

CONSTRUCTION SCHEDULE OPTIMIZATION

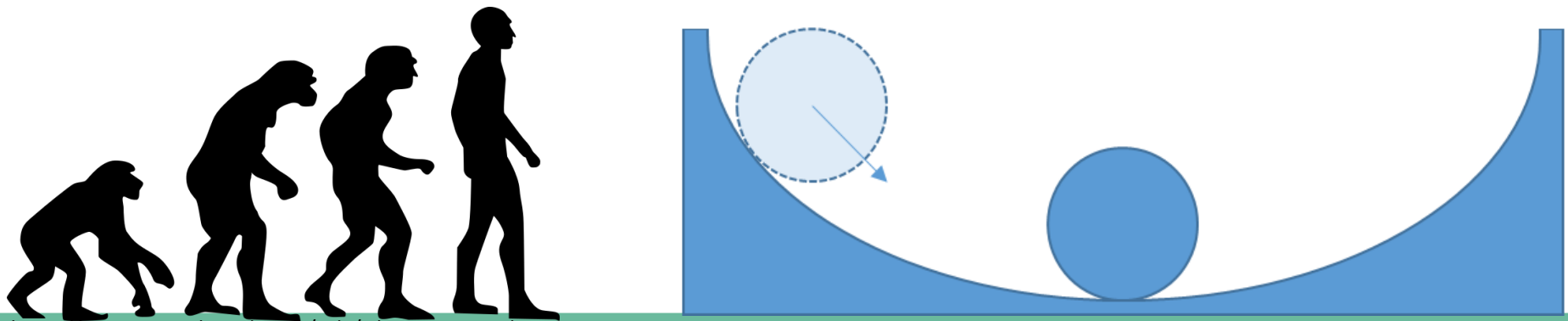
PhD. Eng. Jerzy Rosłon, ACIOB, PSMB, IPMA
Institute of Building Engineering

- **Decision problems**, i.e. problems where the solution is always true or false for the given input data. Associated with decision-making processes.
- **Search problems** in which, for a given input, the solution is a result set that meets certain given conditions. In a special case, the result may be an empty set if there are no results that meet the assumptions. Associated with search processes.
- **Optimization problems** are problems that are described in such a way that, for the given input data, the solution is the best possible result/ variant/ score. Associated with optimization processes.
This group of problems includes basic scheduling problems.

Definition of *optimization* (by www.merriam-webster.com/dictionary)

: an act, process, or methodology of making something (such as a design, system, or decision) as fully perfect, functional, or effective as possible specifically

: the mathematical procedures (such as finding the maximum of a function) involved in this



https://commons.wikimedia.org/wiki/File:Human_evolution.svg

The goal of global optimization is to find the best possible elements x^* from a set \mathbb{X} according to a set of criteria

$$F = \{f_1, f_2, \dots, f_n\}$$

These criteria are expressed as mathematical functions, the so-called **objective functions**.

Such function ($f: \mathbb{X} \rightarrow Y$) is subject to optimization.

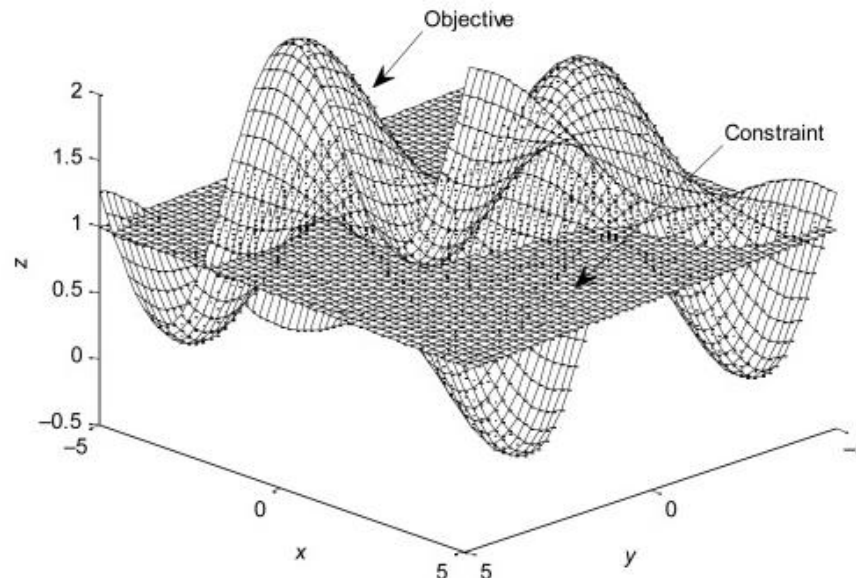
The codomain Y of an objective function as well as its range must be a subset of the real numbers ($Y \subseteq \mathbb{R}$).

