Meta-Heuristic Optimization Algorithm: Effective Machine Learning Techniques for Concrete Structures

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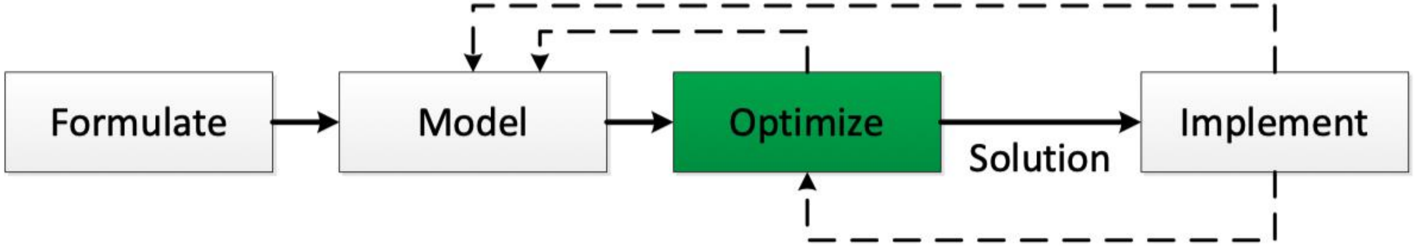
Optimization? Why?

DECISION MAKING

Decision making is everywhere

Due to complexity and to stay in competitive edge, decision making must be in a rational and optimal way

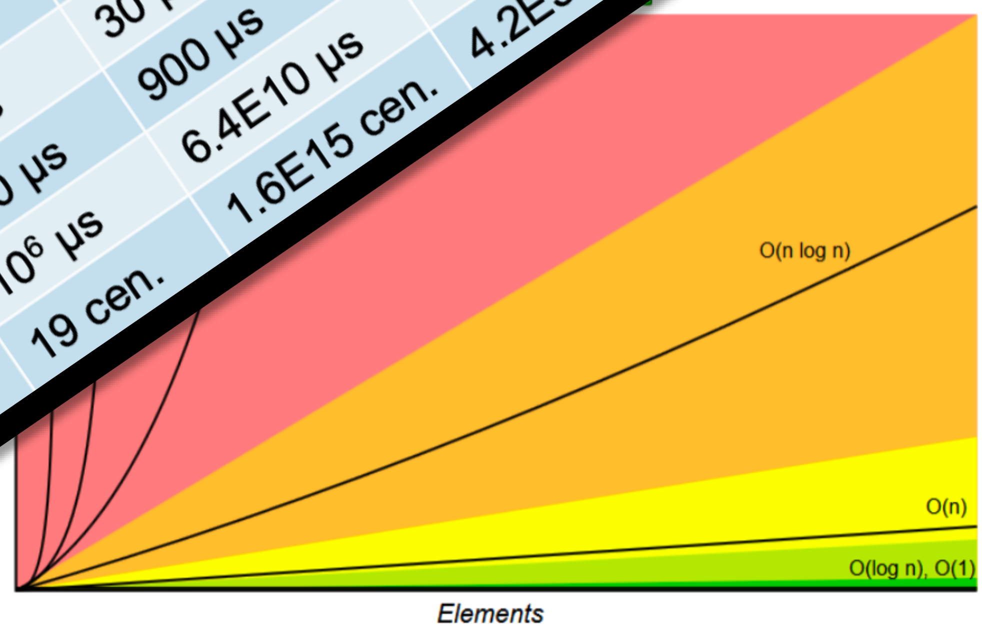
- Problem formulation,
- Problem modeling,
- Problem optimization and
- Solution implementation



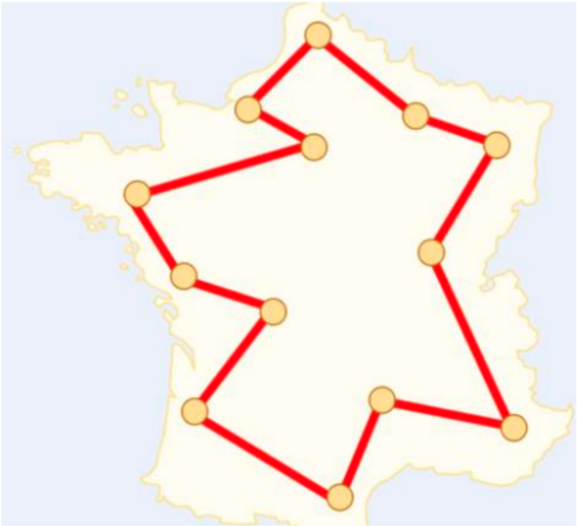
Complexity?

- Complexity of Algorithms
- An algorithm needs two important resources to s
- The *time complexity* of an algorithm is problem of size *n*
- *Logarithmic-time algorithm →*
- *Polynomial-time algorith*
- *Exponential-time alg*
- …

Complexity	Size *n*				
	10	20	30	40	50
$O(n)$	10 µs	20 µs	30 µs	40 µs	50 µs
$O(n^2)$	100 µs	400 µs	900 µs	1600 µs	2500 µs
$O(2^n)$	1000 µs	10^6 µs	6.4E10 µs	12.7 days	35.7 years
$O(n!)$	1.8E5 µs	19 cen.	1.6E15 cen.	4.2E30 cen.	…

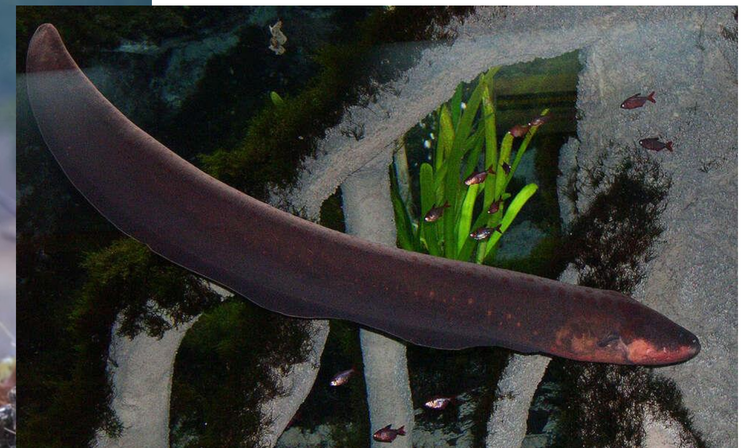


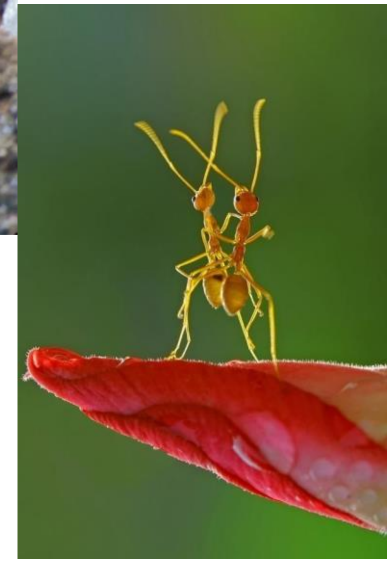
Traveling Salesman Problem



n	$\|\Omega\|$	CPU Time
5	12	12 μs
10	181400	0.18 s
20	6E16	19 cen.
30	4E30	1.4E15 cen.

