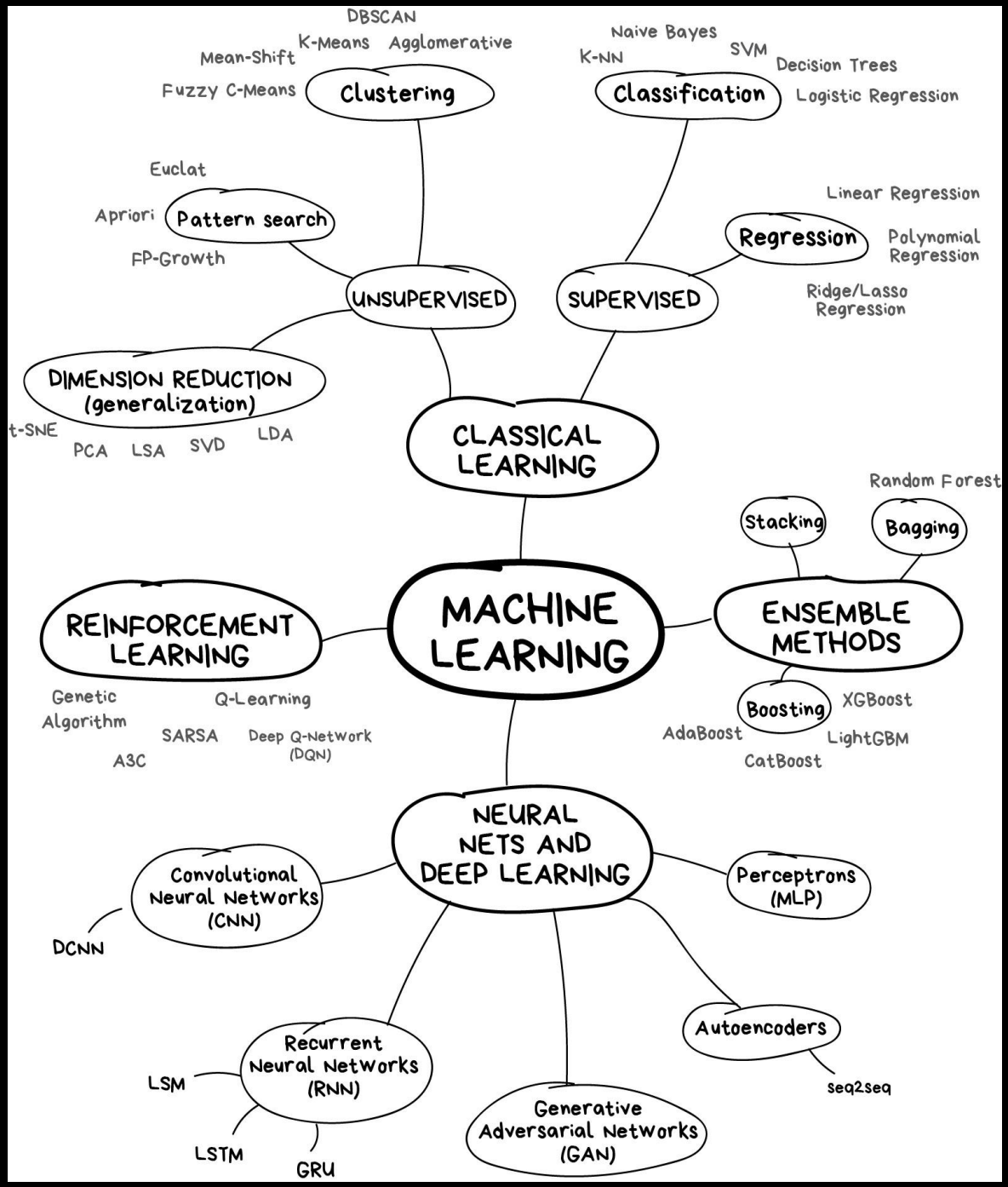
Artificial Neural Networks

An **artificial neuron** is a mathematical function based on a model of biological neurons, where each neuron takes inputs, weighs them separately, sums them up and passes this sum through a nonlinear function to produce output.



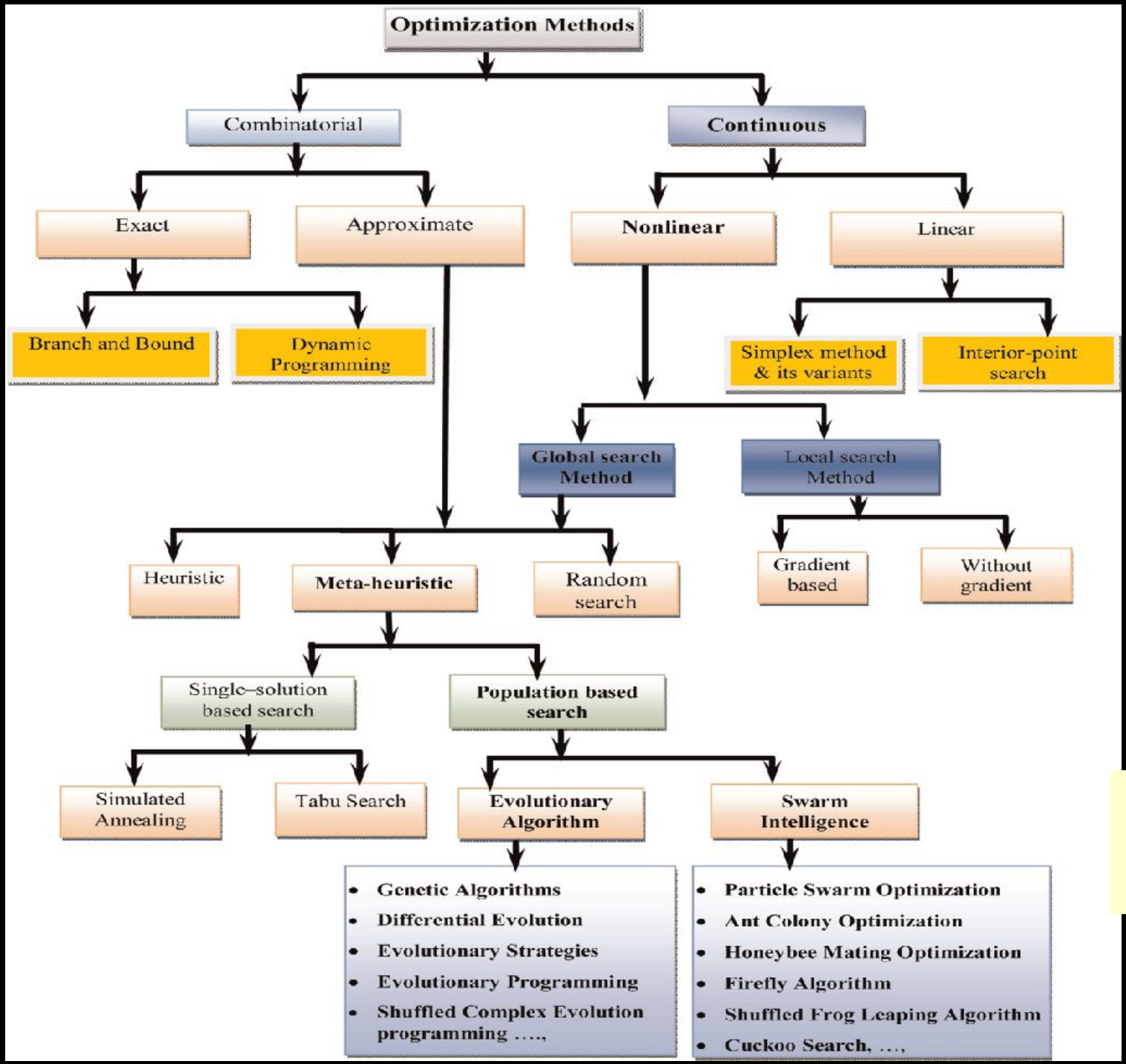
Activation Functions

Zemouri et al., 2019

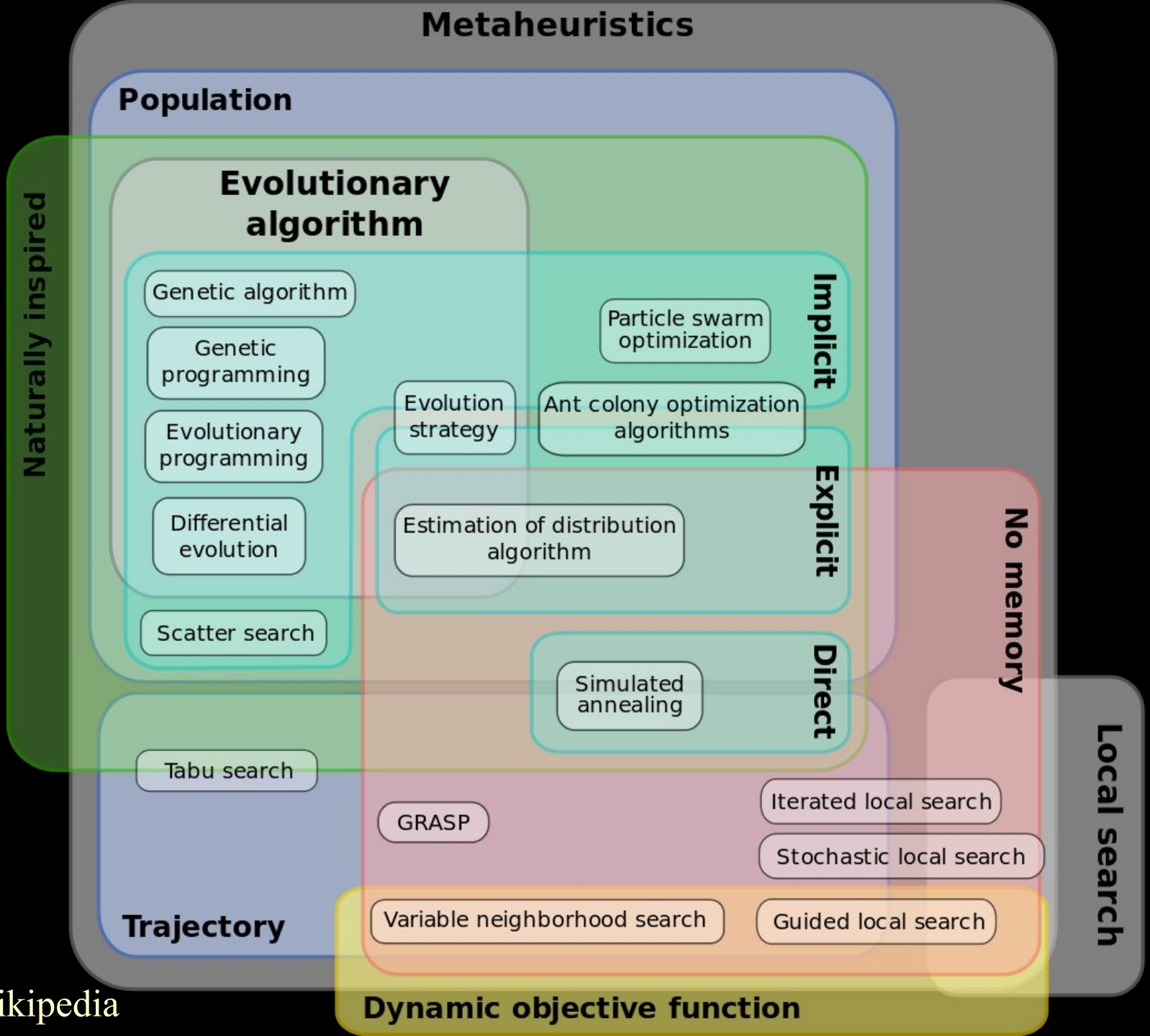


Detailed Map of Machine Learning

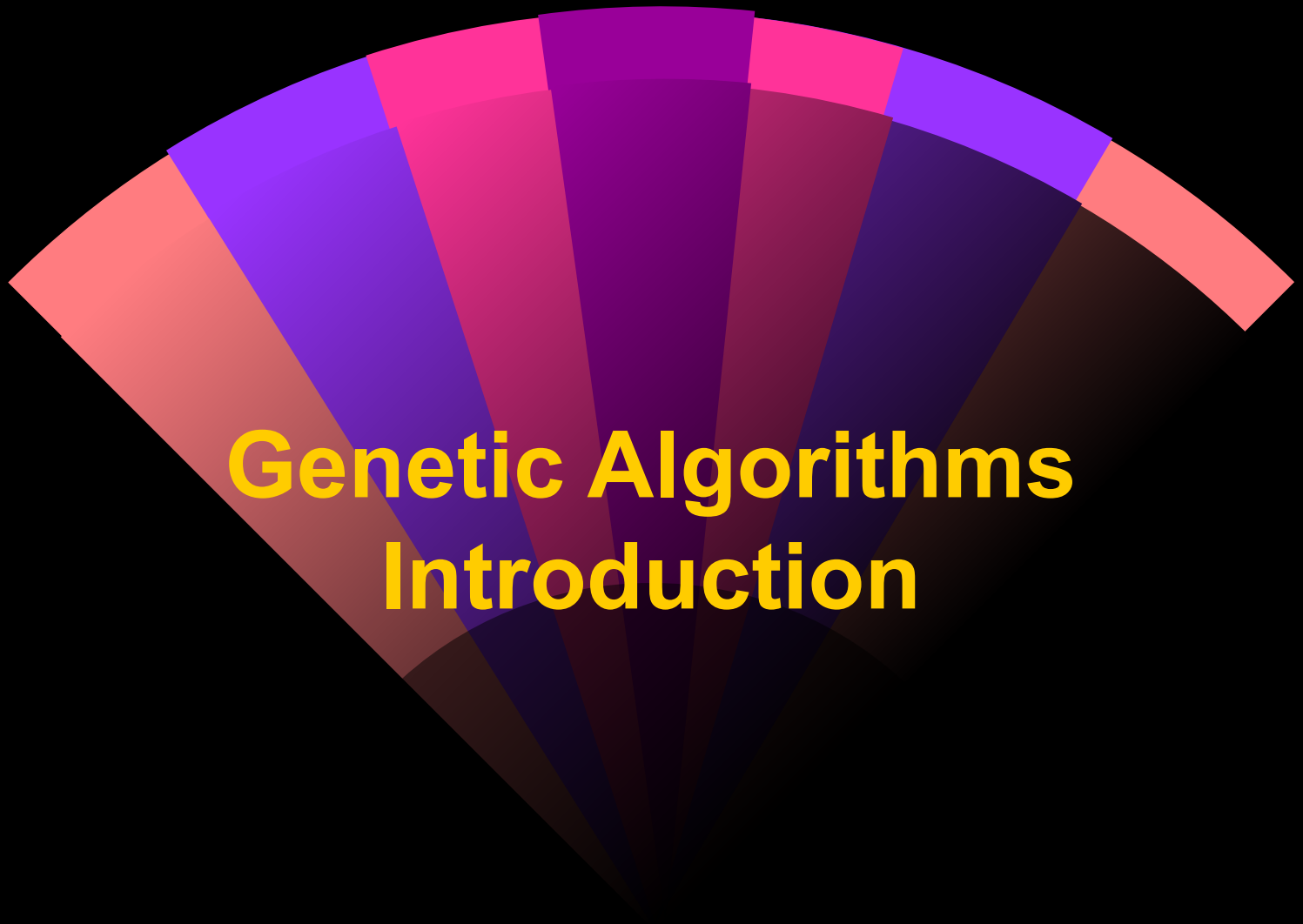
Source: https://vas3k.com/blog/machine_learning/



Janga Reddy and Nagesh Kumar, 2020



Source: Wikipedia



Genetic Algorithms Introduction

Introduction



Introduction

Inspired by Natural Evolution

- Living things evolved into more successful organisms
  - Offspring exhibit some traits of each parent
  - Hereditary traits are determined by genes
  - Genetic instructions are contained in chromosomes
  - Chromosomes are strands of DNA
  - DNA is composed of base pairs, when in meaningful combinations, encode hereditary traits

Mechanisms of Evolutionary Change

- **Crossover**

  Random exchange of parent's chromosomes during reproduction resulting in offspring have some traits of each parent

Crossover requires genetic diversity among the parents to ensure sufficiently varied offspring

Mechanisms of Evolutionary Change

- **Mutation**

  Rare occurrence of errors during the process of copying chromosomes resulting in

  - Changes that are nonsensical/ deadly producing organisms that can't survive
  - Changes are beneficial producing "stronger" organisms
  - Changes aren't harmful/ deadly but aren't beneficial producing organisms that aren't improved

Mechanisms of Evolutionary Change

- **Natural Selection**

  In a competitive environment the fittest survive, resulting in better organisms
  - Individuals with better survival traits generally survive for a longer period
  - This provides a better chance for reproducing and passing the successful traits on to offspring
  - Over many generations the species improve since better traits will out-number weaker ones

Genetic Approach

- Keep a population of individuals that are complete or partial solutions
- Explore solution space by having these individuals interact and compete
  - Interaction produces new individuals
  - Competition eliminates weak individuals
- After multiple generations, a strong individual (i.e., solution) should be found

Terminology

- **Population**

  A set of possible solutions to a problem

- **Elitism**

  Allowing the best members to pass to the next generation

- **Mutation**

  Changing a single member of the population

- **Crossover**

  Combining two members of the population

Terminology – Contd..