The domain \mathbb{X} of f is called problem space and can represent any type of elements (numbers, lists, construction schedules, etc.).

The optimization task is finding such $x^* \in \mathbb{X}$ value, that for each $x \in \mathbb{X} \setminus \{x^*\}$: $f(x) > f(x^*)$ for minimization (finding the minimum of the function) and $f(x) < f(x^*)$ for maximization (finding the maximum of the function).

Optimization tasks can be divided according to the degree of difficulty in finding their solutions, e.g. into the following categories:

- single and multi-criteria,
- unconstrained (such as the UPS class from the previous presentation) and constrained (e.g. RCPSP, MRCPSPP).

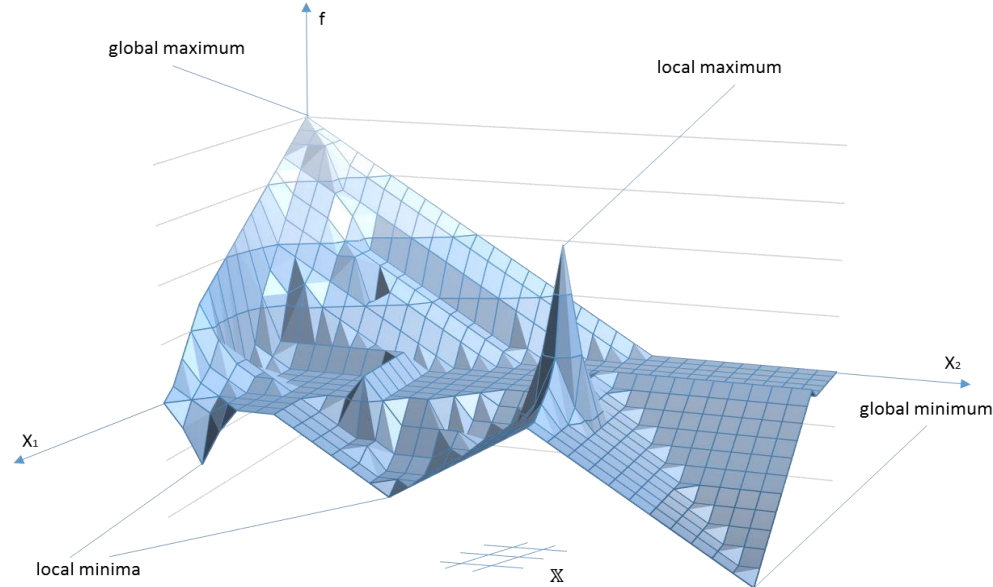


Naeem, M., et al. "Optimization classification and techniques of WSNs in smart grid." Smart Cities and Homes. Morgan Kaufmann, 2016. 323-343.

Some other classifications of optimization tasks:

- static (searching for the extremum of a function, the number of constraints must be countable and finite)
 - dynamic (searching for the extremum of a function - the variables take the form of a functional, which can illustrate e.g. the behavior of an object in time; such tasks have an infinite and countless number of momentary constraints)
-
- continuous (the search space is a Cartesian product of the set of real numbers)
 - discrete (the values of independent variables belong to a discrete set: a set of integers, a set of binary numbers)
 - mixed (the values of independent variables belong to both the set of real numbers and the set of numbers in discrete form).

Single criteria optimization



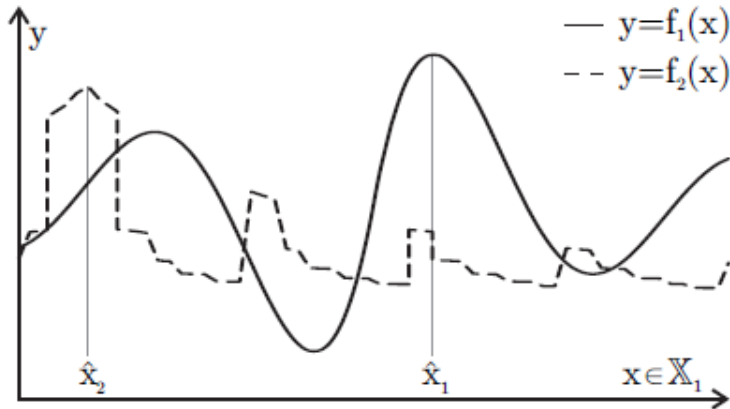
A local minimum $\check{x}_l \in \mathbb{X}$ of an objective function $f: \mathbb{X} \rightarrow \mathbb{R}$ is an input element with $f(x) \geq f(\check{x}_l)$ for all x neighboring \check{x}_l . In other form: $\forall \check{x}_l \exists \varepsilon > 0: f(x) \geq f(\check{x}_l) \forall x \in \mathbb{X}, |x - \check{x}_l| < \varepsilon$