- Data: n cities; Distance matrix $D=(d_{ij})$
- Problem: "*What is the shortest possible route that visits each city exactly once and returns to the origin city?*"
- Ω: Set of permutations of n elements
- $|\Omega| = \frac{(n-1)!}{2}$ for a symmetric problem
- Enumeration algorithm: O(n!)
  - Generate all possible tours
  - Calculate the length of tours
  - Find the tour with the minimum distance
- 1 μs for evaluating each tour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by Nima Khodadadi *, Ehsan Harati, Francisco De Caso and Antonio Nanni

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ORIGINAL ARTICLE

Check for updates

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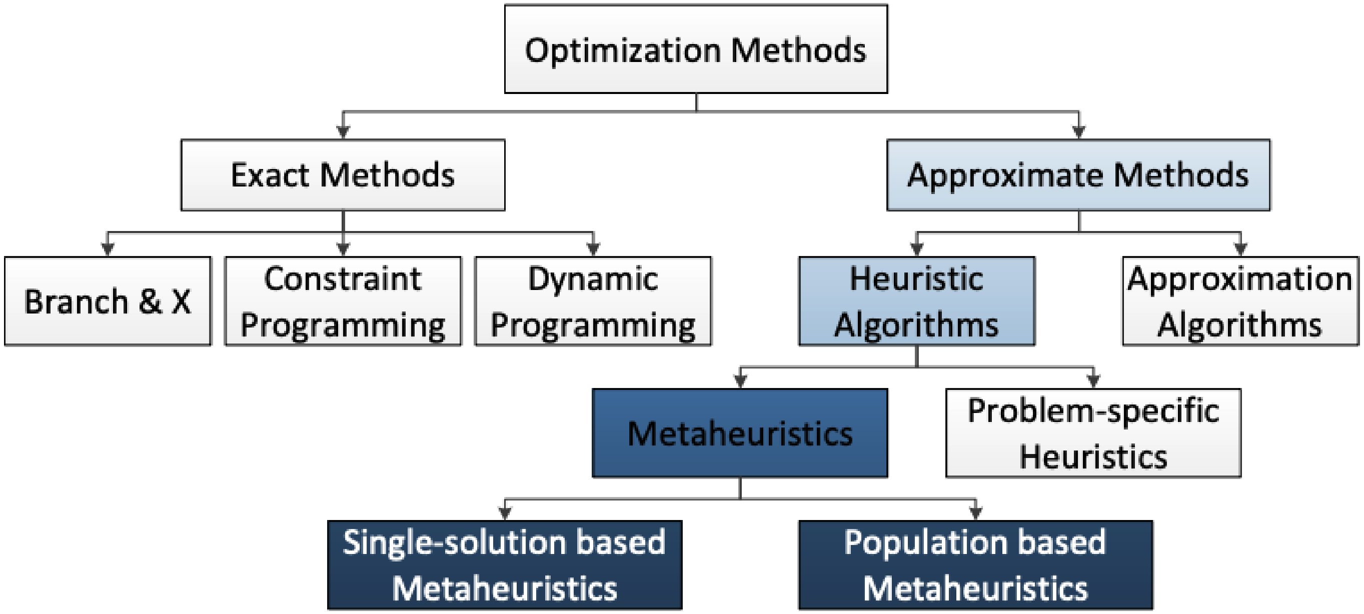
Optimization Methods

- Complete methods: find always a particular solution
- Exact methods: obtain optimal solutions and guarantee their optimality
- Approximate (or heuristic) methods: generate high quality solutions in a reasonable time for practical use, but there is no guarantee of finding a global optimal solution



Metaheuristic algorithm?

- *Heuristic* (from an old Greek word *heuriskein*):

  "*the art of discovering new strategies (rules) to solve problems*"

- *Meta* (a Greek word):

  "*upper level methodology*"

- *Metaheuristic*:

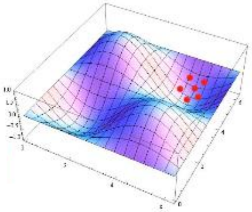
"*Upper level general methodologies that can be used as guiding strategies in designing underlying heuristics to solve specific optimization problems*"

- ***Exploration*** vs. ***Exploitation***
  - Exploration of the search space (*Diversification*) and Exploitation of the best solutions found (*Intensification*)
  - Good solutions are clue for promising regions

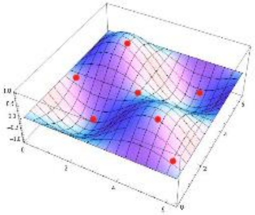
In intensification, the promising regions are explored more thoroughly in the hope to find better solutions

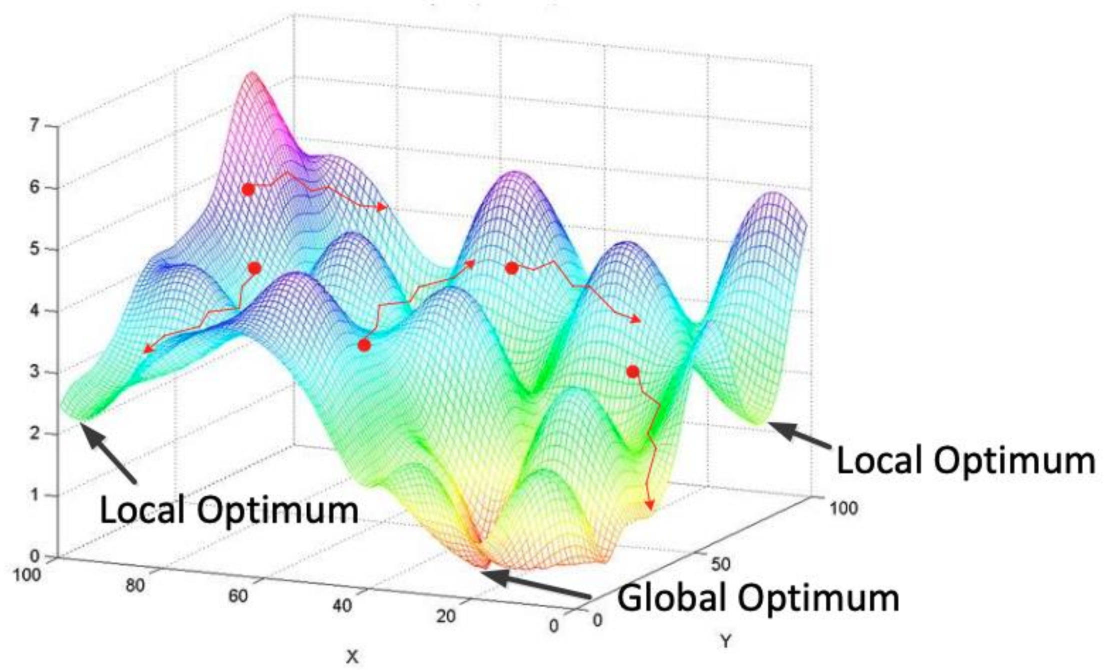
In diversification, non-explored regions must be visited to be sure that all regions of the search space are evenly explored and to avoid from local optima traps

Local Search	**Single-solution based Algorithms**	**Population-based Algorithms**	Random Search
Intensification	← →		Diversification



Best algorithms are good in both




Local Optimum
Local Optimum
Global Optimum
X
Y

- ***Nature inspired*** vs. ***Non-nature inspired***
  - *Biology*: Genetic Algorithm or Artificial Immune Systems
  - *Swarm Intelligence*: Ants or Bees Colony Optimization, Particle Swarm Optimization, Frog Leaping algorithm, …
  - *Physics*: Simulated Annealing Algorithm
  - *Social Behavior*: Imperialist Competitive Algorithm, Teacher Learning Algorithm, …

- ***Memory usage*** vs. ***Memoryless***
  - Local Search, GRASP, Simulated Annealing
  - Tabu Search: short-term and long-term memories

- ***Deterministic*** vs. ***Stochastic***
  - *Deterministic*: Optimization problem is solved by making deterministic decisions (e.g., LS & TS). Same initial solution will lead to the same final solution
  - *Stochastic*: Optimization problem is solved by some random rules (e.g., SA & GA). Different final solutions may be obtained from the same initial solution.