- **Selection**

  How to determine which members of the population will survive to the next generation

- **Fitness function**

  How to evaluate the quality of a member of the population

- **Encoding schemes**

  A binary representation for a member of the population

Genetic Algorithms

- A Non-Linear Optimization Tool based on Combinatorial Optimization methods

- Differ from Traditional Method
  - Work with coding of parameter sets and not with parameters themselves
  - Use objective function alone. Will not depend on continuity and derivatives or other information

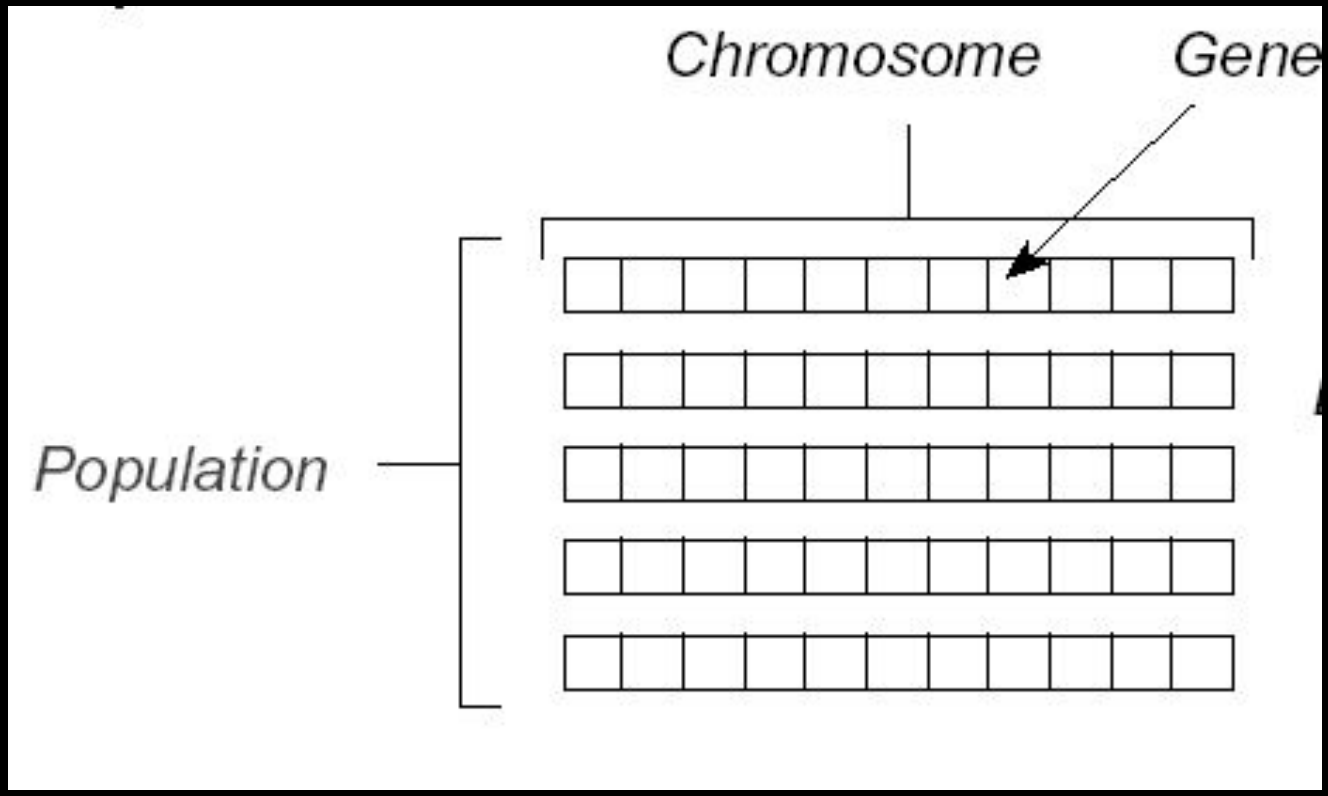
Working Principle

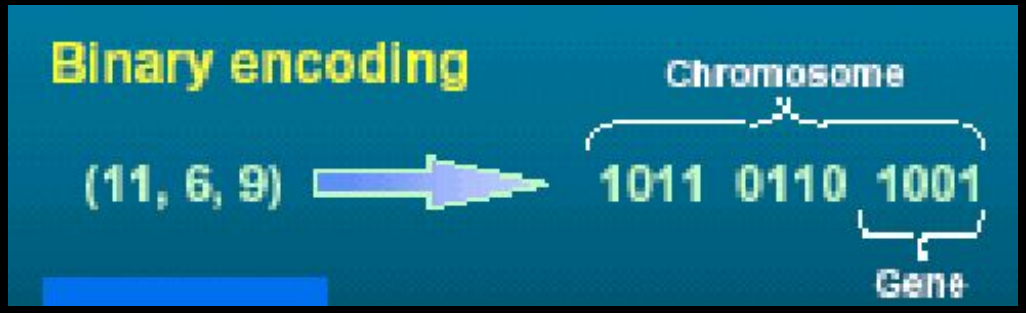
- **Coding**
- **Fitness Evaluation**
- **Genetic Operation**
  - ***Reproduction***
  - ***Crossover***
  - ***Mutation***
- **Termination Criterion**

Coding

- Decision variables are coded into a binary string called chromosomes
- Length of chromosome depends on the desired accuracy
- All decision variables need not have equal sub-string length

Coding – contd..





Initialization: Seeding the Population

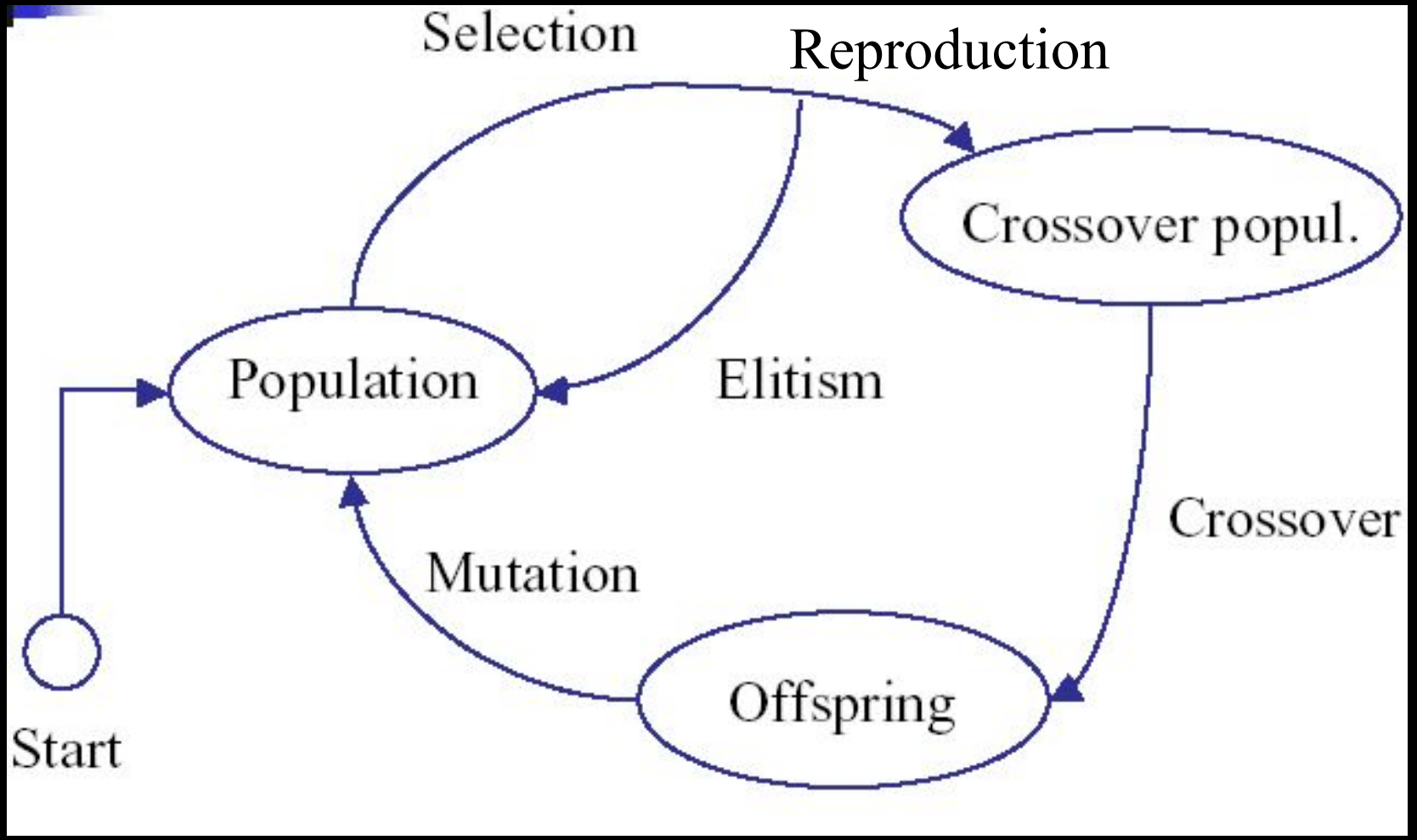
- Initialization sets the beginning population of individuals from which future generations are produced

- Concerns:
  - Size of the initial population
  - Experimentally determined for problem
  - Diversity of the initial population (genetic diversity)
  - A common issue resulting from the lack of diversity is premature convergence on non-optimal solution

Fitness Evaluation

- Evaluation ranks the individuals by some fitness measure that corresponds with the quality of the individual solutions.
- Derived from the objective function
- Fitness function value of a string is known as String's Fitness
- All decision variables will be coded into one string (chromosome)
- For example, given individual *i*:
  - Classification: $(correct(i))^2$
  - TSP: *distance(i)*
  - SAT: *#of Terms Satisfied(i)*
  - walking animation: *subjective rating*
- Often fitness functions have local minima

GA Operating Cycle



Selection Techniques

- Proportional Fitness Selection Example
  - **Given the following population**

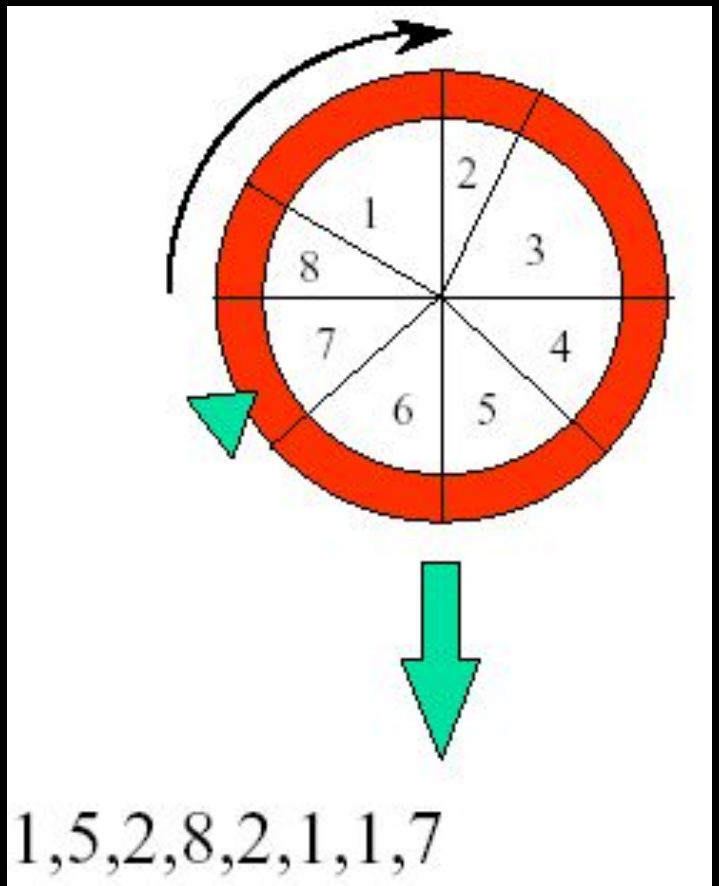
Individual	Fitness	Prob.
A	5	10%
B	20	40%
C	11	22%
D	8	16%
E	6	12%

  - **Sum the Fitness**

    $5 + 20 + 11 + 8 + 6 = 50$
  - **Determine probabilities**
  - $Fitness(i) / 50$

Reproduction

- Selects good strings in a population and forms a mating pool
- Roulette wheel simulation is used for selection



Selection Techniques

- Crowding
- A potential problem associated with the selection
  - Occurs when the individuals that are most fit quickly reproduce so that a large percentage of the entire population looks very similar
  - Reduces diversity in the population
  - May hinder the long-run progress of the algorithm

Cross Over

- Crossover for vector representations:
  - Pick one or more pairs of individuals as parents and randomly swap their segments
  - Also known as "cut and splice“

- Parameters
  - Crossover rate
  - Number of crossover points
  - Positions of the crossover points

Cross Over – contd..

- Single point crossover

  (1-point crossover)
  - Pick a dividing point in the parents' vectors and swap the segments

- For Example
  - Given parents:

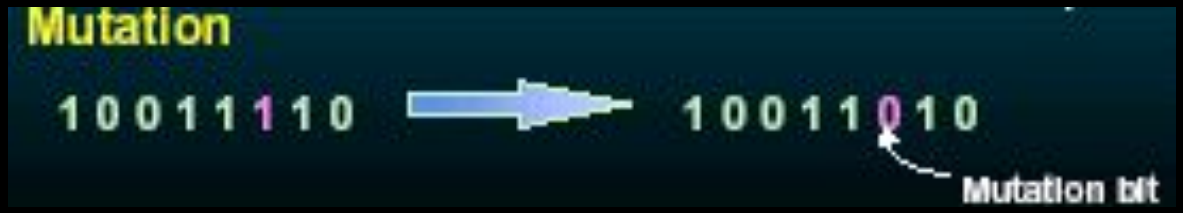
    1101101101 and 0001001000
  - Crossover point: after the 4th digit

    1101101101 and 0001001000
  - Children produced are:

    1101001000 and 0001101101

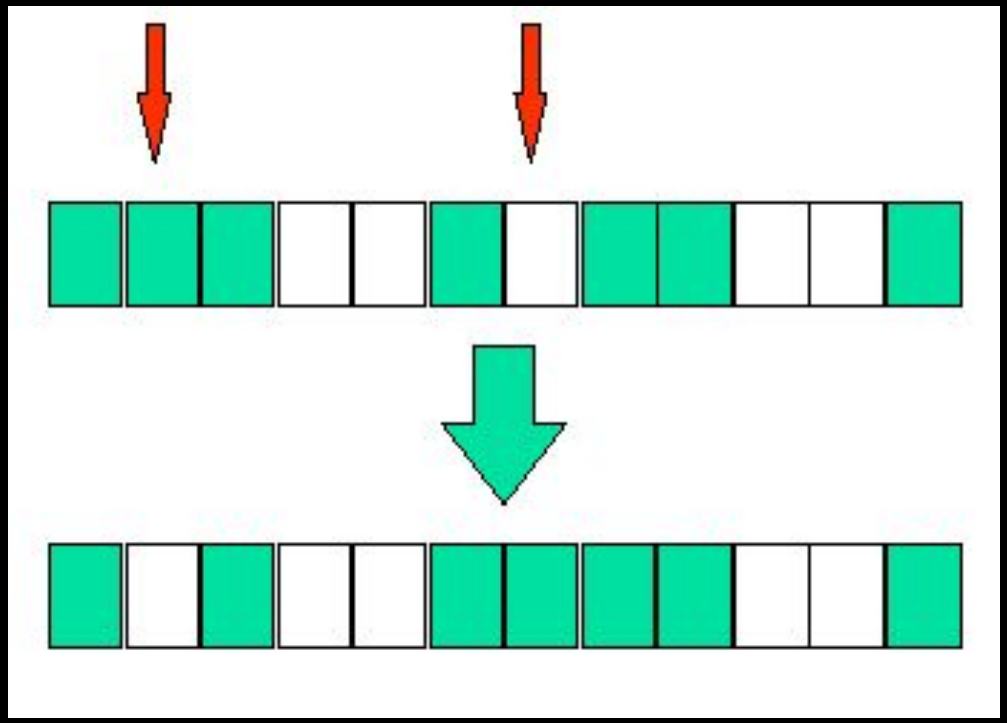
Mutation

- Randomly change an individual

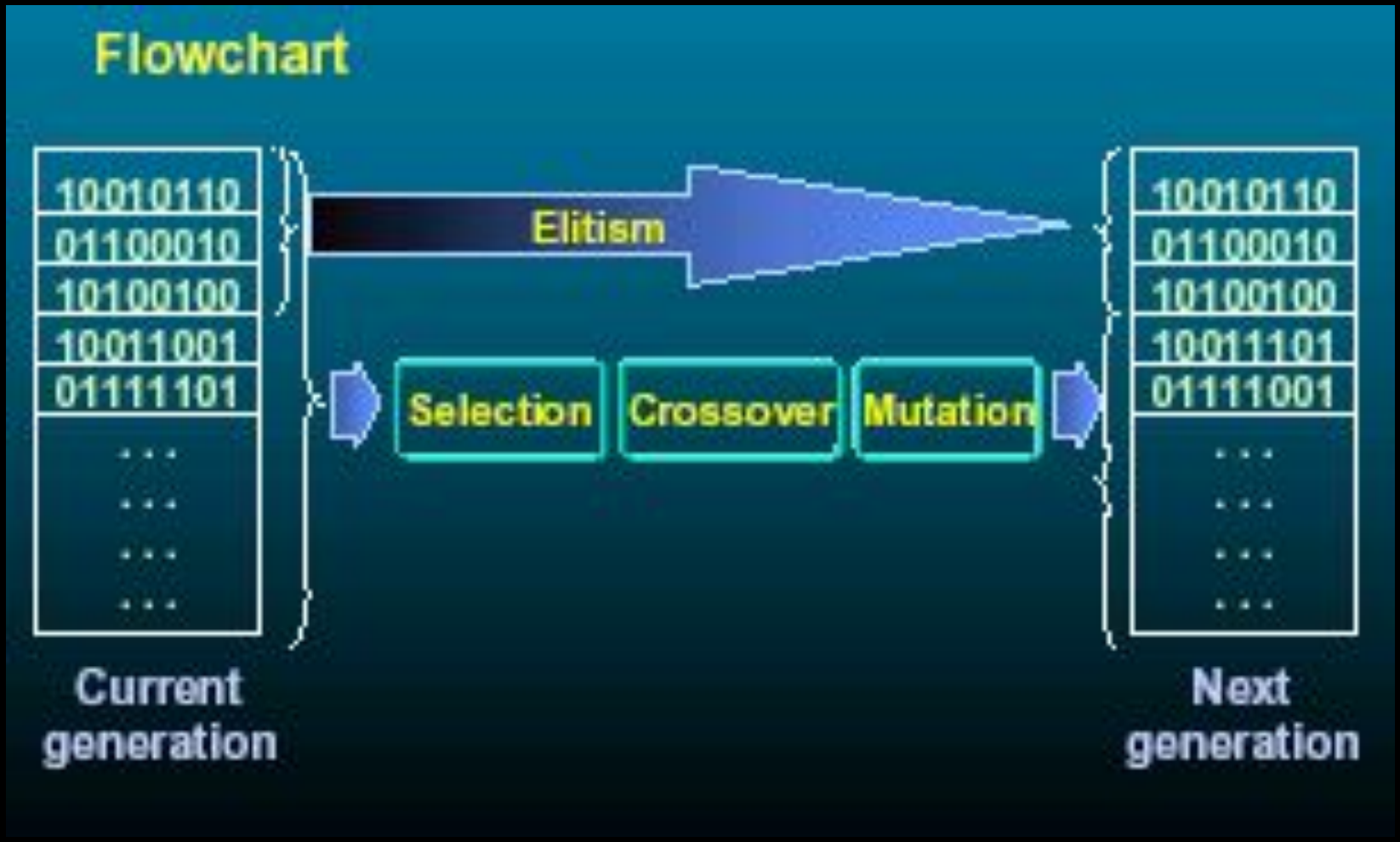


- Bit-wise mutation is performed bit by bit by flipping a coin with a probability p_m
- Uses
  - Create a point in the neighborhood of the current point for local search
  - Maintain diversity in the population
- Parameters
  - Mutation rate
  - Size of the mutation

Mutation



GA Operations Summary

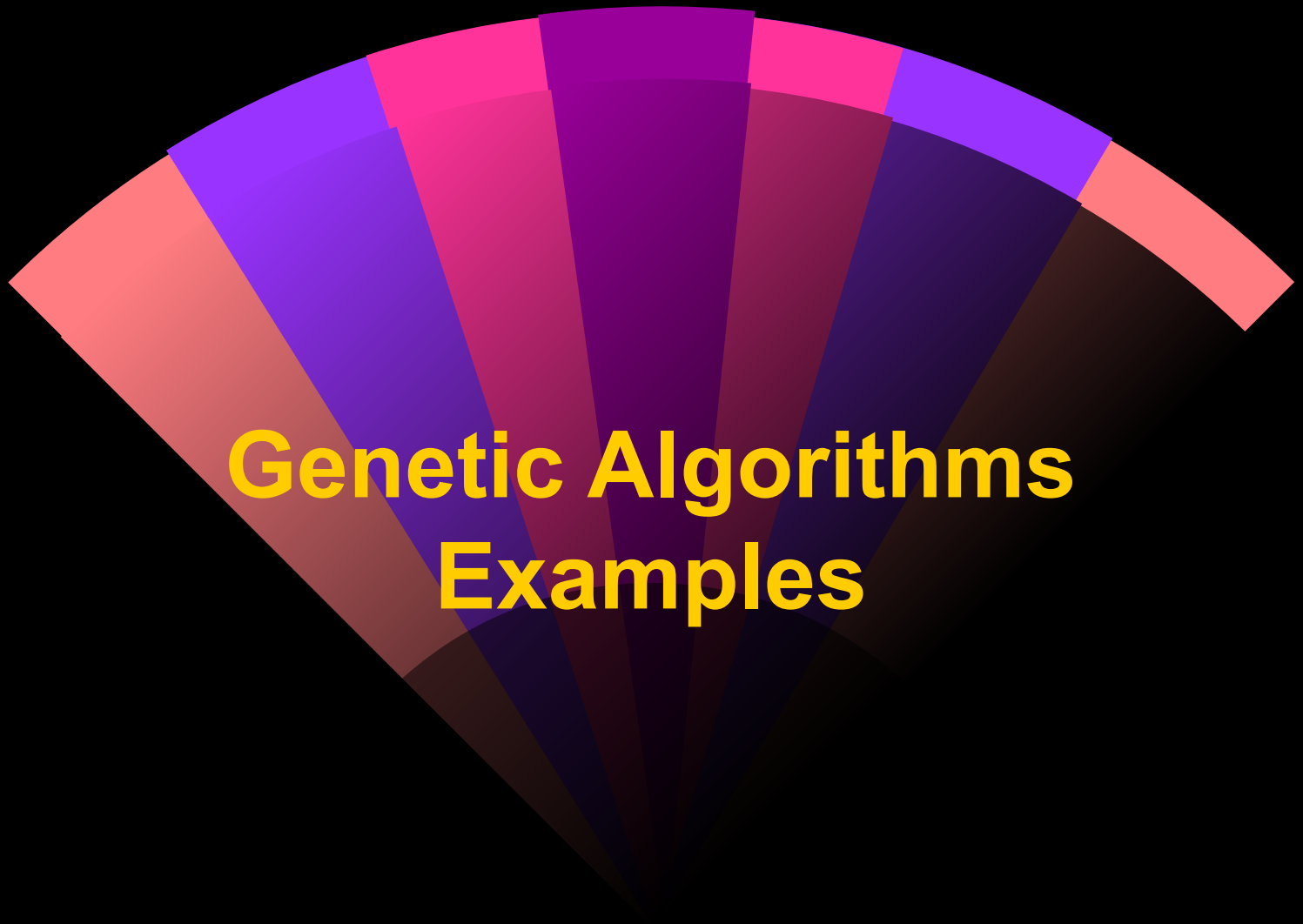


GA Operations Summary – contd..