- ***Population-based*** vs. ***Single-solution based***
- ***Iterative*** vs. ***Greedy*** *(Constructive)*
  - Starting from a *complete solution* vs. starting from an *empty solution*

ACO

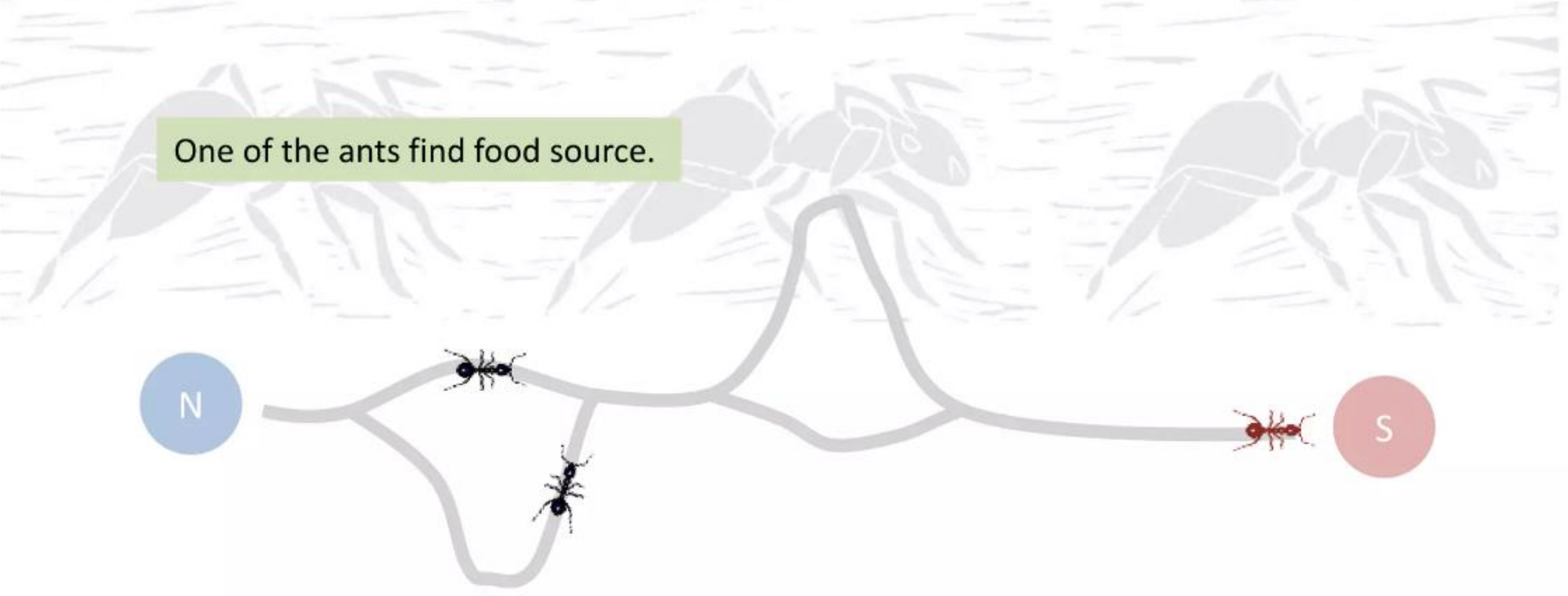
Ants are able, without using any spatial Information, to identify a sudden appearance of a food source around their nest, and to find the shortest available path to it.

Let us describe the algorithm:

A small amount of ants travel **randomly** around the nest.

ACO

Ants are able, without using any spatial Information, to identify a sudden appearance of a food source around their nest, and to find the shortest available path to it.



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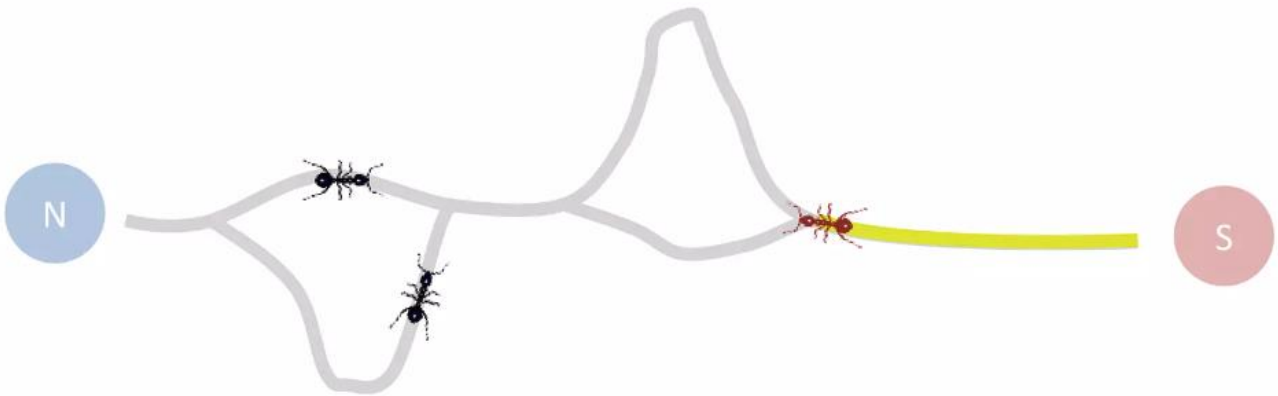
When ant finds food, it returns to the nest while **laying down pheromones trail**.



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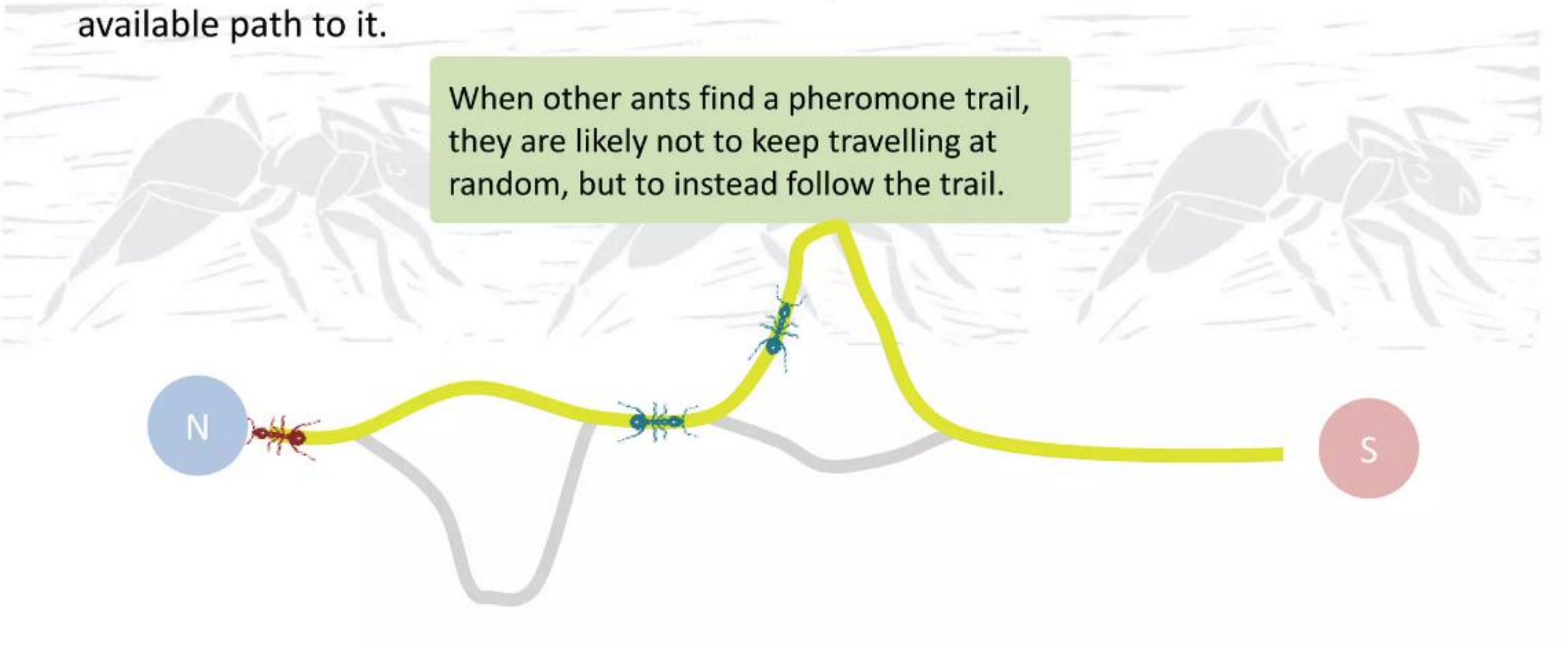