- Three operators are simple and straight forward
- Reproduction operator selects good strings
- Crossover operator recombines good substrings from good strings together to hopefully create a better substring
- Mutation operator alters a string locally to hopefully create a better string
- Although none of these claims are guaranteed and/or tested while creating a string, it is expected that if bad strings are created, they will be eliminated by the reproduction operator in the next generation

Genetic Algorithm - Pseudo-Code

```
1:  begin
2:  define problem dimension (D), generate initial population P_0 of size NP
3:  evaluate the fitness of NP individuals in P_0
4:  initialize generation counter t ← 0
5:  while termination criterion not satisfied do
6:  |   selection of parents on the basis of their fitness
7:  |   create offspring for the new generation P_{t+1} from the parents using
8:  |  crossover operation
9:  |   perform mutation on new generation P_{t+1}
10: |   evaluate the fitness of population P_{t+1}
    |   t ← t+1
11:     end
12: end
```



Genetic Algorithms Examples

Problem 1

Find the Minimum of the function (Himmelblau function) (in the range 0 to 6)

$f(x_1,x_2) = (x_1^2+x_2-11)^2 + (x_1+x_2^2-7)^2$

True Solution (3,2)

Solution from the GA

The function is minimum at point (2.997, 2.029) and the value is 0.013

GA Parameters - Step 1

Number of objective functions	1
Objective function	Minimize
Crossover type	Binary GA (Single-pt)
Strategy	1 cross - site with swapping
Population size	20
Total no. of generations	30
Cross over probability	0.8
Mutation probability	0.05
Random no. seed entered	0.76
String length	20
Number of variables Binary	2
Epsilon for closeness	0
Sigma-share value	0.1500
Sharing Strategy	sharing on Parameter Space

Lower and Upper bounds

0 <= x1 <= 6

0 <= x2 <= 6

Procedure

- Binary Coding
  - With 10 bits, we can get a solution accuracy of $(6-0)/(2^{10}-1)$ or 0.006 in the interval of (0,6).
- Step 2
  - Evaluate each string in the population
  - Sub string 1010010001 decodes to a value of $(2^9+2^7+2^4+2^0)=657$. Corresponding parameter value is $0+(6-0)*657/1023 = 3.853$
  - For minimization: $F(X)=1/(1+f(X))$

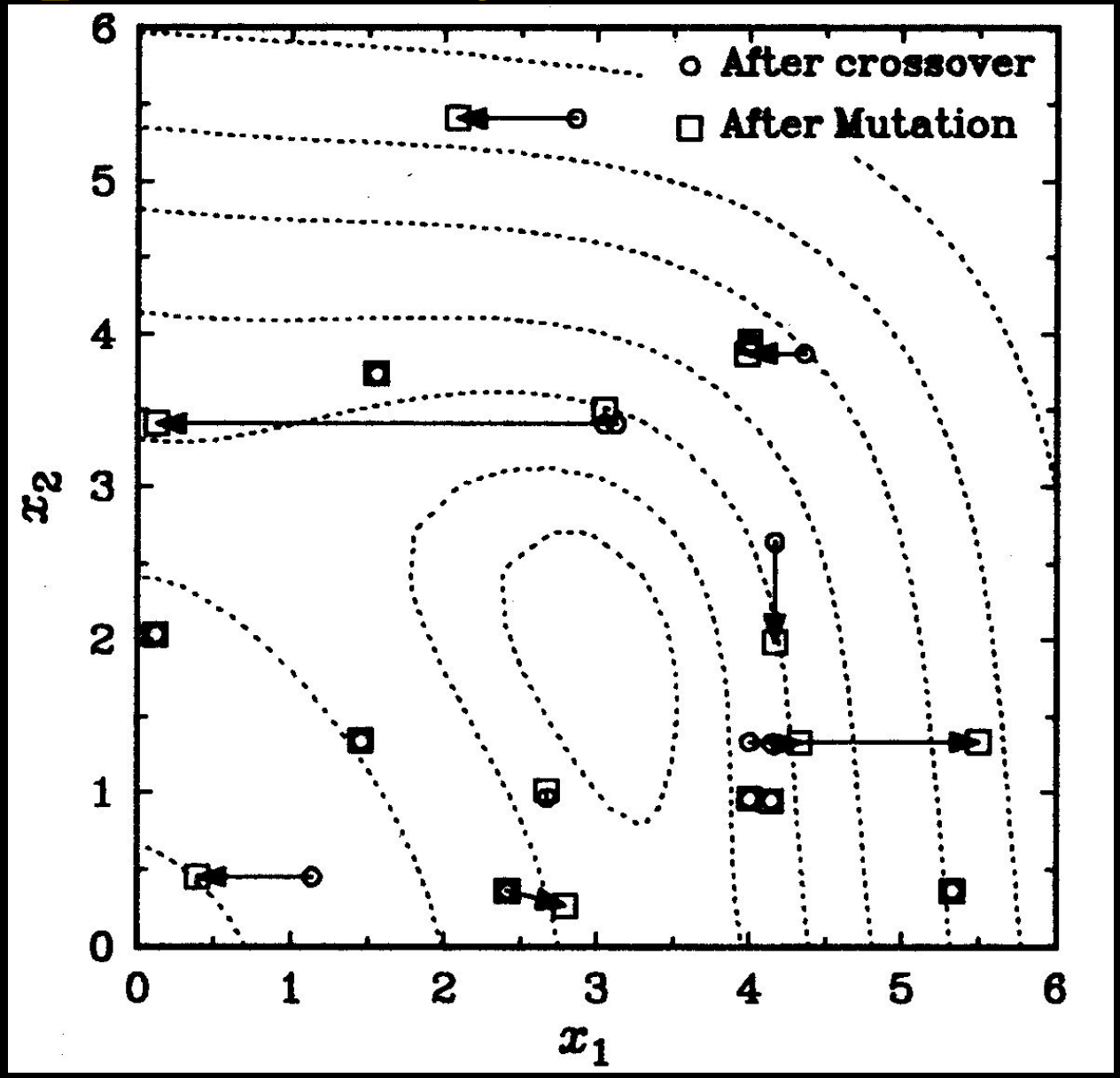
GA Operations (Steps 4-6)

Mating pool				Intermediate population		Mutation					
Substring-2	Substring-1	G	H	Substring-2	Substring-1	Substring-2	Substring-1	x_1	x_2	$f(x)$	$\mathcal{F}(x)$
0010100100	1010101010	Y	9	0010100101	0111001000	0010101101	0111001000	1.015	2.674	18.886	0.050
1010100001	0111001000	Y	9	1010100000	1010101010	1010100001	1010101010	3.947	4.000	238.322	0.004
0001001101	0011100111	Y	12	0001001101	0011000010	0001001101	0001000010	0.452	0.387	149.204	0.007
1110011011	0111000010	Y	12	1110011011	0111100111	1110011011	0101100011	5.413	2.082	596.340	0.002
0010100100	1010101010	Y	5	0010100010	1011000011	0010100010	1011000011	0.950	4.147	54.851	0.018
0011100010	1011000011	Y	5	0011100100	1010101010	0011100100	1110101010	1.337	5.501	424.583	0.002
0011100010	1011000011	N		0011100010	1011000011	0011100011	1011100011	1.331	4.334	83.929	0.012
0111000010	1011000110	N		0111000010	1011000110	0101010010	1011000110	1.982	4.164	70.472	0.014
0101011011	0000000111	Y	14	0101011011	0000010100	0101011011	0000010100	2.035	0.117	87.633	0.011
1001000110	1000010100	Y	14	1001000110	1000000111	1001010110	1000000111	3.507	3.044	72.789	0.014
0011100101	0011111000	Y	1	0011100101	0011111000	0011100101	0011111000	1.343	1.455	70.868	0.014
0011100101	0011111000	Y	1	0011100101	0011111000	0011100101	0011111000	1.343	1.455	70.868	0.014
0000111101	0110011101	N		0000111101	0110011101	0000101101	0111011100	0.264	2.792	25.783	0.037
0000111110	1110001101	N		0000111110	1110001101	0000111110	1110001101	0.364	5.331	318.746	0.003
0000111101	0110011101	Y	18	0000111101	0110011100	0000111101	0110011100	0.358	2.416	42.922	0.023
1001000110	1000010100	Y	18	1001000110	1000010101	1001000110	0000010101	3.413	0.123	80.127	0.012
1001111101	1011100111	Y	10	1001111101	0100001001	1001111101	0100001001	3.736	1.554	95.968	0.010
1010010100	0100001001	Y	10	1010010100	1011100111	1010010100	1010100111	3.871	3.982	219.426	0.005
0000111101	0110011101	N		0000111101	0110011101	0000111101	0110011101	0.358	2.422	42.598	0.023
0010100100	1010101010	N		0010100100	1010101010	0010100100	1010101010	0.962	4.000	39.849	0.024

G : Whether crossover (Y yes, N no), H : Crossing site

Source: Deb, 2002

Population after Mutation



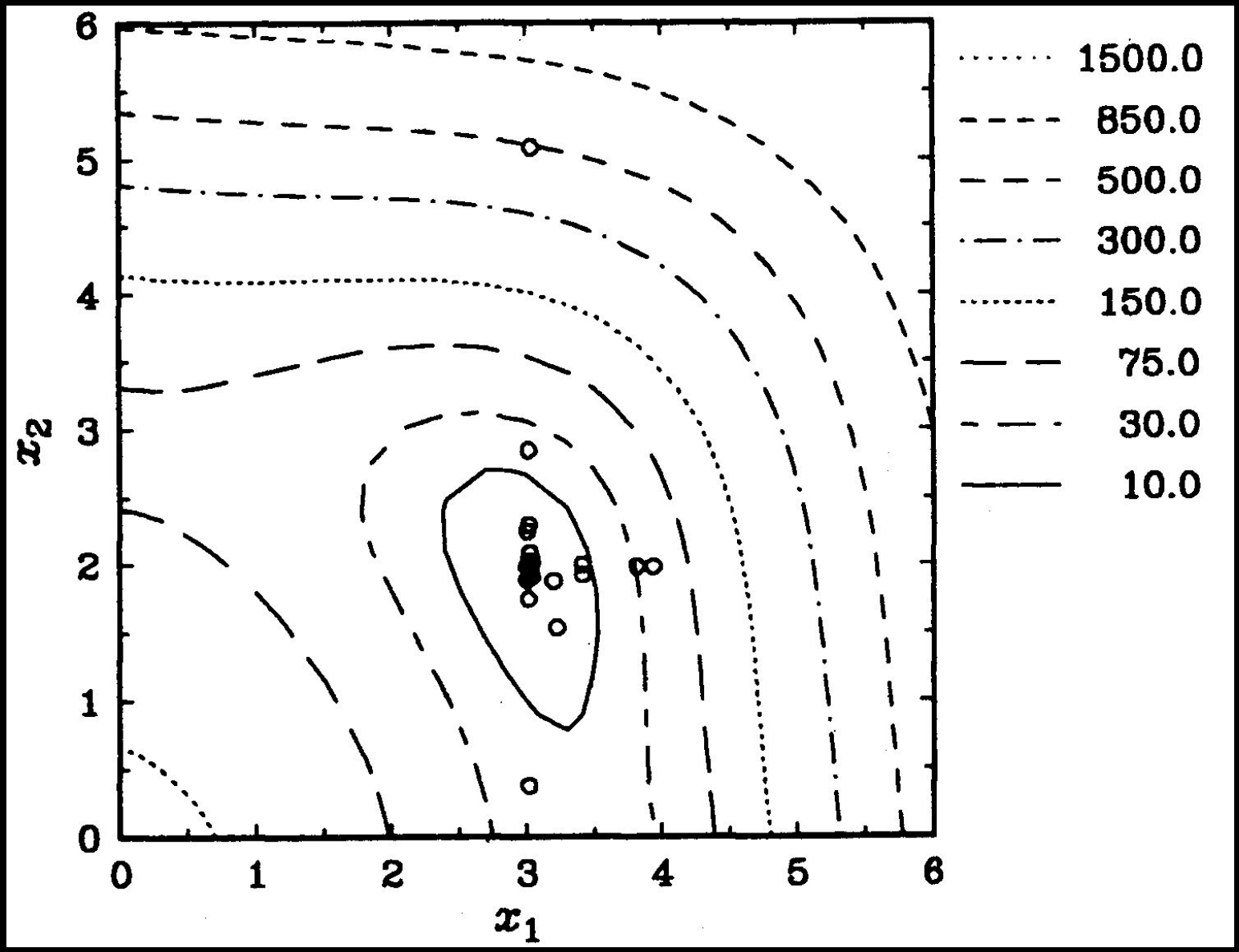
GA Results for 1st Generation

Population size	Values of x_1	Values of x_2	f(x) Values	String
1	3.85	1.84	32.44	1010010001_0100111010
2	0.70	1.31	105.36	0001111000_0011100000
3	1031	5.89	1661.14	1110010100_1111101101
4	5.37	4.45	345.85	1010010000_1011110111
5	3.85	5.15	691.48	1011000101_1101101110
6	1.54	3.39	63.90	0100000110_1001000010
7	4.02	3.52	164.26	1010101101_1001011001
8	3.53	4.96	379.97	0100000000_1101001110
9	2.05	2.93	28.13	0101011101_0111110011
10	0.91	5.64	679.93	0010011011_1111000001
11	0.03	3.11	69.61	0000000101_1000010011
12	5.44	0.54	366.43	1110011111_0001011100
13	2.48	3.54	65.52	0110100110_1001011011
14	3.15	0.28	14.89	1000011001_0000101111
15	4.60	5.77	1212.63	1100010010_1111011000
16	0.41	2.92	66.31	0001000110_0111110001
17	5.54	0.72	416.10	1110110000_0001111011
18	0.18	4.50	223.24	0000011111_1100000000
19	3.81	4.89	500.10	1010001001_1101000010
20	2.92	2.60	7.16	0111110010_0110111011

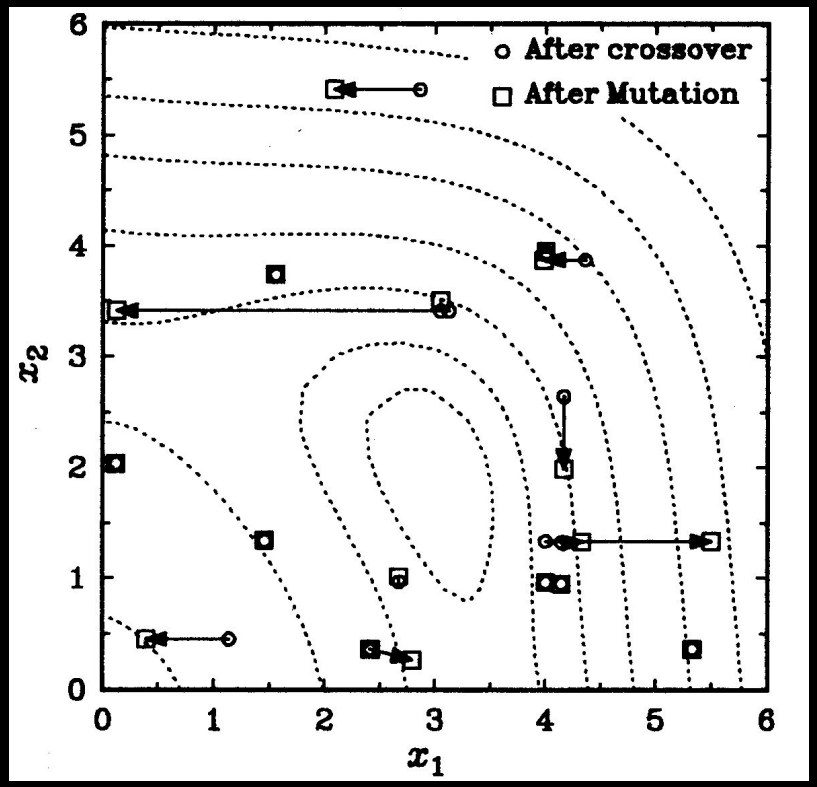
GA Results after 30th Generation

Population size	Values of X_1	Values of X_2	f(x) Values	String
1	5.81	0.58	543.42	1111011110_0001100011
2	2.99	2.09	0.124	0111111110_0101100100
3	2.92	1.56	3.53	0111110010_0100001010
4	2.30	1.95	0.05	0111111111_0101001100
5	2.30	2.03	0.01	0111111111_0101011010
6	2.05	2.45	20.11	0101011101_0110100001
7	2.78	1.89	2.34	0111011010_0101000010
8	2.00	2.12	0.24	0111111111_0101101001
9	2.42	1.92	11.26	0110011100_0101001000
10	2.95	5.46	670.58	0111110111_1110100010
11	2.94	2.13	0.28	0111110101_0101101011
12	2.80	1.91	1.84	0111011110_0101000101
13	2.94	2.10	0.17	0111110101_0101100100
14	3.00	2.12	0.23	0111111110_0101101001
15	2.77	2.07	1.54	0111011001_0101100000
16	2.75	1.72	4.55	0111010101_0100100110
17	2.41	2.10	9.58	0110011011_0101100110
18	2.76	5.90	940.77	0111010110_1111101110
19	2.96	2.11	0.19	0111111001_0101101000
20	2.30	2.14	0.35	0111111111_0101101101