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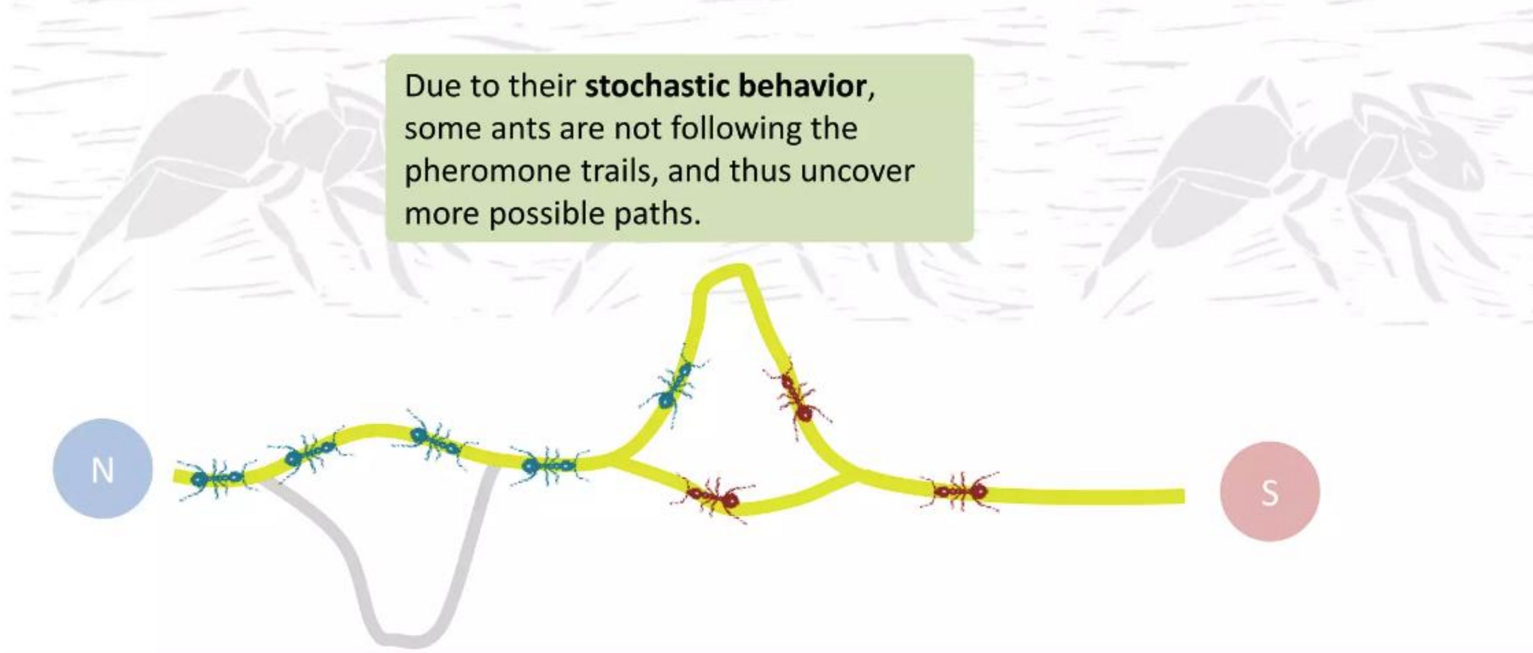

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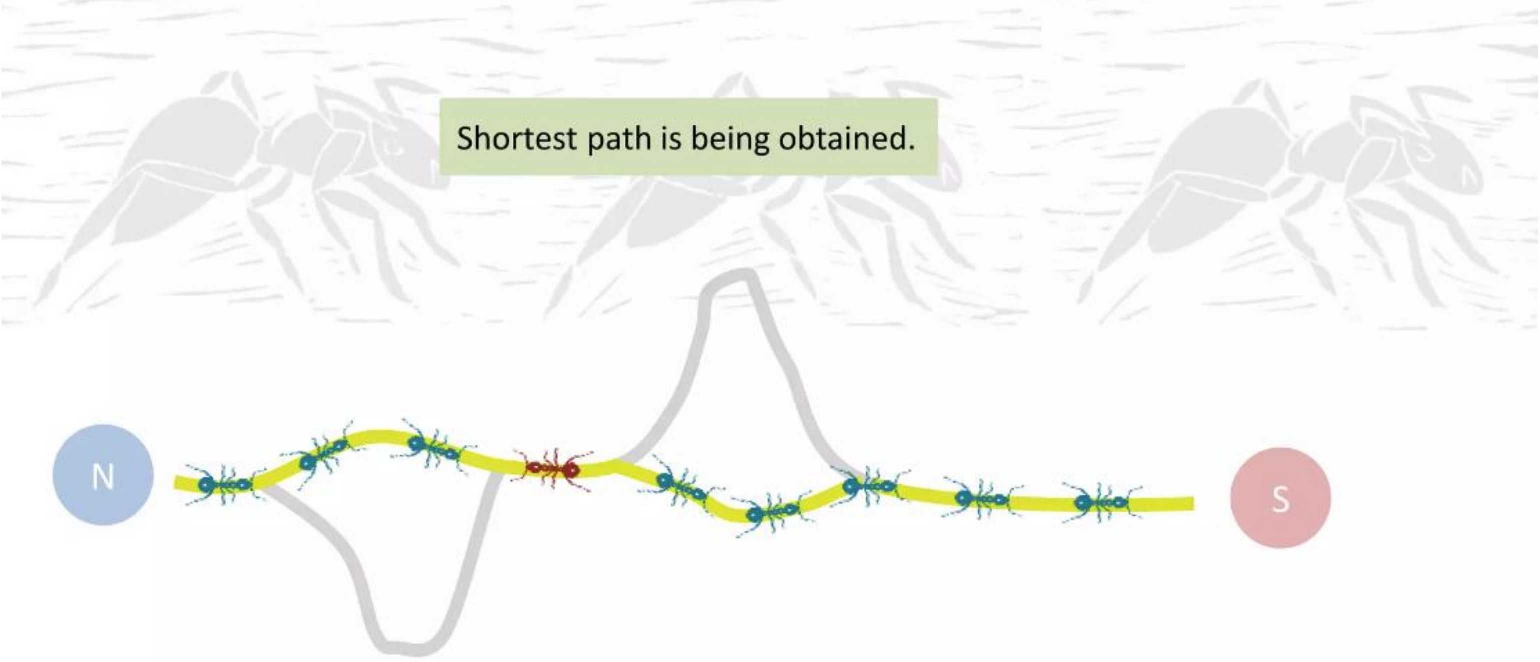