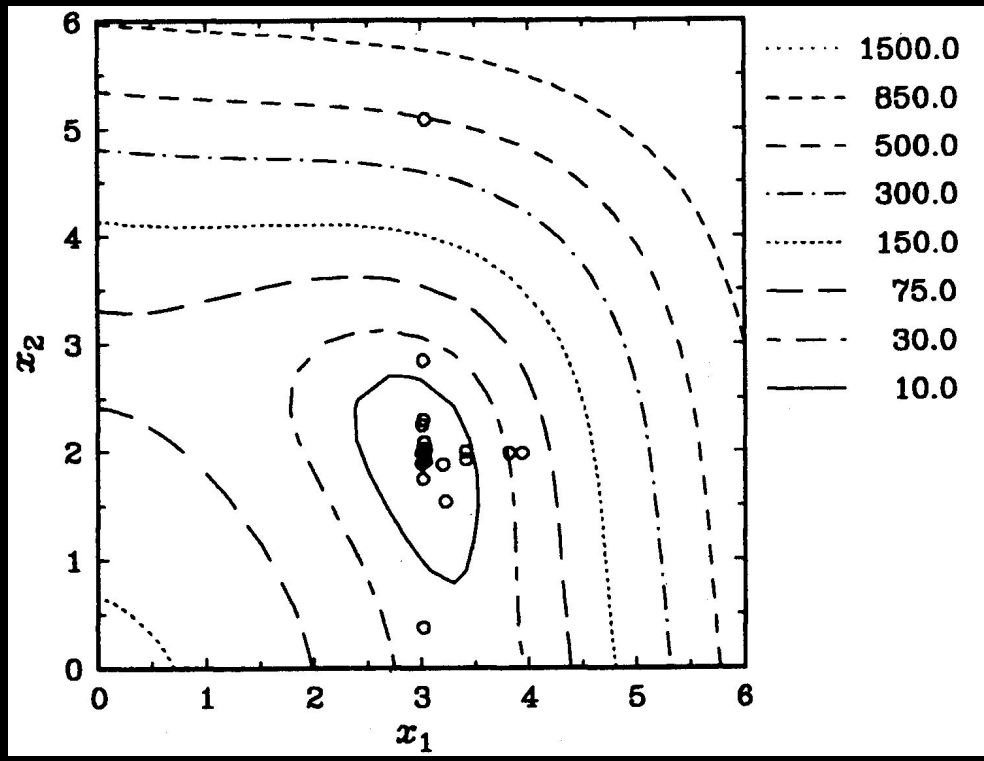
Population after 30th Generation



Population after 1st Generation



Population after 30th Generation



Source: Deb, 2002

GA Results

After Generation 1

Max. Fitness = 1661.135
Min. Fitness = 7.155 Avg. Fitness = 354.719
No. of mutations = 0 ; No. of crossovers = 0

After Generation 30

Max. Fitness = 940.774
Min. Fitness = 0.013 Avg. Fitness = 110.557
No. of mutations = 20 ; No. of crossovers = 245

Problem 2

Find the max. of the "peaks" function

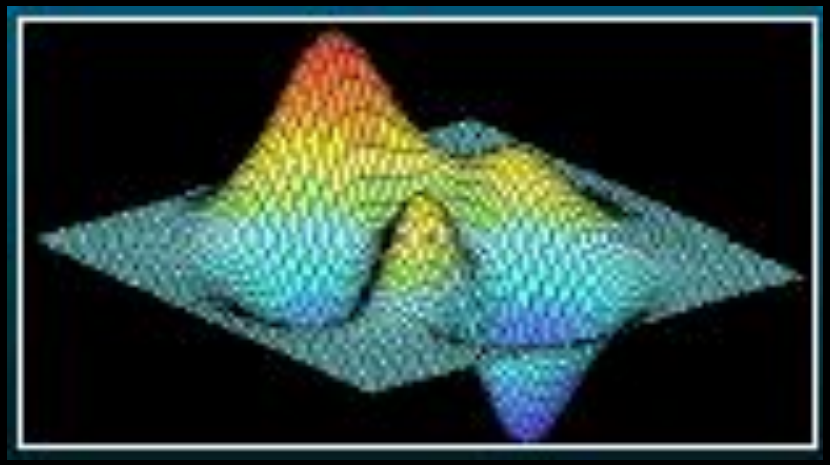
$z = f(x, y)$

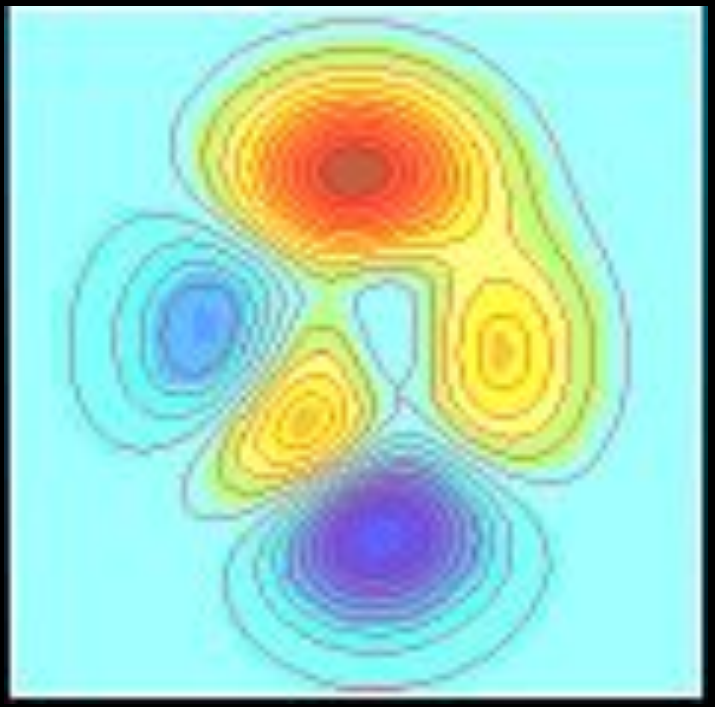
$= 3\,(1-x)^2 \exp(-x^2 - (y+1)^2)$

$- 10\,(x/5 - x^3 - y^5) \exp(-x^2-y^2)$

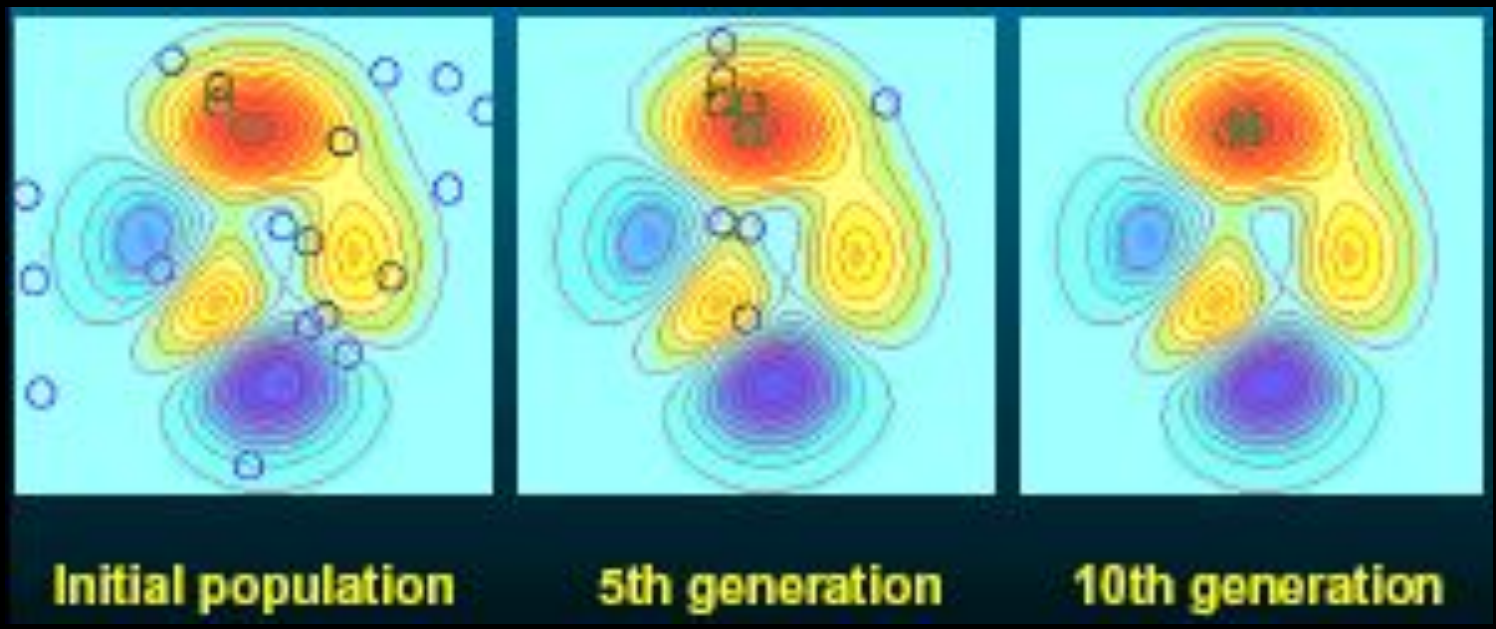
$-1/3 \exp(-(x+1)^2 - y^2)$

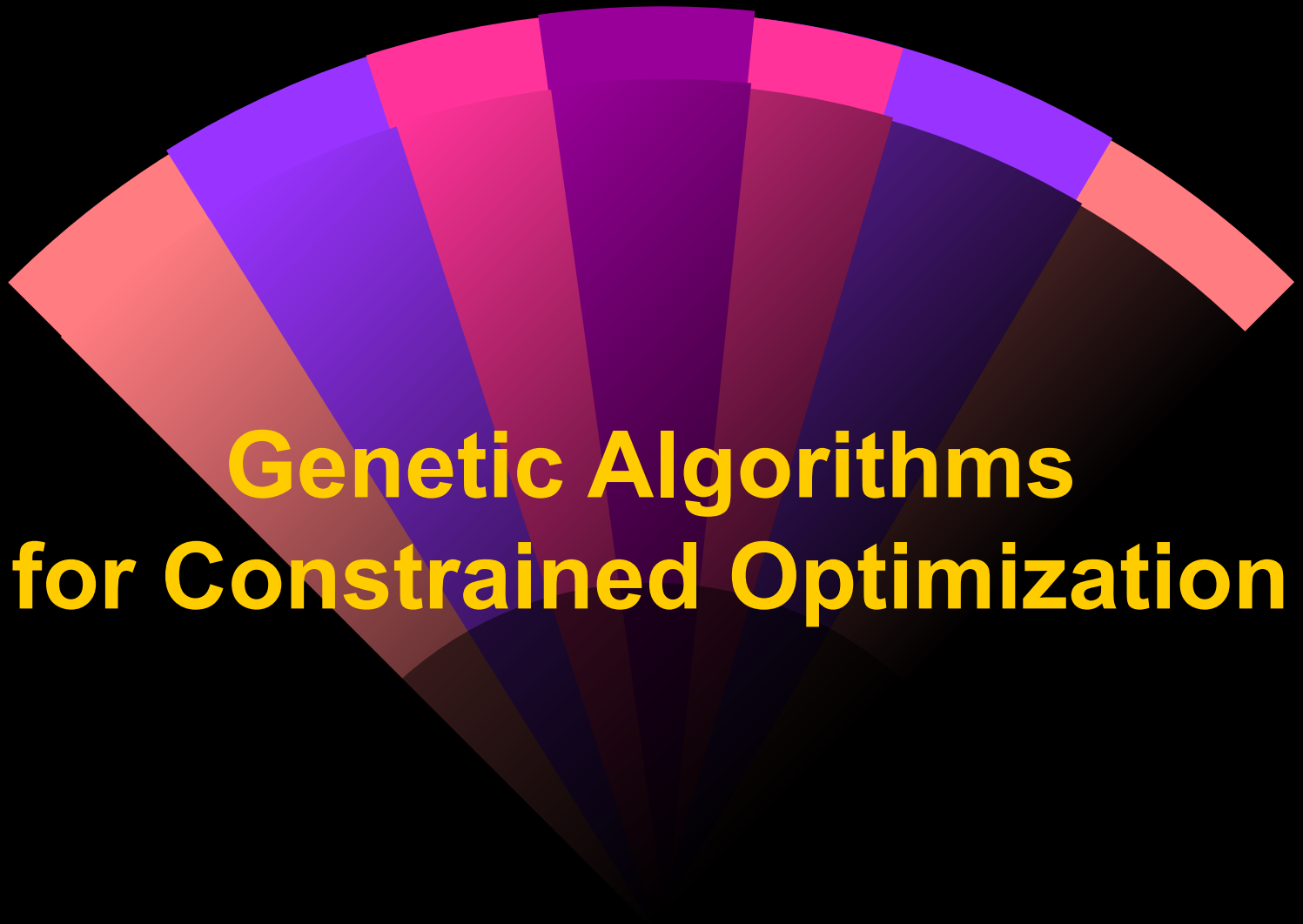
Plotting ‘Peaks’ Function





GA Process





Genetic Algorithms for Constrained Optimization

GA for Constrained Optimization

- Constrained problem is converted into unconstrained problem by Penalty Function method
- Solution falling outside the restricted solution region is considered at a very high penalty

GA for Constrained Optimization

- Bracket operator penalty term is used

$$\delta_i \, (\varphi_i)^2$$

- F_i is fitness value
- $f(x)$ is objective function value
- k is total number of constraints
- $\in$ is -1 for maximization and +1 for minimization
- δ_j is penalty co-efficient
- φ_j is amount of violation

Problem 1

Find the Minimum of the function (Himmelblau function)

$f(x_1,x_2) = (x_1^2+x_2-11)^2 + (x_1+x_2^2-7)^2$

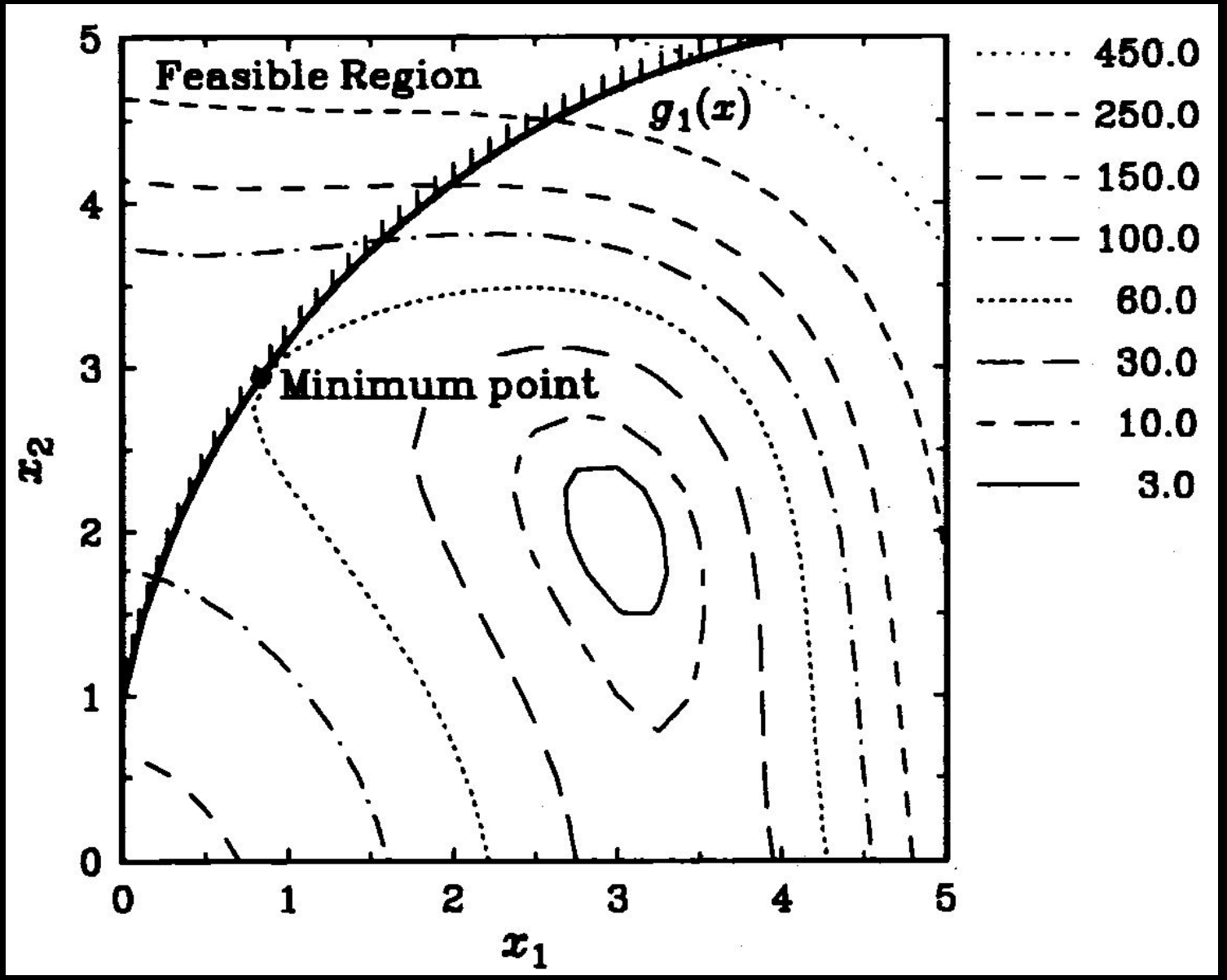
Subject to

$(x_1-5)^2 + x_2^2 - 26 \geq 0$

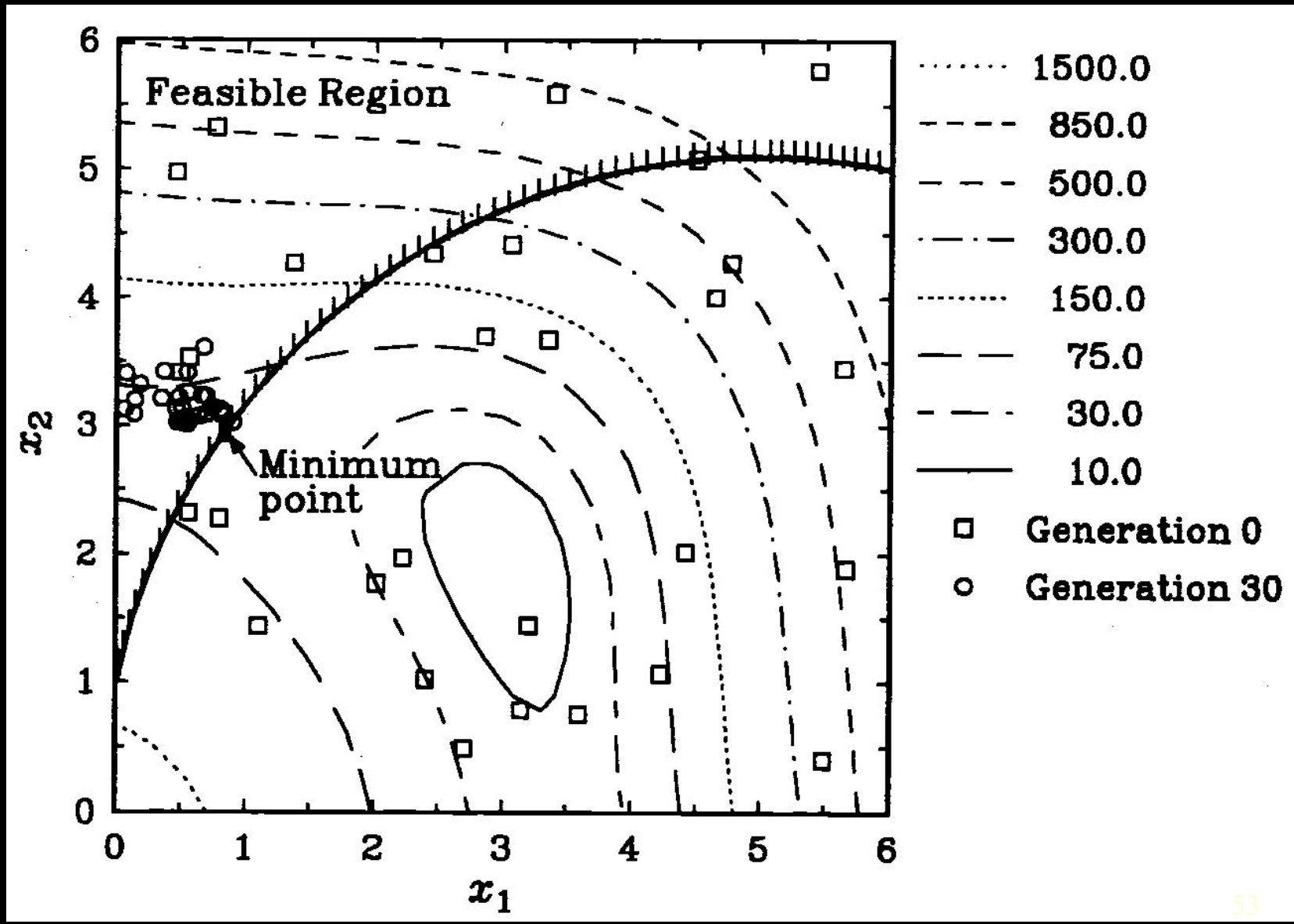
$x_1 \geq 0$ and $x_2 \geq 0$

$x_1 \leq 6$ and $x_2 \leq 6$

Solution


Feasible Region
$g_1(x)$
Minimum point
x_2
x_1
0
1
2
3
4
5
450.0
250.0
150.0
100.0
60.0
30.0
10.0
3.0

GA Solution


Feasible Region
Minimum point
x_1
x_2
0
1
2
3
4
5
6
1500.0
850.0
500.0
300.0
150.0
75.0
30.0
10.0
Generation 0
Generation 30



Single Objective Optimization for Reservoir Operation

GA Application in WRE

- Hydropower Optimization from a Reservoir
  - Maximize the total hydropower produced in a year with other demands from the reservoir as constraints
  - Monthly time period is used for demonstration of GA applicability
    - 12 periods in the Year

Case Study Area Description

- **Hirakud Dam: A multipurpose project on Mahanadi River, Odisha State, India**
  - **Flood Control, Irrigation and Hydropower**
- **Location: Lat 21º 32’ N; Long. 83º 52’ E**
- **Catchment area upto Dam site: 83,400 sq.km.**
- **Active storage capacity: 7,189 million m^3**
- **Installed turbine capacity: 307.5 MW**
- **Irrigated area**
  - **First crop season, *Kharif* : 1,565.5 sq.km.**
  - **Second crop season, *Rabi* : 1,084.0 sq.km.**

Optimization Problem

Objective Function

$P_t = 2725\ RP_t\ h_t$

RP - water released for Power (million m^3)

h - Head in meters

Constraints

- Releases for Firm Power and Turbine Capacity

$$RP_t \leq TC \quad \forall \quad t = 1,2,.....12$$

$$RP_t \geq FP_t \quad \forall \quad t = 1,2,.....12$$

- Irrigation Demand Constraints

$$RI_t \geq ID_{MIN_t} \quad \forall \quad t = 1,2,.....12$$

$$RI_t \leq ID_{MAX_t} \quad \forall \quad t = 1,2,.....12$$

Constraints – contd..

- Reservoir Storage Continuity Constraints

$$(1+a_t)S_{t+1} = (1-a_t)S_t + Q_t - RI_t - RP_t - OVF_t - A_o e_t \quad \forall \text{ t}$$

- Reservoir Storage Continuity Constraints

$$S_t \leq S_{\max} \qquad \forall \; t = 1,2,.....12$$

Implementation in GA

- Identification of decision variable
  - Release for power in each month (12)
- Fixation of upper and lower bound
  - Lower bound is the firm power
  - Upper bound is the capacity of the turbines
- Fixation of binary string length
  - Based on the difference between the upper and lower bound of each decision variable
- Coding of string
  - Binary coding is done by generating random numbers

Implementation in GA – contd..

- Decoding of decision variable
  - Linear mapping rule
- Calculation of fitness
  - Values of the decision variables and the effective head are substituted into fitness function to evaluate fitness of each string
- G A operations
  - All 3 steps involved in GA operation viz., Reproduction, Crossover and Mutation are performed on the strings
  - Cross over Probability : 0.8
  - Mutation Probability : 0.006
- Repeat until termination criterion is met

Lower & upper bounds and string length for the decision variable

Month	Decision Variable	Lower bound	Upper bound	String length
January	RP_1	616.50	2000	10
February	RP_2	370.00	2000	15
March	RP_3	370.00	2000	15
April	RP_4	245.00	2000	15
May	RP_5	370.00	2000	15
June	RP_6	370.00	2000	15
July	RP_7	615.00	2000	10
August	RP_8	1233.00	2000	10
September	RP_9	1110.00	2000	10
October	RP_{10}	615.00	2000	10
November	RP_{11}	615.00	2000	10
December	RP_{12}	615.00	2000	10

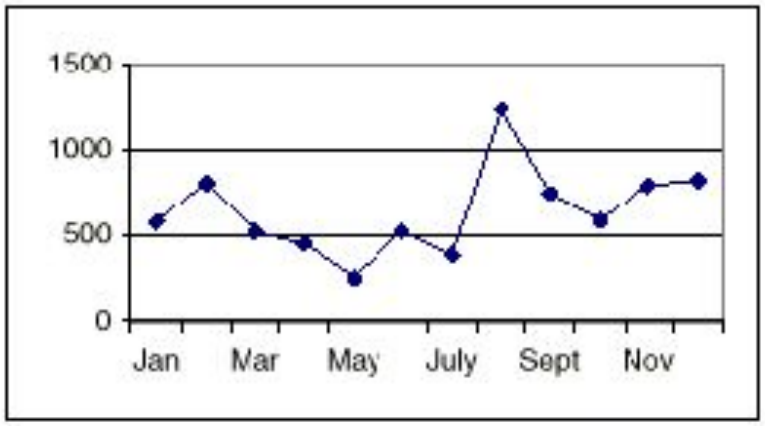
Average Inflows and Irrigation Demands for different months

Month	Inflows M.cu.m.	Irrigation Demand M.cu.m
January	397.026	229.831
February	178.785	268.671
March	33.291	323.046
April	46.854	313.428
May	6.165	57.334
June	431.550	107.518
July	4,151.511	249.683
August	18,377.865	243.271
September	5,611.383	265.588
October	1,392.057	295.304
November	626.364	45.005
December	556.083	117.135

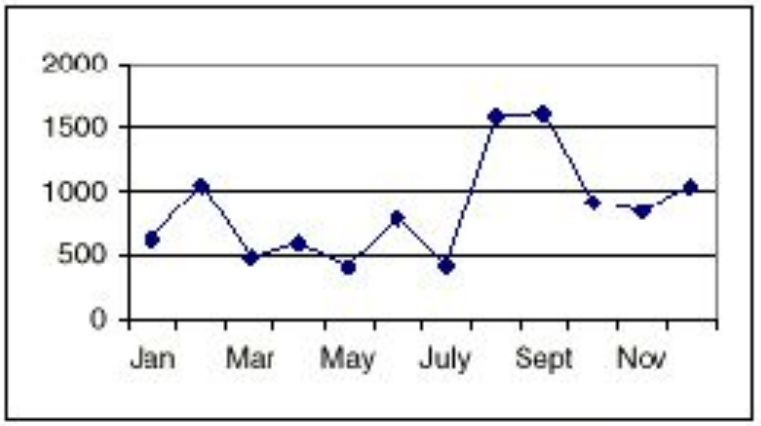
Inflow scenarios

- Model was run for four different dependable levels of inflows
  - 40% & 20% below average inflows
  - Average inflows and 20 % above average inflows

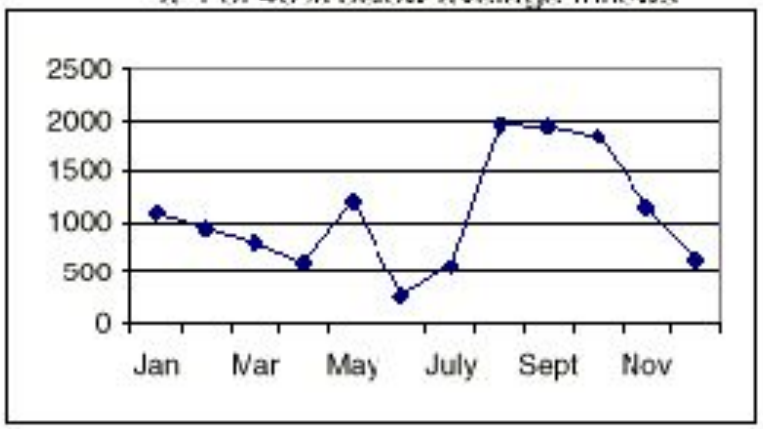
Optimal Releases for Power (M.cu.m)



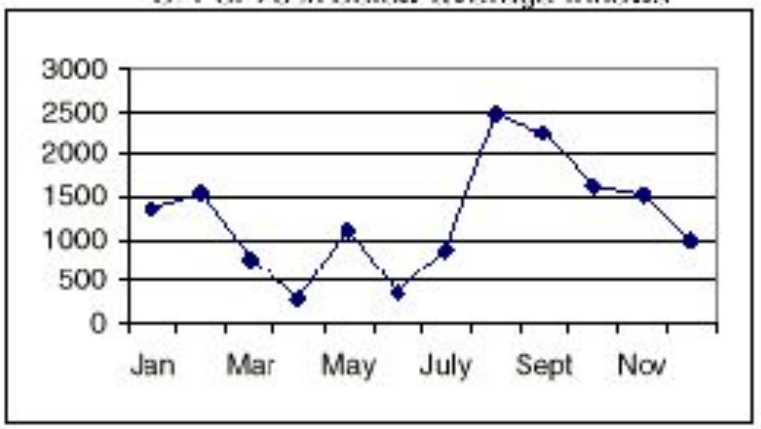
a. For 40% below average inflows



b. For 20% below average inflows



c. For average inflows



d. For 20% above average inflows



Multi Objective Optimization

Mutiple Objectives in Reservoir Operation

- ***Water resource system***
  - *involves conflicting objectives/goals*
  - *involves many variables which nonlinearly affects all the features and the behavior of the system*

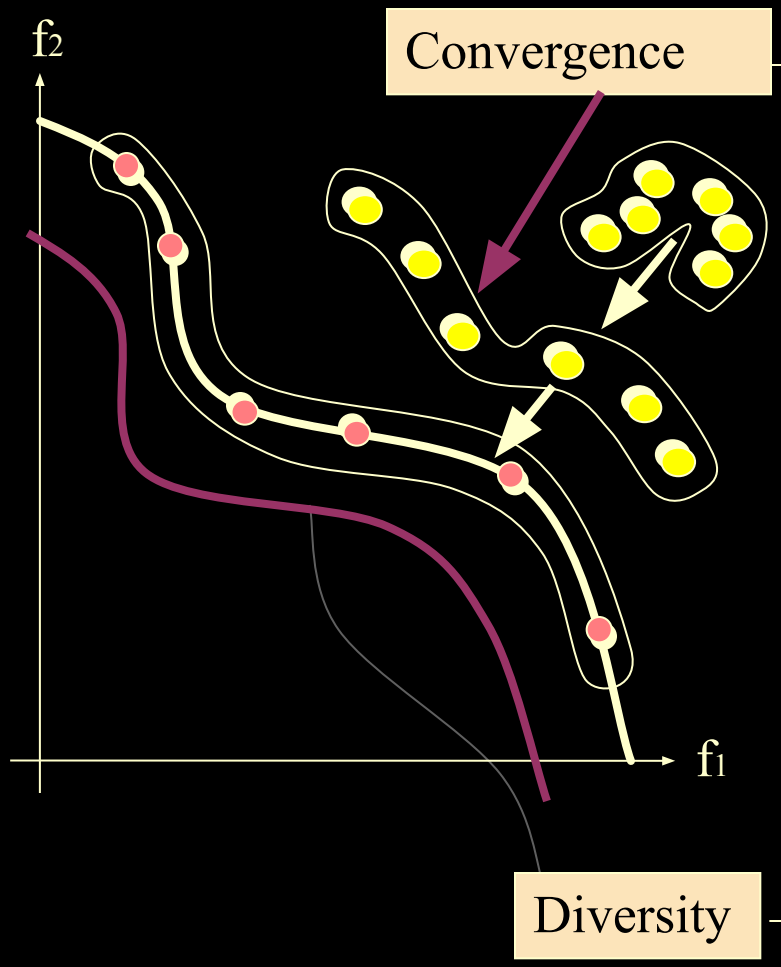
Examples:



Reservoir Operation

- Minimize ***flood*** risk (f_1) as low as possible to 0
- Maximize ***hydropower*** generation (f_2) as maximum as possible
- Minimize ***irrigation*** deficits (f_3) as low as possible
- Maximize ***water quality*** in the d/s river (f_4) as maximum as possible

Issues in MOEAs



- How to guide the population towards the Pareto set?

  ❶ **fitness assignment**

How to prevent nondominated solutions from being lost?

❸ **environmental selection**

- How to maintain a diverse Pareto set approximation?

  ❷ **density estimation**



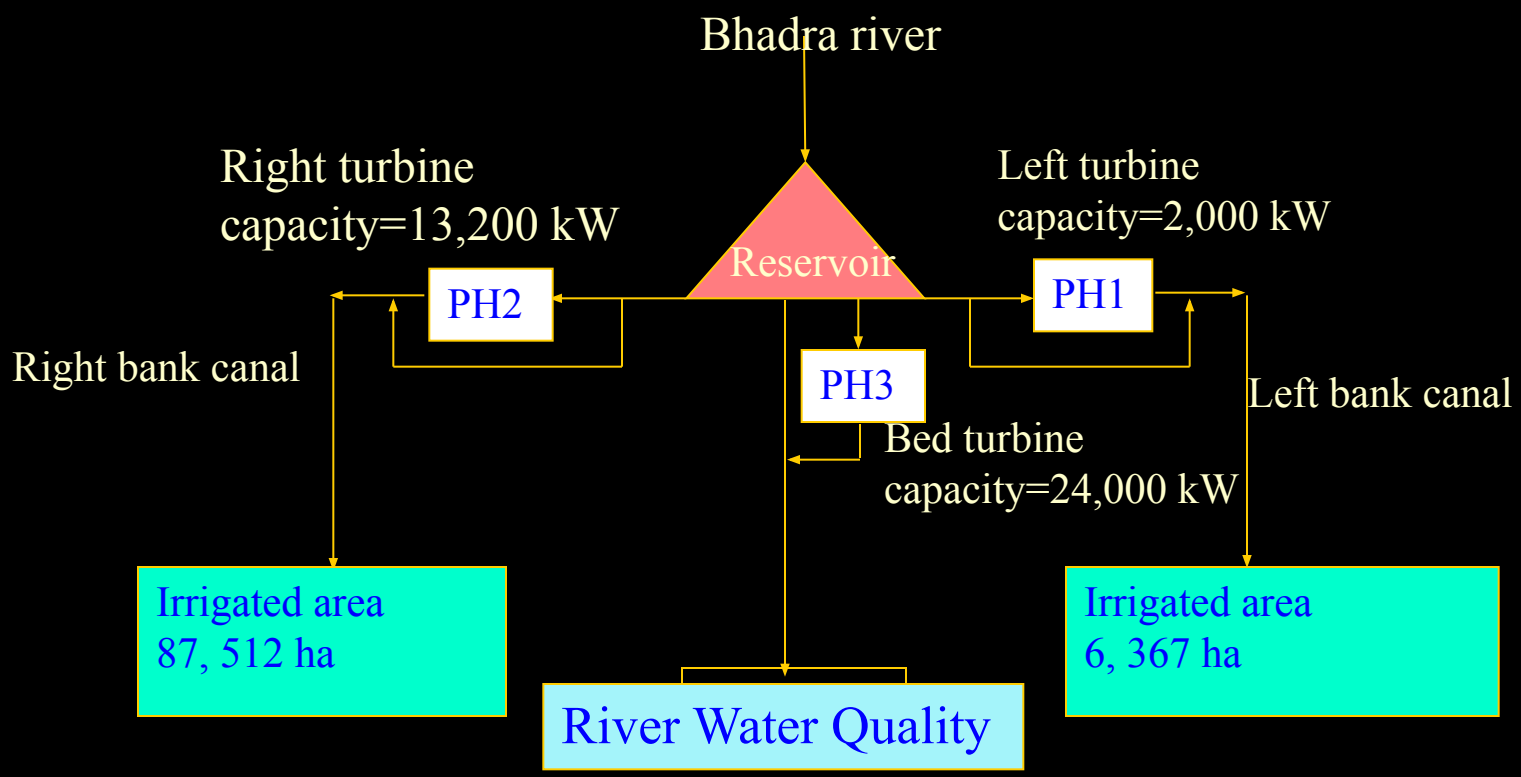
Multi Objective Optimization for Reservoir Operation

Multi-objective reservoir system optimization – Case Study

Bhadra Reservoir – a multipurpose reservoir

Location - Chickmangalur Dt, Karnataka state, India

75°38'20" E longitude and 13°42' N latitude



Schematic diagram of Bhadra reservoir Project

Multi Objective Reservoir Operation Model

1. **Minimize**

Irrigation deficit (f_1):

$$SQDV = \sum_{t=1}^{12} \left(D_{l,t} - IR_{l,t}\right)^2 + \sum_{t=1}^{12} \left(D_{r,t} - IR_{r,t}\right)^2$$

2. **Maximize**

Hydropower production (f_2):

$$E = \sum_{t=1}^{12} (k_1 R_{l,t} H_{l,t} + k_2 R_{r,t} H_{r,t} + k_3 R_{b,t} H_{b,t})$$

Subject to constraints on

- **System dynamics**
- **Storage bounds**
- **Maximum power production limits**
- **Irrigation demands and**
- **Water quality requirements**