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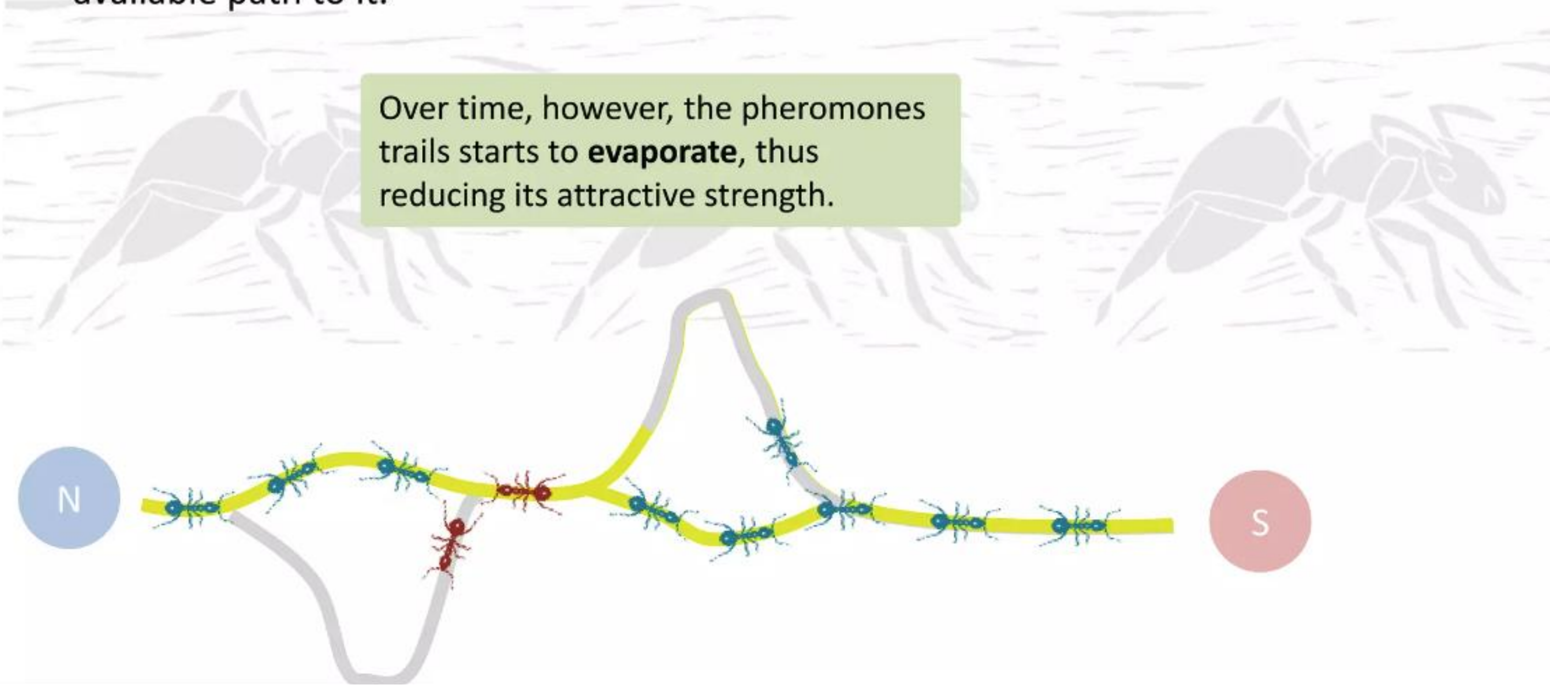
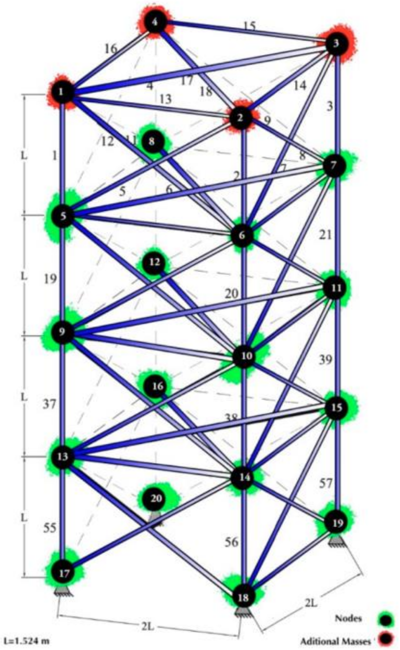
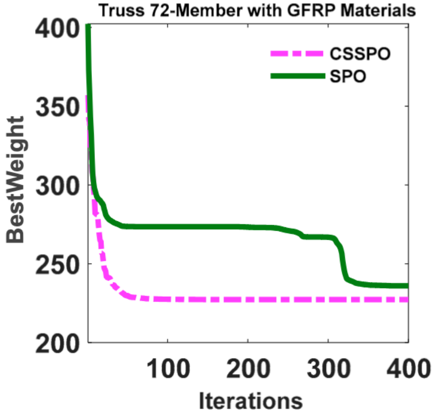
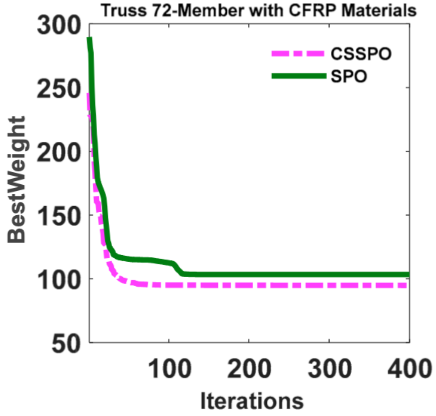