Constraints

Reservoir storage continuity constraints

for all t=1, 2,…,12

Storage bound constraints

$$S_{min} \le S_t \le S_{max}$$ for all t=1, 2,…,12

Turbine capacity Limits

$$p\,R_{1,t}\,H_{1,t} \le E_{1,max} \quad p\,R_{r,t}$$

$$H_{2,t} \le E_{2,max} p\,R_{3,t}\,H_{3,t} \le E_{3,max}$$ for all t=1, 2,…,12

Canal capacity limits

$$R_{1,t} \le C_{1,max}$$

$$R_{2,t} \le C_{2,max}$$ for all t=1, 2,…,12

Irrigation demands

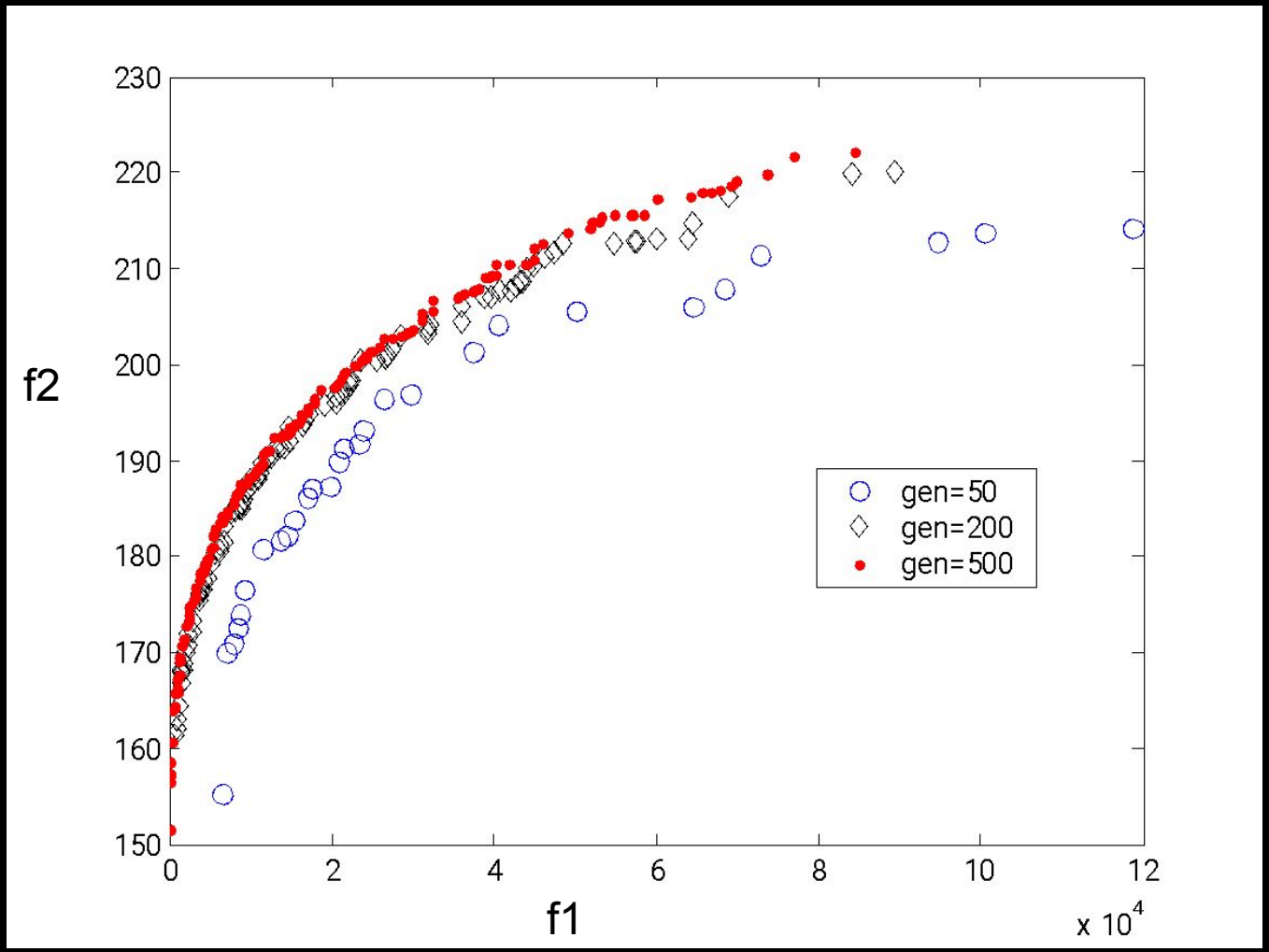
$$D1_{min,\,t} \le R_{1,t} \le D1_{max,\,t}$$

$$D2_{min,\,t} \le R_{2,t} \le D2_{max,\,t}$$ for all t=1, 2,…,NT

Water Quality Requirements

$$R_{3,t} \ge MDT_t$$ for all t=1, 2,…,NT

Pareto optimal solution for reservoir operation



Improvement in Pareto optimal front over the iterations.

f1 is annual squared irrigation deficit; f2 is hydropower generated MkWh

Model Application

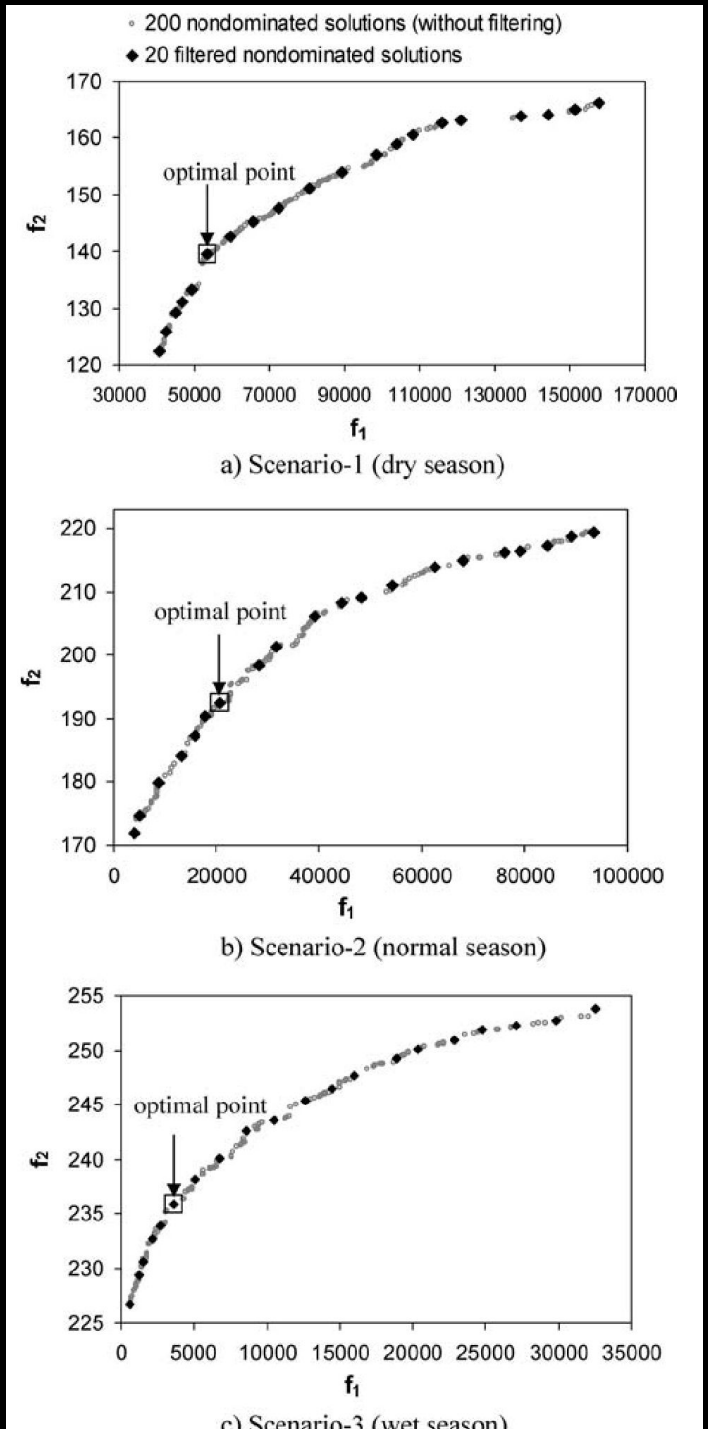
MOGA model is solved for three different inflow scenarios into the reservoir

Scenario 1: Mean monthly inflows – 0.5* SD
Scenario 2: Mean monthly inflows
Scenario 3: Mean monthly inflows + 0.5* SD
where SD = standard deviation of monthly inflows

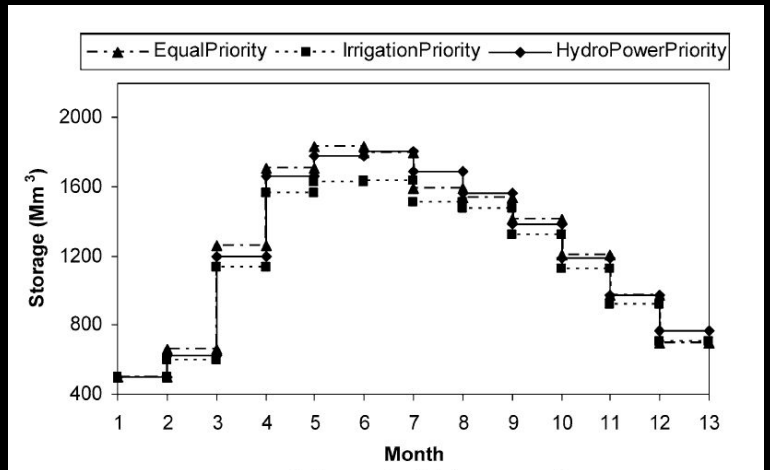
Pareto optimal front, showing the trade-off between irrigation (f_1) and hydropower (f_2) for different inflow scenarios.

f_1 = sum of squared irrigation deficits, $(Mm^3)^2$;

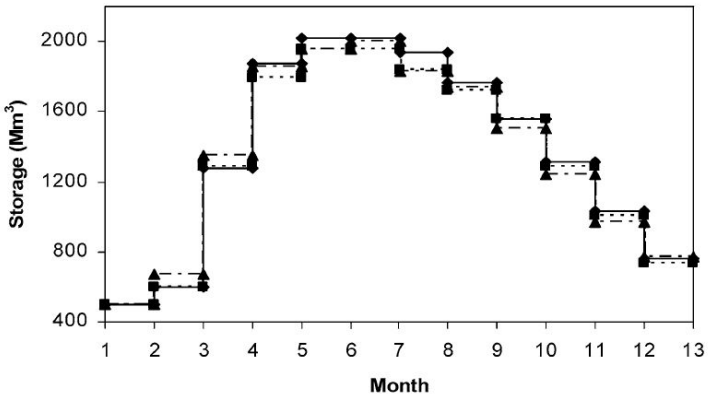
f_2 = hydropower generated, (MkWh)



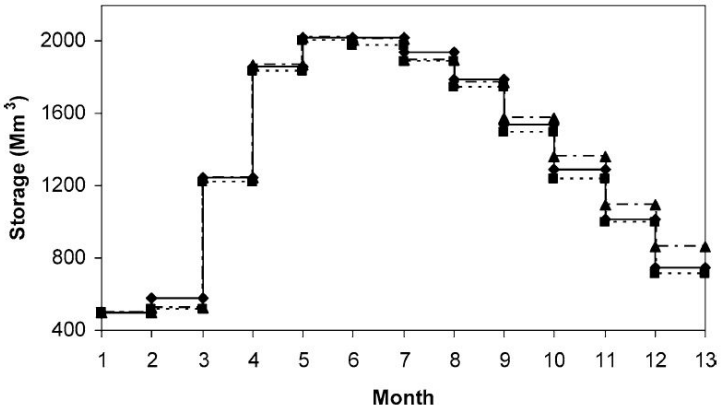
Reservoir operating policies for different inflow scenarios, showing the initial storages for different situations,
viz., equal priority case, irrigation only priority case and
hydropower only priority case.



a) Scenario 1 (dry season)

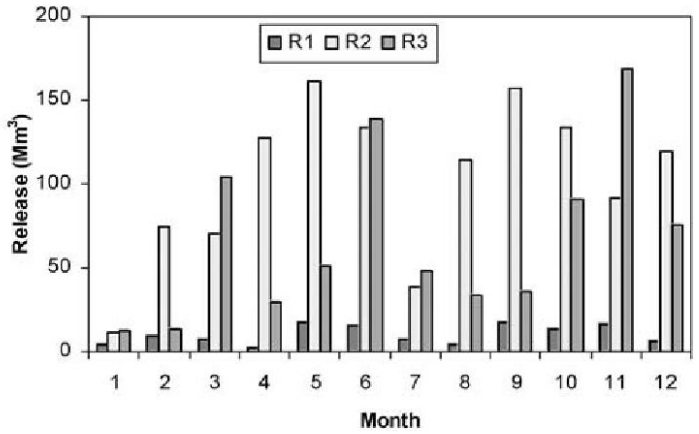


b) Scenario 2 (normal season)

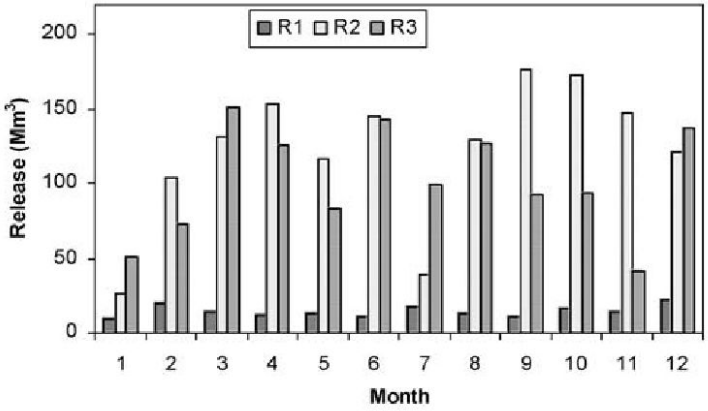


c) Scenario-3 (wet season)

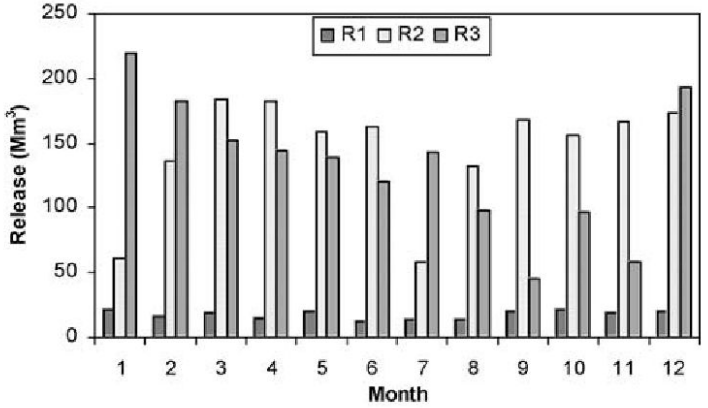
Optimal release policy obtained for equal priority case, showing releases in Mm^3 for
Left bank canal (R1),
Right bank canal (R2) and
River bed (R3)
for different inflow scenarios.



a) Scenario 1 (dry season)



b) Scenario-2 (normal season)



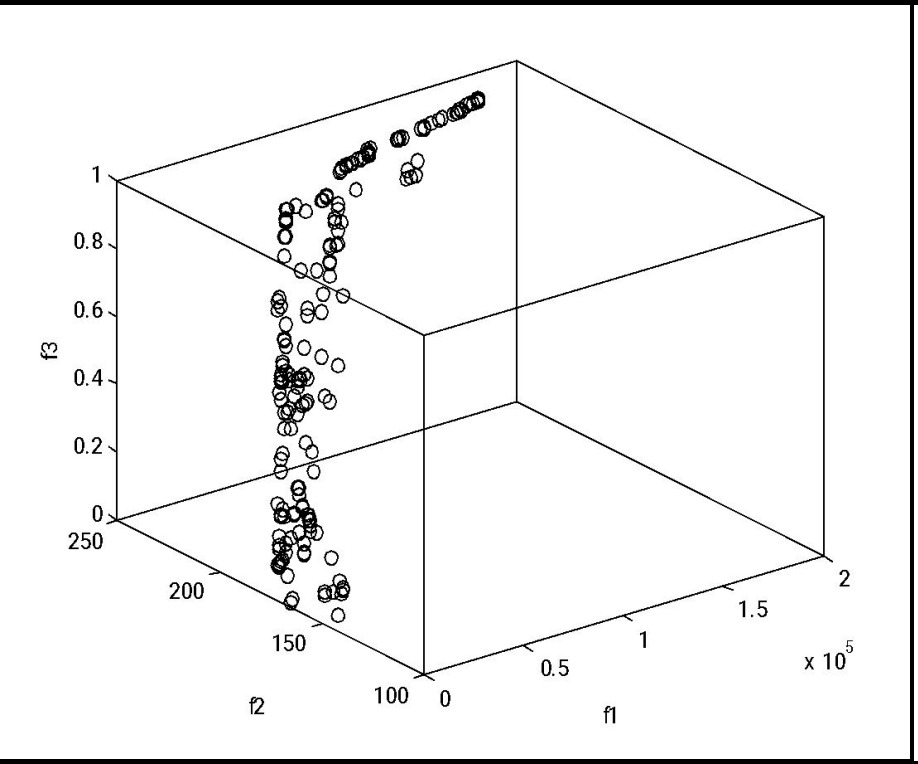
c) Scenario-3 (wet season)