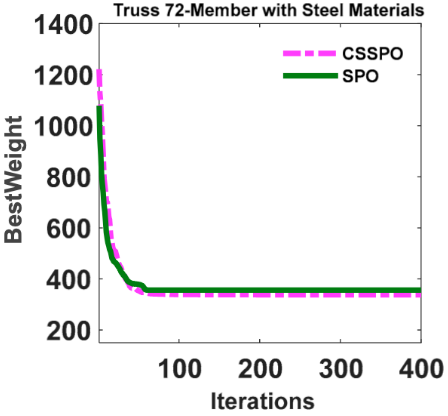
Cuckoo Search and SPO



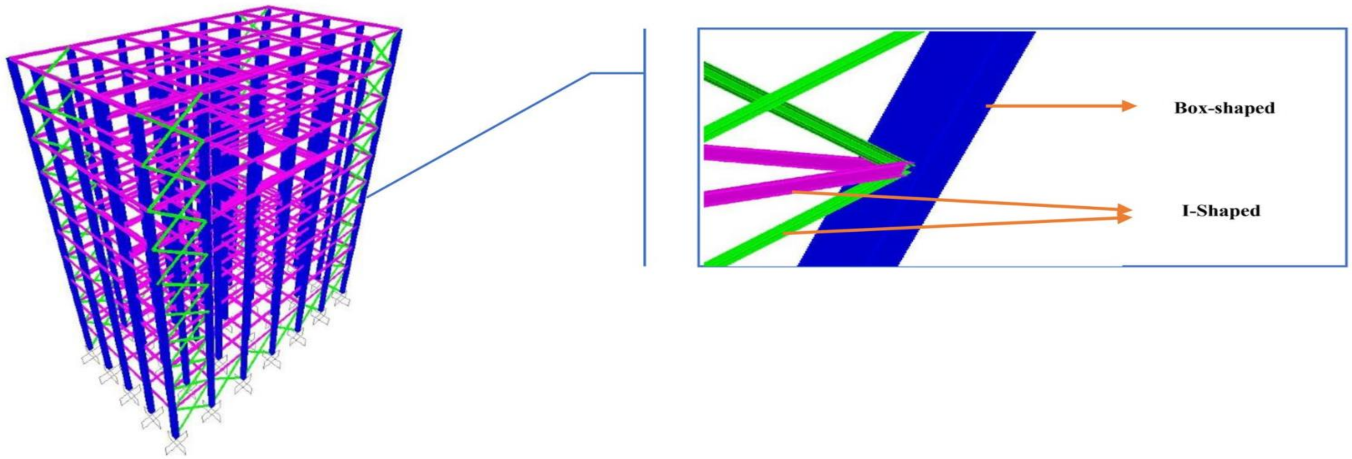
Materials	GFRP		CFRP		STEEL	
Member Group	SPO	CSSPO	SPO	CSSPO	SPO	CSSPO
1 (A_1-A_4) cm^2	13.3972	4.7702	1.4932	1.4932	1.4932	1.1560
2 (A_5-A_{12}) cm^2	9.4481	9.9981	3.4486	3.4486	3.4486	2.6751
3 (A_{13}-A_{16}) cm^2	0.6450	0.6450	0.6450	0.6450	0.6450	0.6450
4 (A_{17}-A_{18}) cm^2	0.6724	0.7181	0.6450	0.6450	0.6450	0.6450
5 (A_{19}-A_{22}) cm^2	12.0096	10.5253	3.4111	3.4111	3.4111	2.6876
6 (A_{23}-A_{30}) cm^2	11.3740	10.0562	3.5042	3.5042	3.5042	2.6555
7 (A_{31}-A_{34}) cm^2	0.6450	0.6450	0.6450	0.6450	0.6450	0.6450
8 (A_{35}-A_{36}) cm^2	0.6450	0.6450	0.6450	0.6450	0.6450	0.6453
9 (A_{37}-A_{40}) cm^2	13.6289	16.9763	5.7274	5.7274	5.7274	4.2783
10 (A_{41}-A_{48}) cm^2	8.6208	10.0865	3.5086	3.5086	3.5086	2.6824
11 (A_{49}-A_{52}) cm^2	0.6450	0.6450	0.6450	0.6450	0.6450	0.6450
12 (A_{53}-A_{54}) cm^2	0.6450	0.6450	0.6450	0.6450	0.6450	0.6452
13 (A_{55}-A_{58}) cm^2	20.0000	20.0000	7.3112	7.3112	7.3112	5.6892
14 (A_{59}-A_{66}) cm^2	11.2354	9.9604	3.4397	3.4397	3.4397	2.7112
15 (A_{67}-A_{70}) cm^2	0.6450	0.6450	0.6450	0.6450	0.6450	0.6450
16 (A_{71}-A_{72}) cm^2	0.6450	0.6450	0.6450	0.6450	0.6450	0.6450
Best weight (kg)	236.0334	227.2641	103.4361	94.8585	356.0184	337.7553
Average weight (kg)	268.0583	227.3044	129.3833	94.8953	472.1857	337.8333
Standard deviation	23.0932	0.0311	18.6853	0.0271	65.8768	0.0600
No. Analyses	19,100	6900	6800	4900	4150	4050

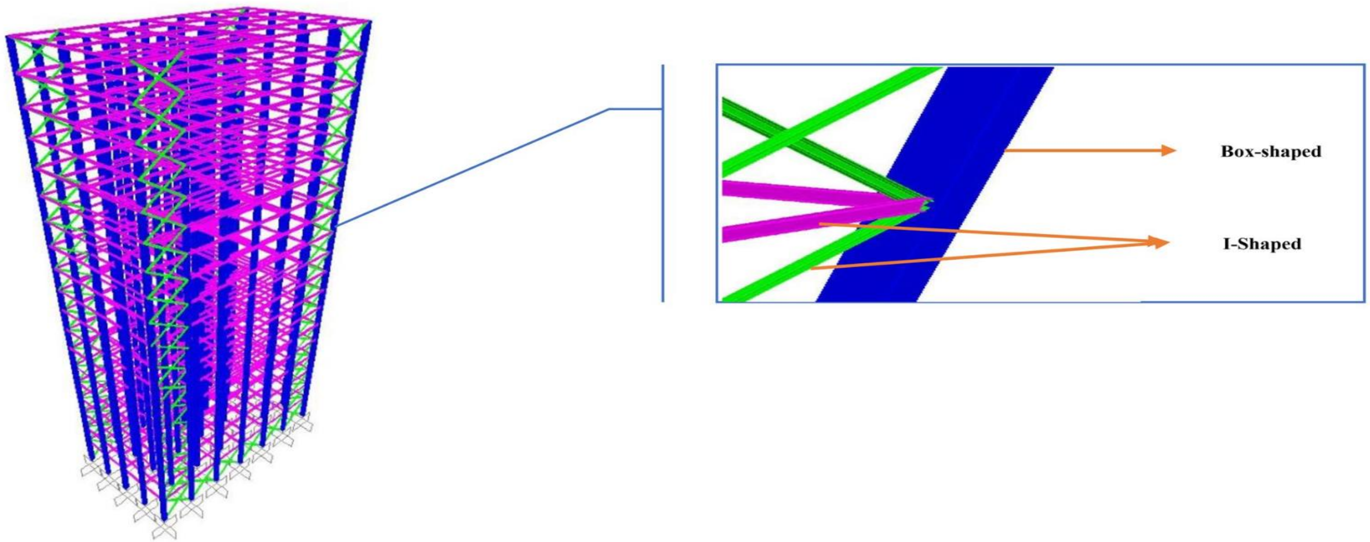






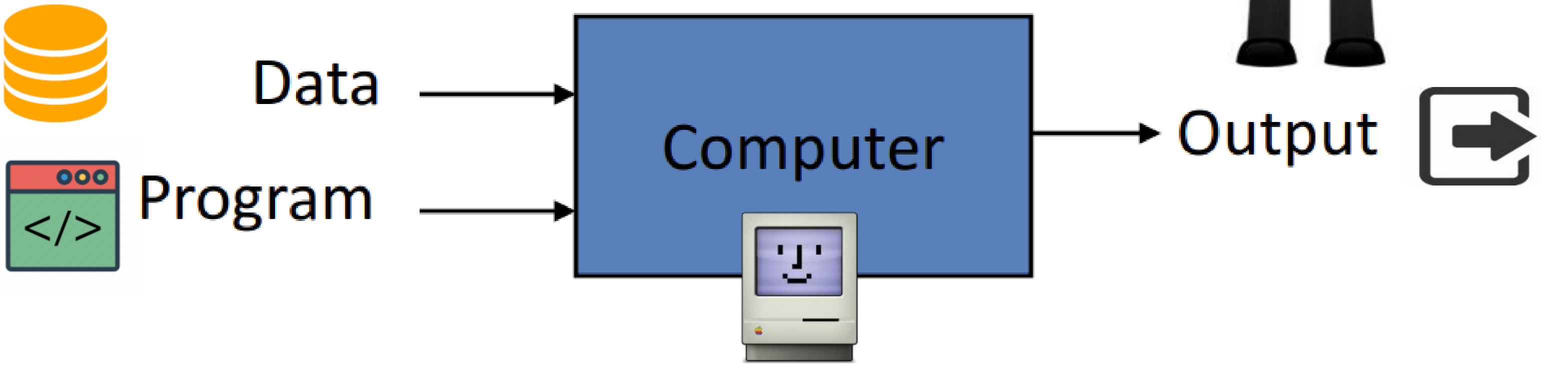
SPO



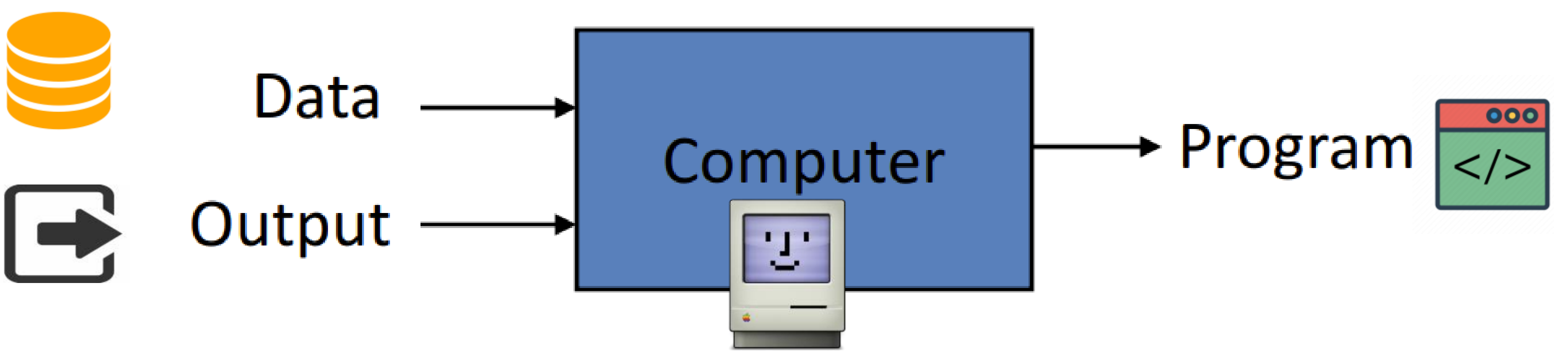


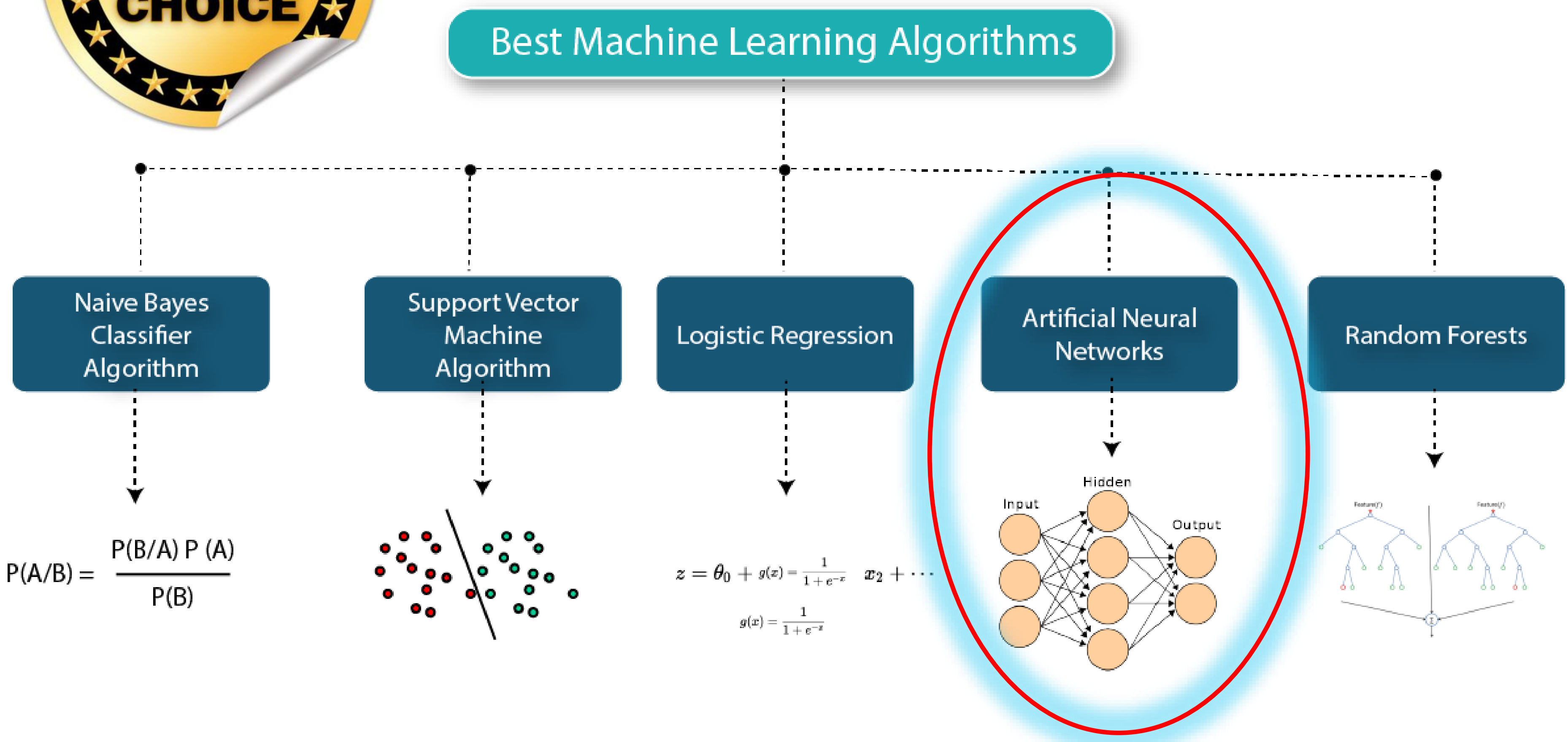
ML

Traditional Programming



Machine Learning





Using Metaheuristic Algorithm

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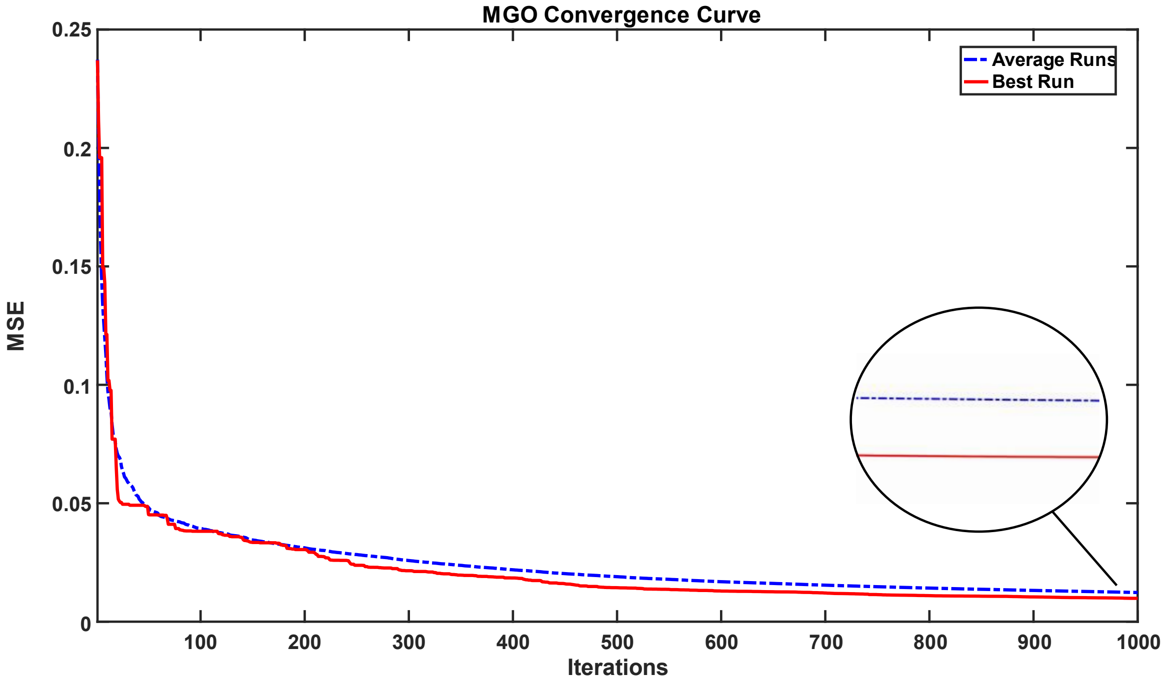
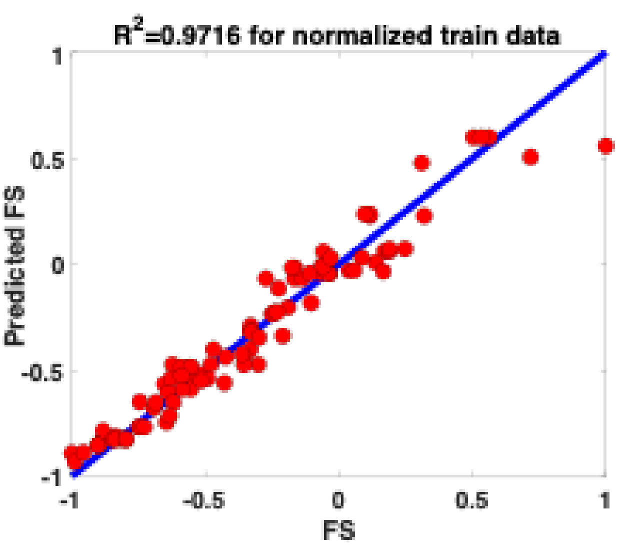
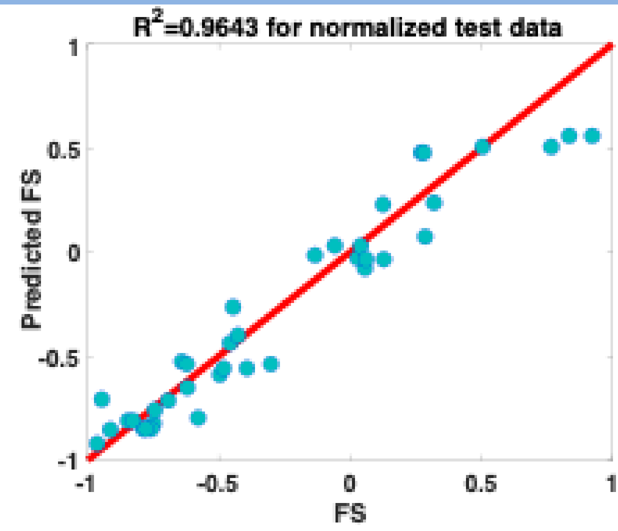
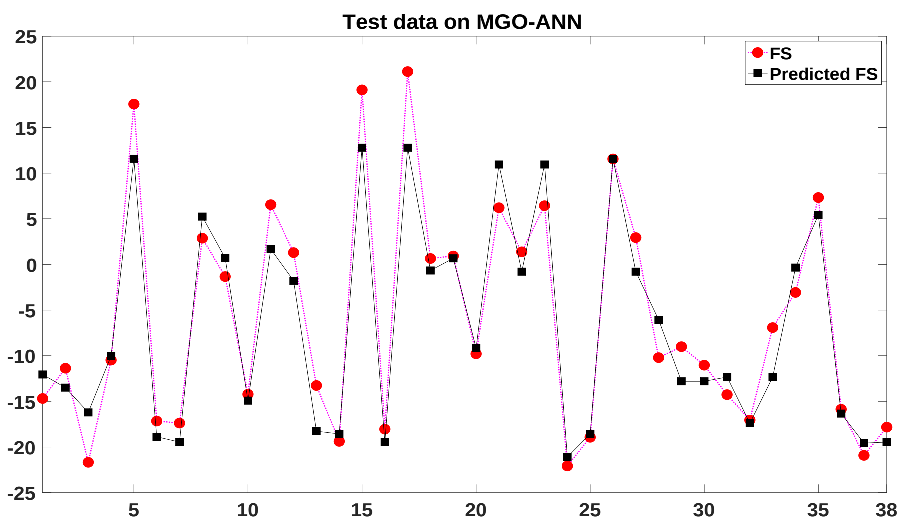
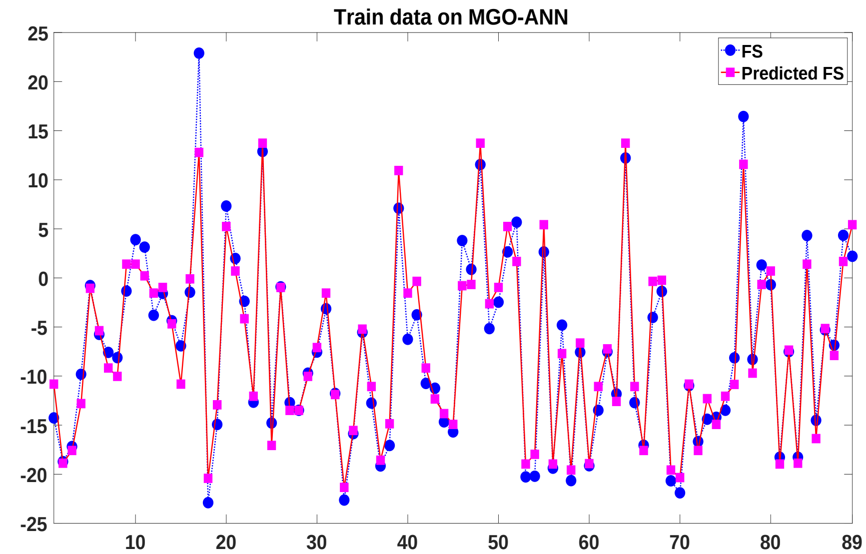
Predicting the flexural strength of 3D printed fiber-reinforced concrete (3DP-FRC) using efficient training of artificial neural networks with the meta-heuristic algorithm




R2=0.9716 for normalized train data
Predicted FS
FS


R2=0.9643 for normalized test data
Predicted FS
FS


Test data on MGO-ANN
FS
Predicted FS


Train data on MGO-ANN
FS
Predicted FS

GUI

flexural strength 3DP-FRC

Ordinary Portland cement (OPC)	655
Sand (S)	246
Water/Binder Ratio (W/b)	0.2636
Fly Ash (FA)	604
Ground Slag (GS)	0
Silica Fume (SF)	118
Superplasticizer (SP)	3.5
Hydroxypropyl methylcellulose (HPMC)	0
Water (W)	363
Fiber Volume fraction (Fvolf)	0.01
Aspect Ratio of Fiber (Lf/Df)	480
Diameter of Fiber (Df)	25
Length of Fiber (Lf)	12

Loading Direction (LD) ○ *X* ○ *Y* ◉ *Z*

Fiber Type (Ftype)

◉ *Polyethylene* ○ *Steel* ○ *Polyvinyl Alcohol* ○ *Polypropylene* ○ *Basalt*

Click to Predict Flexural Strength (MPa) — 15.60

Predicting the flexural strength of 3D printed fiber-reinforced concrete (3DP-FRC) using MGO-ANN

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