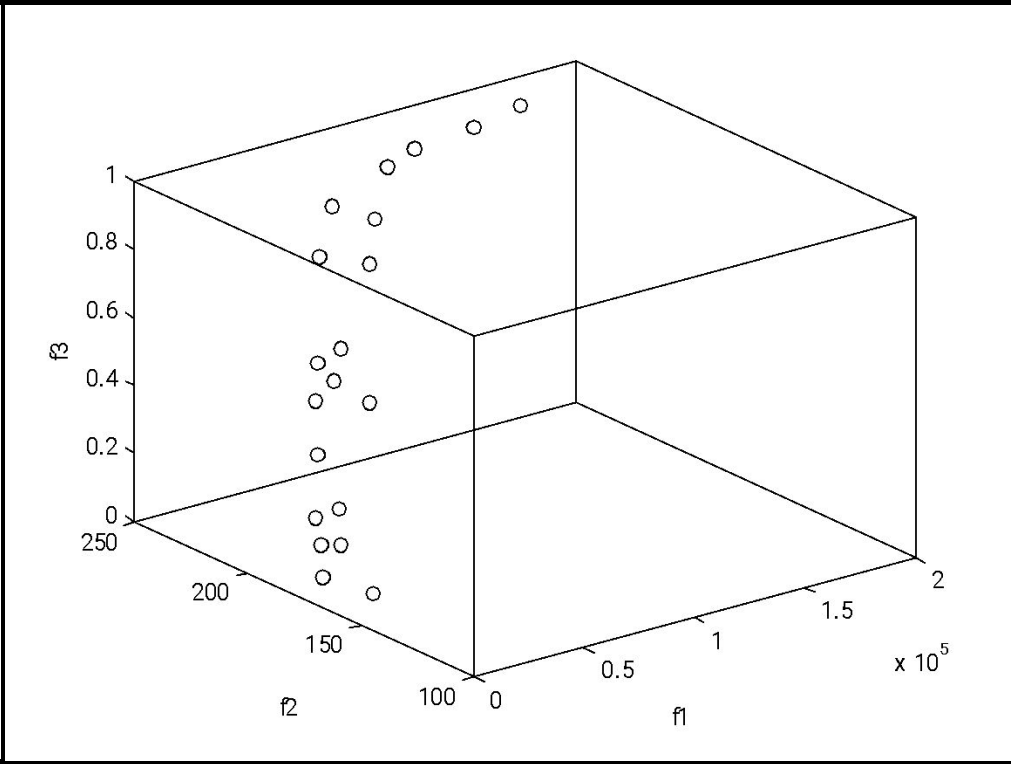
Multi-objective Reservoir Operation

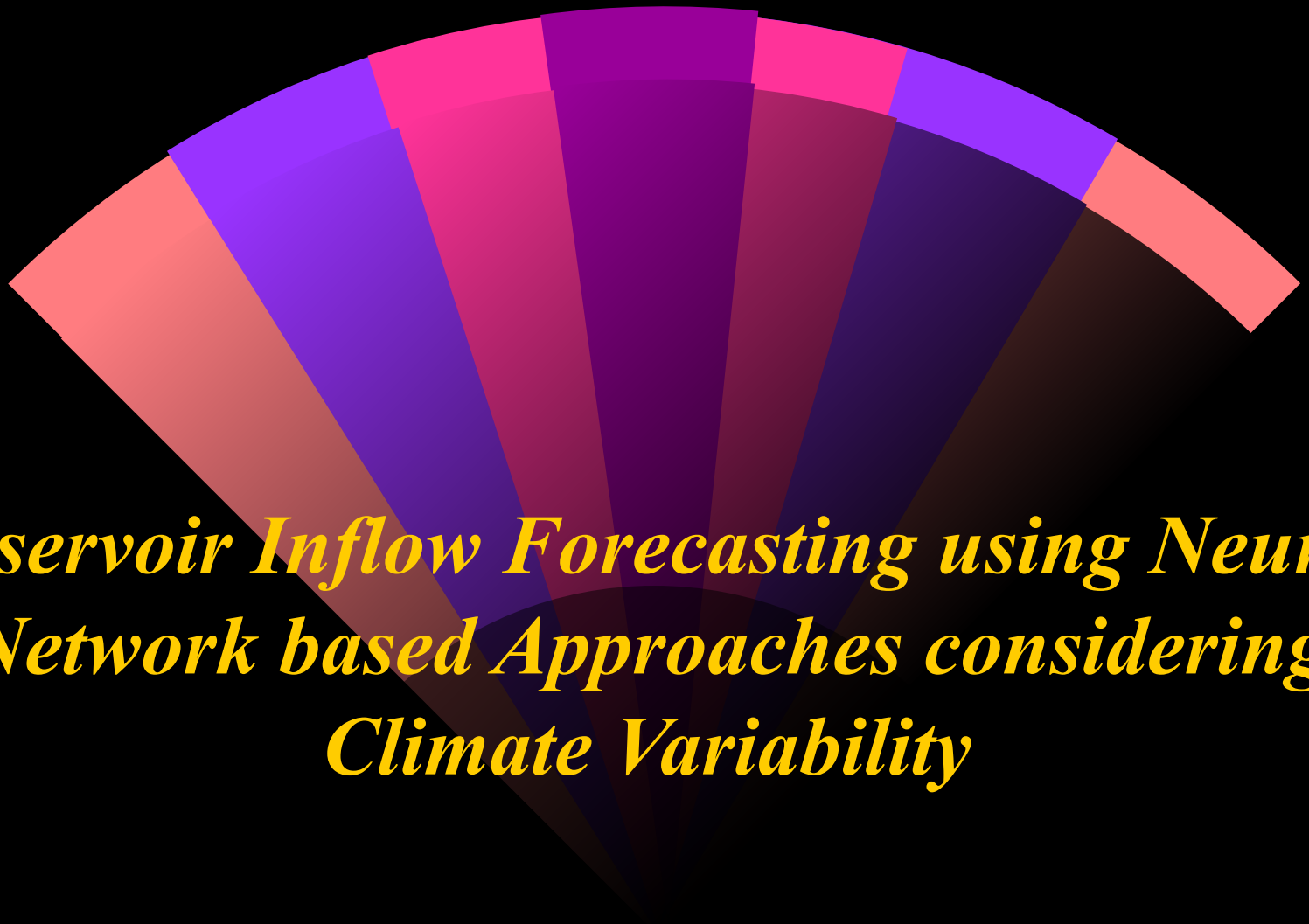
Generated Pareto optimal solutions (200)

f1 - irrigation deficit
f2 –hydropower
f3 – water quality

K-means clustering technique for reducing large set to representative Pareto optimal solutions





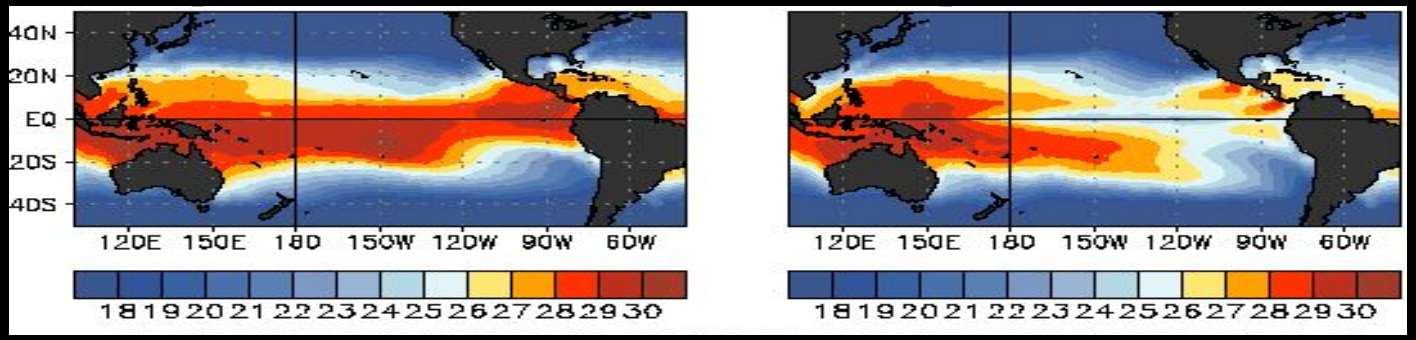


Reservoir Inflow Forecasting using Neural Network based Approaches considering Climate Variability

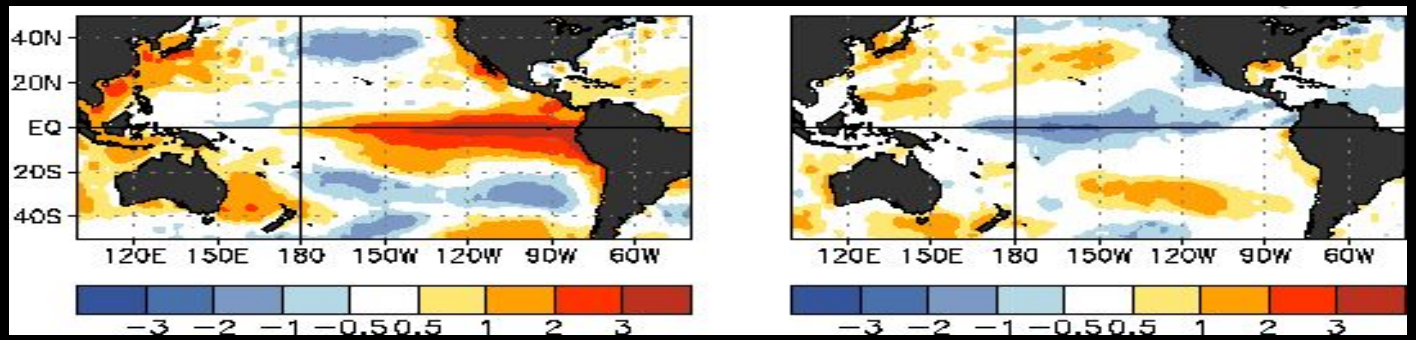
El Niño-Southern Oscillation (ENSO)

El Niño condition

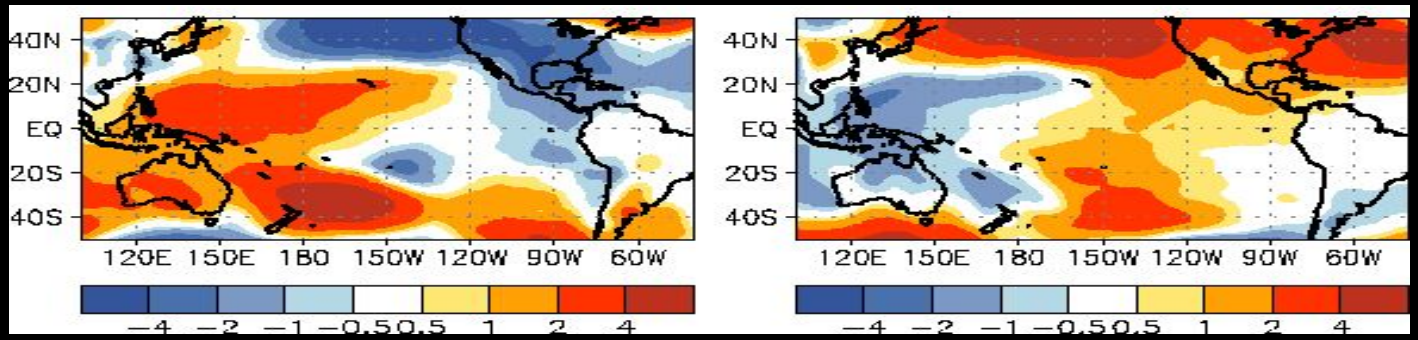
La Niña condition



SST (°C)



Anomalous SST (°C)



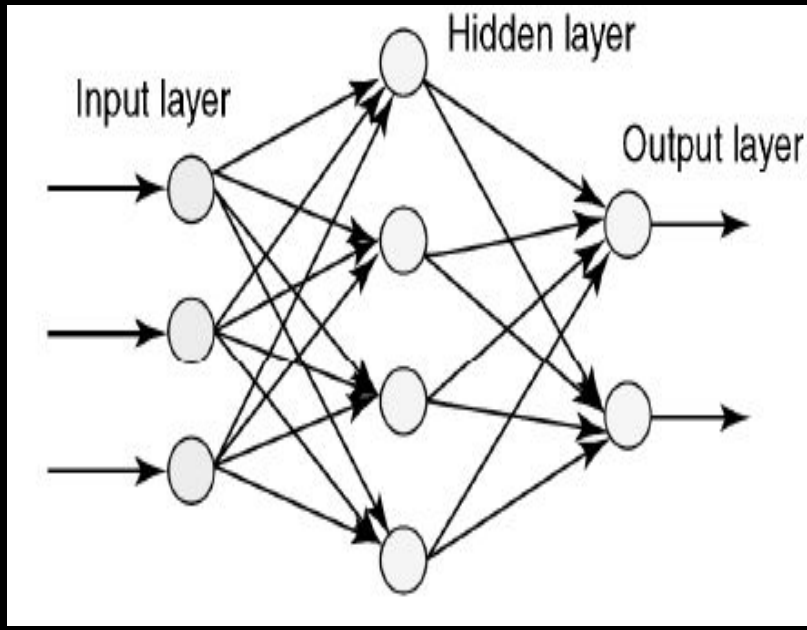
Anomalous pressure (mb)

Artificial Neural Networks (ANNs)

Features of standard ANNs:

-Supervised learning with batch mode training

-Back-propagation algorithm: gradient descent technique that minimizes the network error function.



Multilayered feed forward ANNs

-Activation function:
Tangent sigmoid function

-Performance Measure: MSE

PSO Neural Networks (PSO NN)

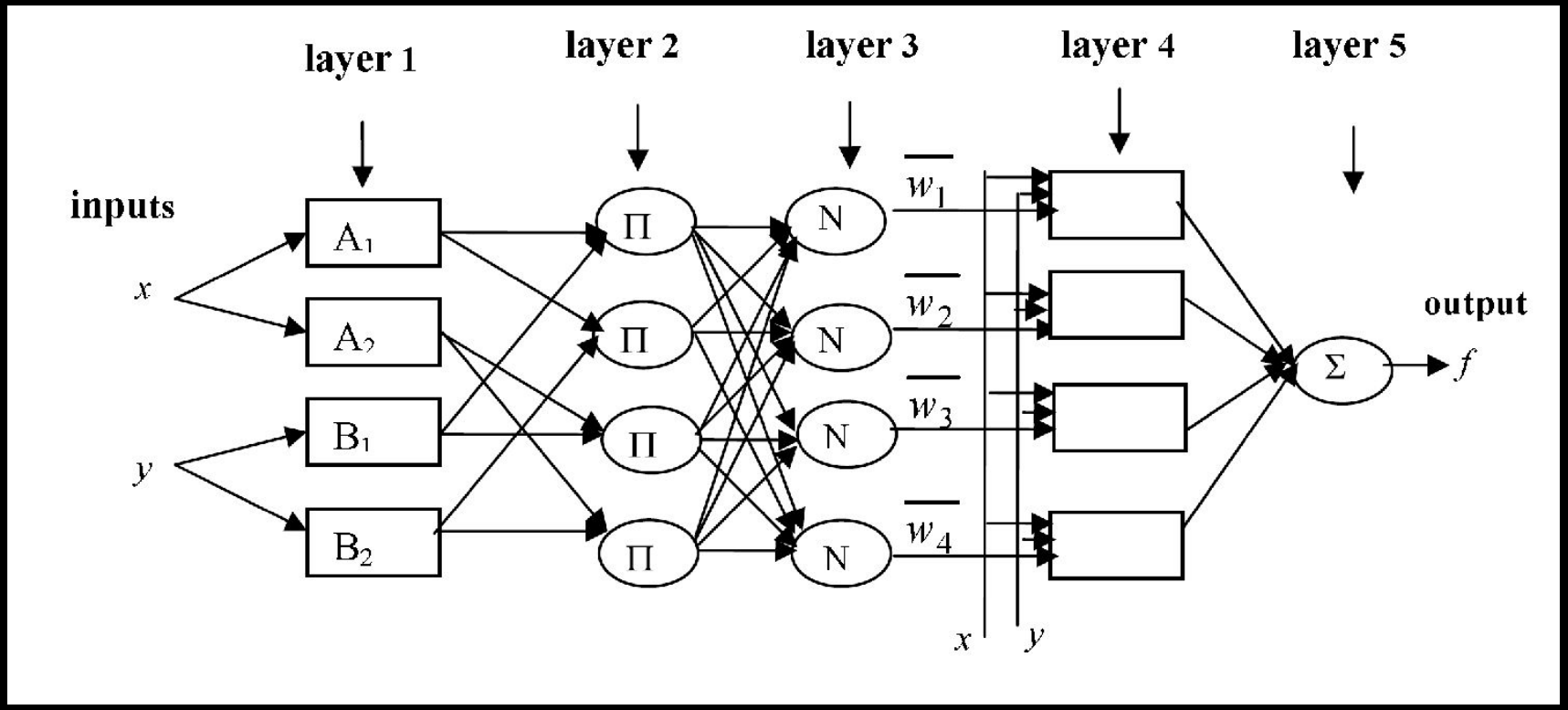
Here decision variables are weights & bias values of the network

Step 1. Initialize parameters
Step 2. Generate initial population
Step 3. Evaluate fitness function
Step 4. Perform EMPSO operations on decision variables
Step 4. Check for termination criteria

-Activation function:
Tangent sigmoid function

-Performance Measure: MSE

Adaptive Network Fuzzy Inference System (ANFIS)



Layer 1: Premise part (input nodes)

Layer 2: Implication (rule nodes)

Layer 3: Normalization (average nodes)

Layer 4: Consequent part (consequent nodes)

Layer 5: Output (output nodes)

ANFIS

Layer 1: Premise part (input nodes)

for i =1,2

for i =3,4

Layer 2: Implication (rule nodes)

Layer 3: Normalization (average nodes)

Layer 4: Consequent part (consequent nodes)

Layer 5: Output (output nodes)

Training ANFIS

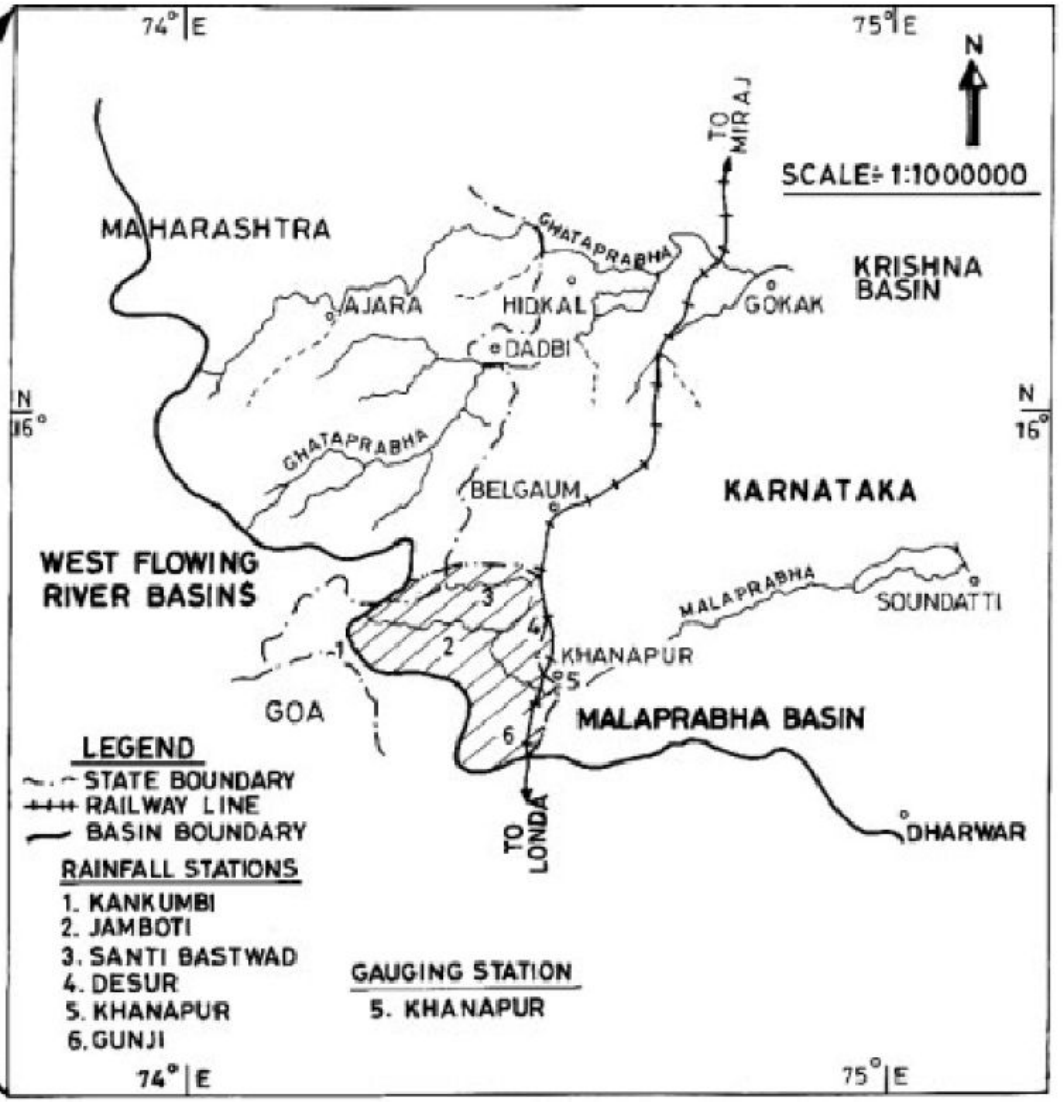
- In the first step, during forward move, the least square method identifies the consequent parameters, while the antecedent parameters (membership functions parameters) are assumed to be fixed for the current cycle through the training set

- The error between observed and trained model is calculated. Then error signals are propagated backward. Gradient descent method is used to update and fine tune the premise parameters, through minimizing the overall quadratic cost function, while the consequent parameters remain fixed

Case Study

Inflow Forecasts into Malaprabha Reservoir





Inflow Forecast Models

Annual Inflow Forecast Model

$$Q_t = f(Nino_{feb}, Nino_{mar}, Q_{t-2}, Q_{t-1})$$

Monthly Inflow Forecast Model

$$Q_t = f(Nino_{t-2}, Nino_{t-1}, Q_{t-2}, Q_{t-1})$$

Ten-daily inflow Forecast Model

$$Q_t = f(Rain_{t-1}, Q_{t-2}, Q_{t-1})$$

Criteria for the Models

- Periodicity
- Data Preprocessing
- Stopping Criteria

Performance Measures

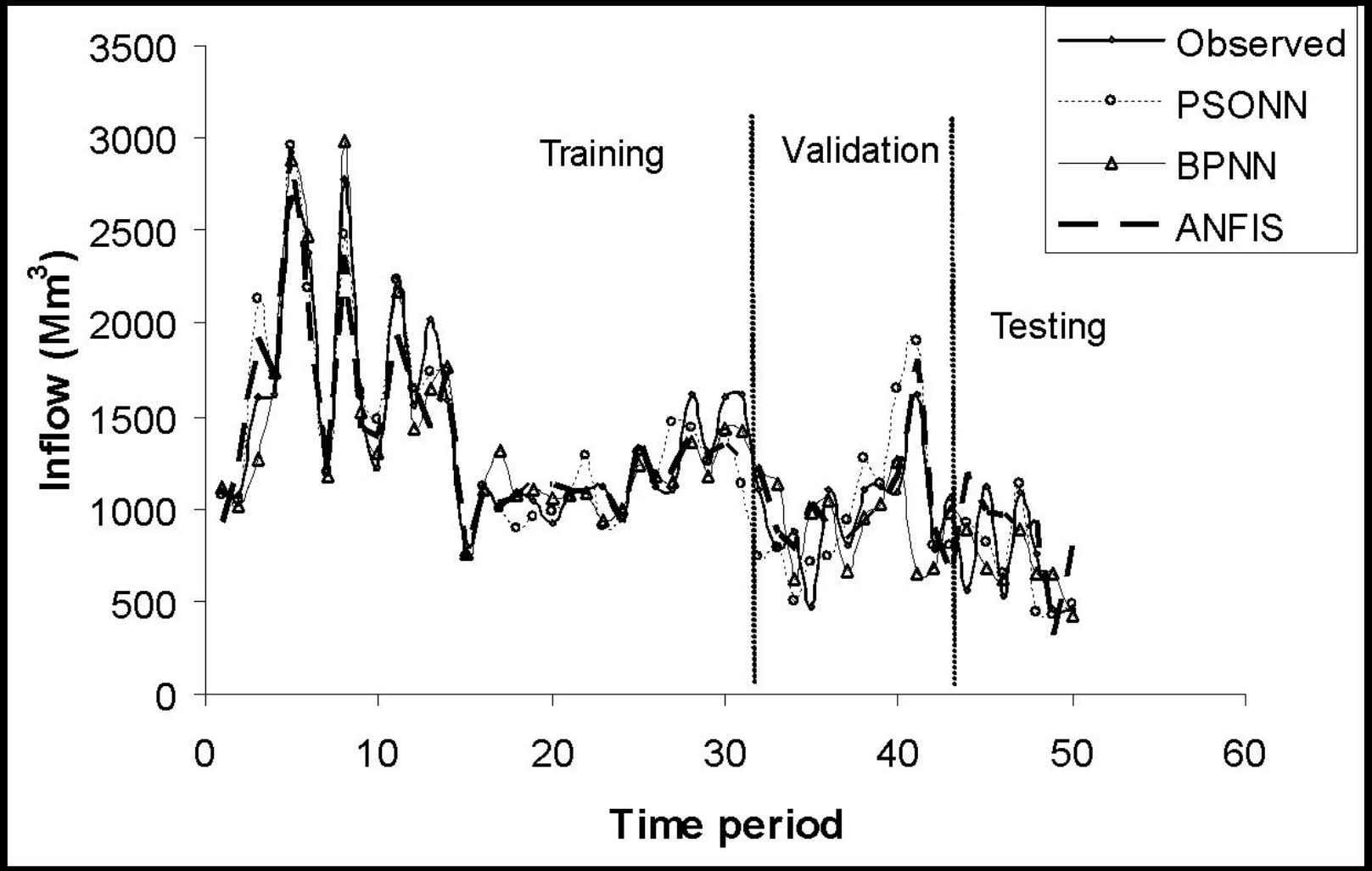
Root Mean Squared Error

Mean Absolute Error

Correlation Coefficient

Nash-Sutcliffe coefficient of efficiency

Model Results for Annual Inflow Forecasts



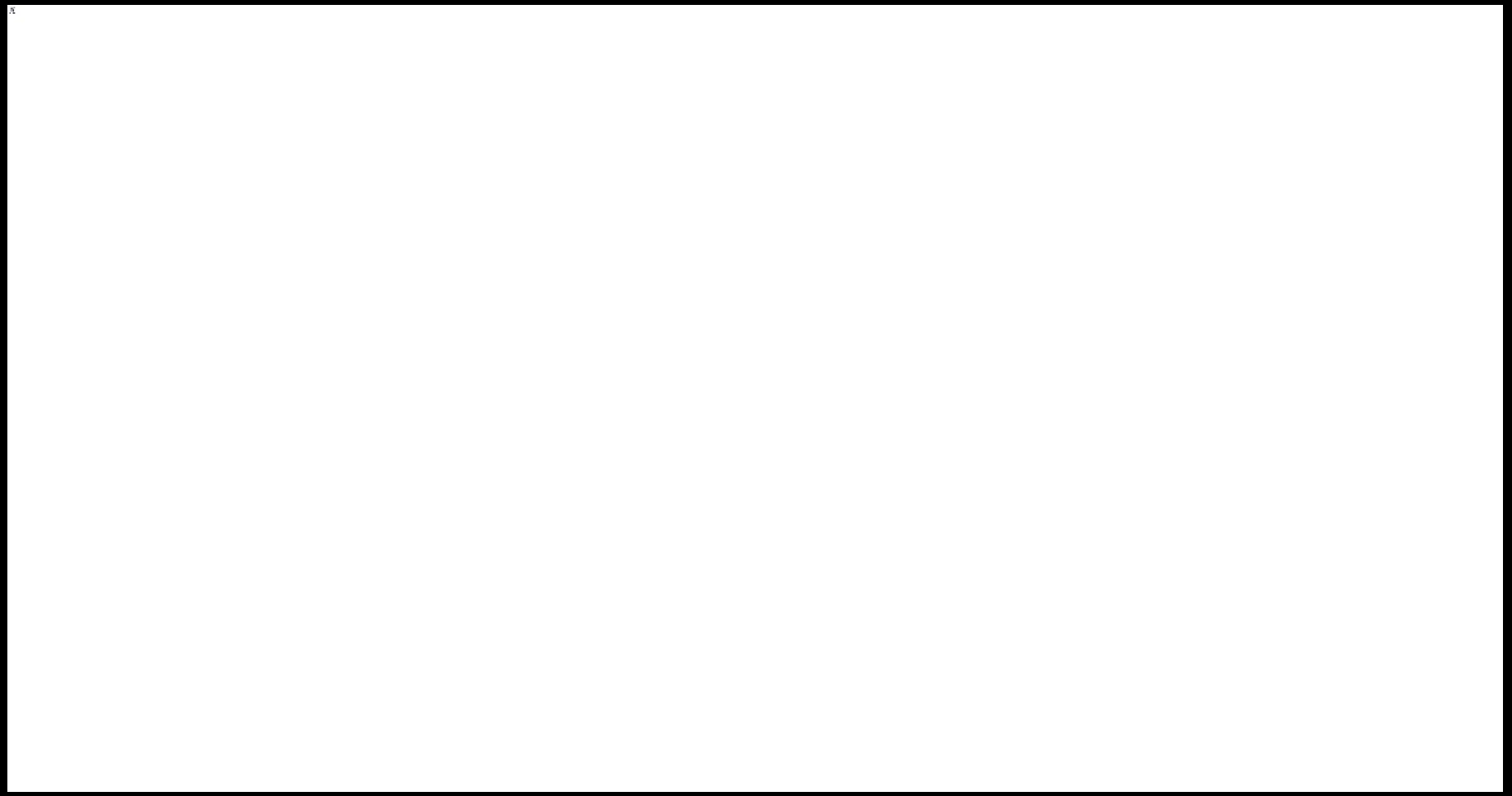
Monthly model forecasts for monsoon season



Monthly model forecasts for dry season



Performance Satistics



Real Time Reservoir Operation

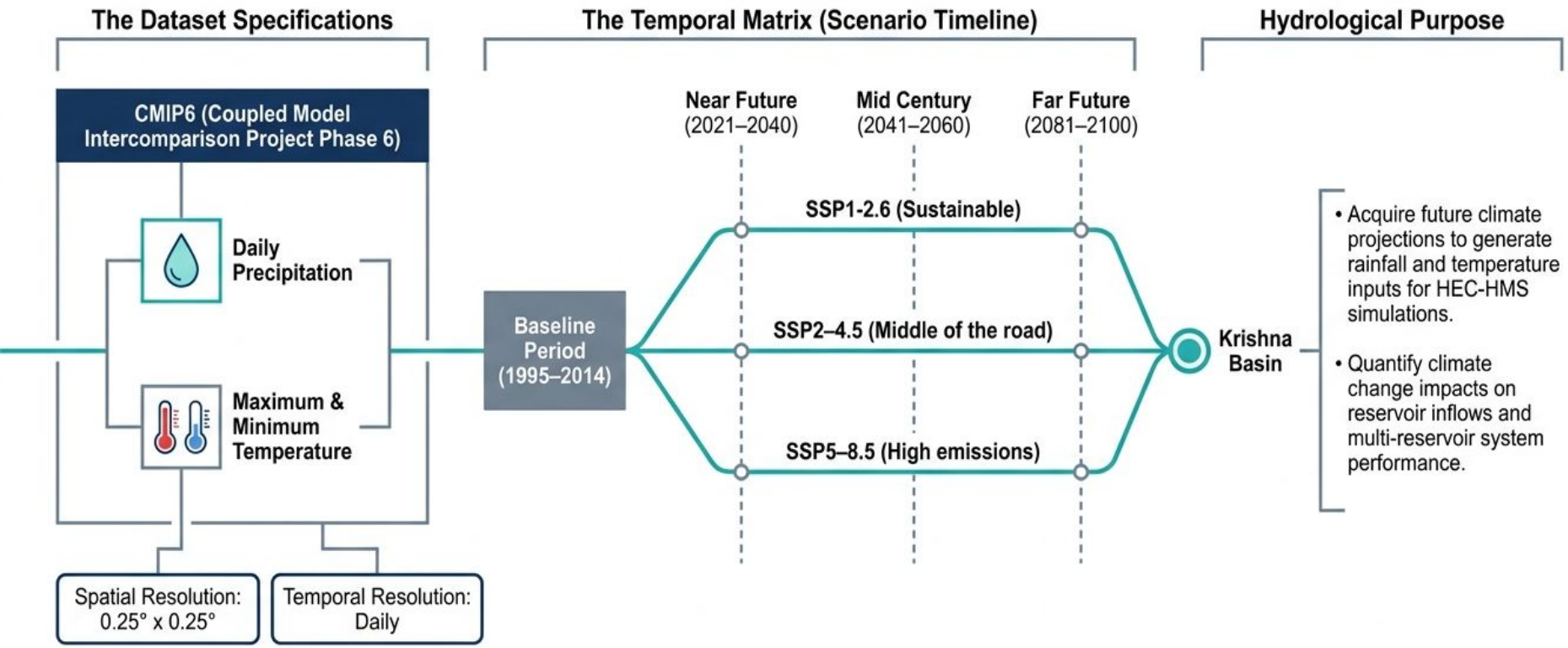
Forecast Annual Inflows at Start of Season

Decide Optimal Reservoir Operation using Multi-objective model

Implement Real Time Reservoir Operation

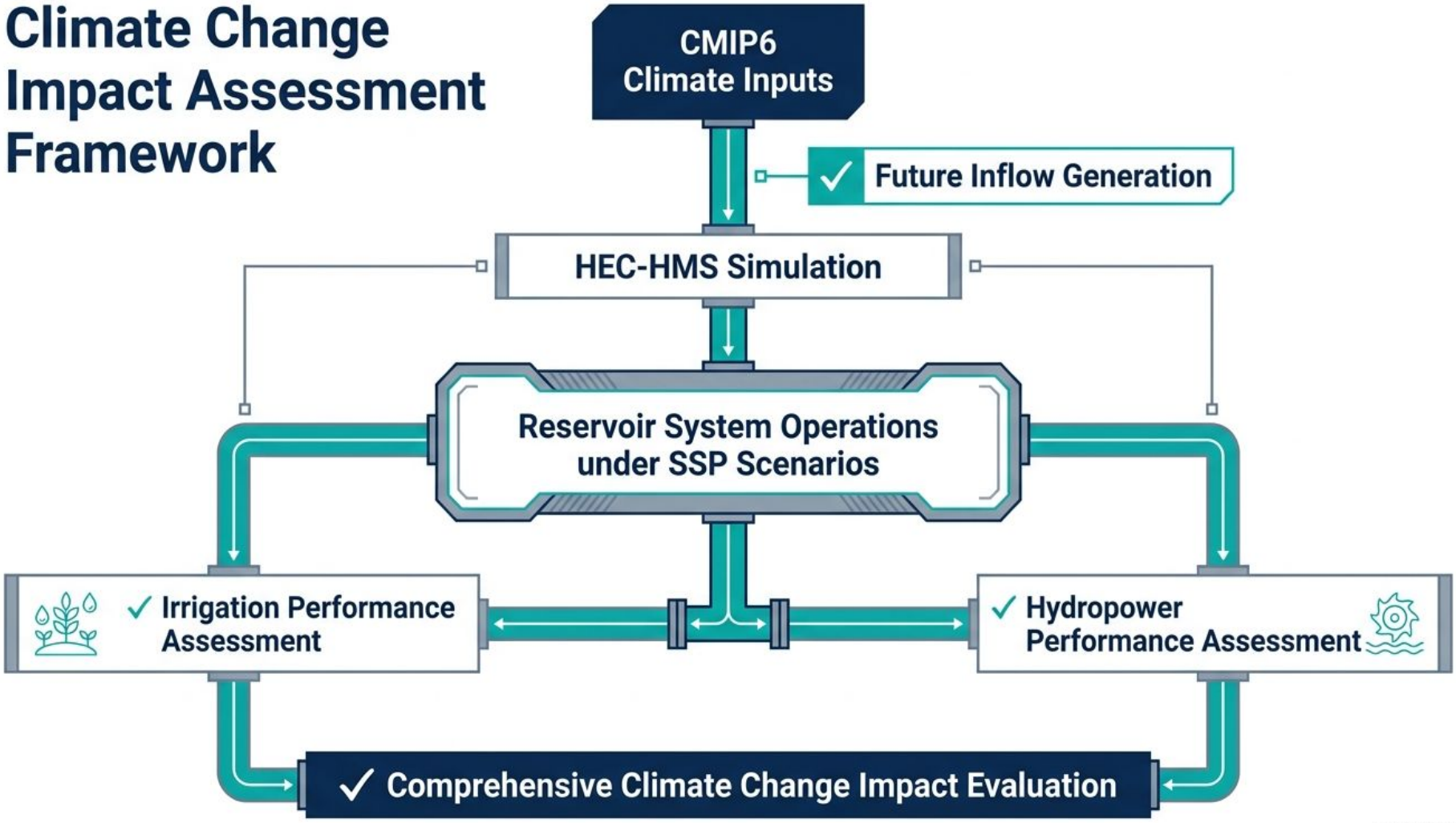
- Ten daily Inflow forecasts using PSO NN model
- Optimal reservoir operation Model
- EM PSO technique for optimization

CMIP6 Climate Data Architecture and Scenario Selection



CMIP6 - Coupled Model Intercomparison Project, Phase 6
SSPs - Shared Socioeconomic Pathways
SSP 4.5 - SSP with a target radiative forcing of 4.5 w/m²

Climate Change Impact Assessment Framework



Conclusions

- Genetic Algorithms are powerful non-linear optimization techniques
- They can be used for multi objective optimal operation of reservoir system
- Different forms of ANNs play a crucial role in inflow forecasting for real time reservoir operation

Future Scope

- CNN (1D & 2D)
- Transformer Networks
- AI for data mining
- PINN
- Explainable AI

- AI based Integrated Climate-Resilient Optimal Reservoir Operation Decision Support System

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Evolutionary algorithms, swarm intelligence methods, and their applications in water resources engineering: a state-of-the-art review

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[b] Department of Civil Engineering, Indian Institute of Science, Bangalore 560012, India

Komaragiri Srinivasa Raju · Dasika Nagesh Kumar

Artificial Intelligence and Machine Learning Techniques in Engineering and Management

The present book covers various facets of Artificial Intelligence, Machine Learning, and Fuzzy Logic. It includes a brief discussion on performance indicators, Classical and Advanced Machine Learning algorithms, Fuzzy logic-based modelling algorithms, Emerging Research Areas, including Blockchain, recent ML techniques, Evolutionary Algorithms, Large Language Model (LLM)-based Generative AI, the Internet of Things, Big Data, Decision Support Systems, Taguchi design of experiments, data augmentation, and Cross-Validation, and representative case studies. The appendix covers representative AI tools, data sources, books, and journals on AI. The present book can support undergraduate, postgraduate, and Ph.D. students in Artificial Intelligence, Generative Artificial Intelligence, Machine Learning, Data Sciences, Soft Computing, and Fuzzy Logic in Engineering and Management and allied fields. The proposed book has immense value in the interdisciplinary and cross-disciplinary context.

ISBN 978-981-96-2620-5

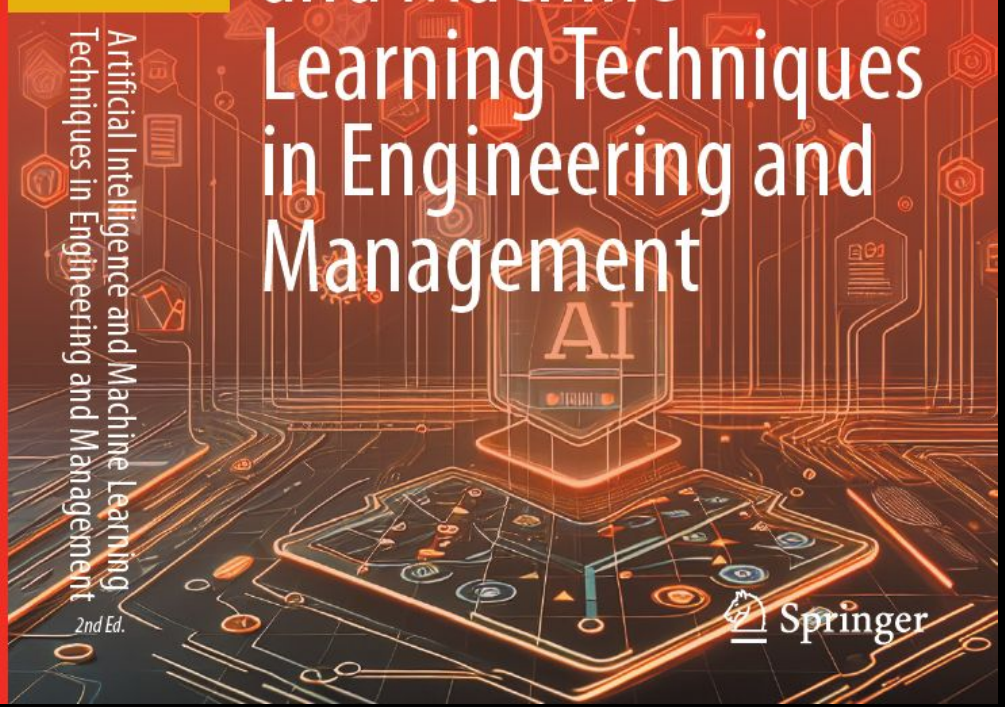
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Artificial Intelligence and Machine Learning Techniques in Engineering and Management 2nd Ed.

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Dasika Nagesh Kumar

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Thank you

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