A local maximum $\hat{x}_l \in \mathbb{X}$ of an objective function $f: \mathbb{X} \rightarrow \mathbb{R}$ is an input element with $f(x) \leq f(\hat{x}_l)$ for all x neighboring \hat{x}_l . In other form: $\forall \hat{x}_l \exists \varepsilon > 0: f(x) \leq f(\hat{x}_l) \forall x \in \mathbb{X}, |x - \hat{x}_l| < \varepsilon$

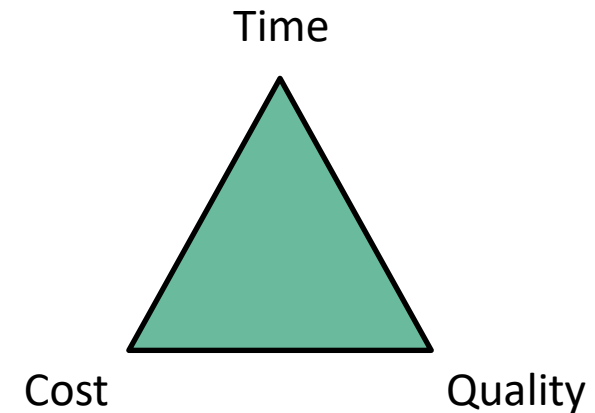
The global minimum $\check{x} \in \mathbb{X}$ of the objective function $f: \mathbb{X} \rightarrow \mathbb{R}$ exists if $\forall x \in \mathbb{X}, f(x) \geq f(\check{x})$.
The global maximum $\hat{x} \in \mathbb{X}$ of the objective function $f: \mathbb{X} \rightarrow \mathbb{R}$ exists if $\forall x \in \mathbb{X}, f(x) \leq f(\hat{x})$.

A (local) optimum / (local) extremum of an objective function is either a (local) maximum or a (local) minimum.

Multi-criteria optimization



Two functions f_1 and f_2 with different maxima \hat{x}_1 and \hat{x}_2 .



In many real-world design or decision making problems, optimization techniques are applied to sets F consisting of $n = |F|$ objective functions f_i , each representing one criterion to be optimized.

$$F = \{f_i : \mathbb{X} \mapsto Y_i : 0 < i \leq n, Y_i \subseteq \mathbb{R}\}$$

Algorithms designed to optimize such sets of objective functions are usually named with the prefix multi-objective (for example multi-objective evolutionary algorithms).

Pareto optimization

An element (solution) x_1 dominates (is preferred to) an element x_2 ($x_1 \vdash x_2$) if x_1 is better than x_2 in at least one objective function and not worse with respect to all other objectives. Based on the set F of objective functions f , we can write:

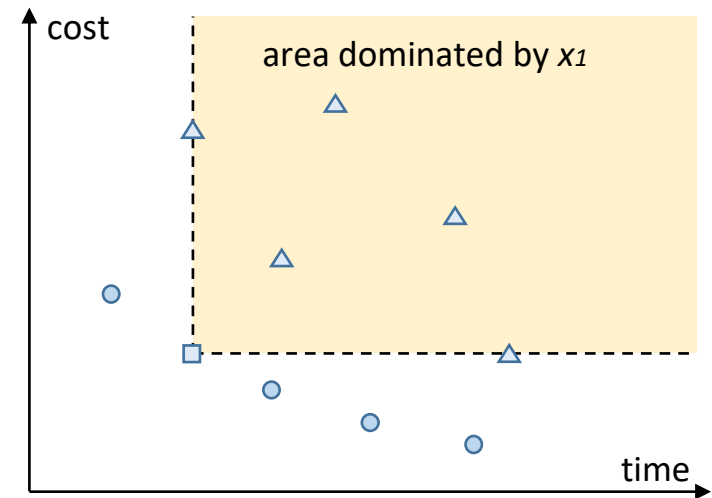
$$x_1 \vdash x_2 \Leftrightarrow \forall i : 0 < i \leq n \Rightarrow \omega_i f_i(x_1) \leq \omega_i f_i(x_2) \wedge \exists j : 0 < j \leq n \Rightarrow \omega_j f_j(x_1) < \omega_j f_j(x_2)$$

where

$$\omega_i = \begin{cases} 1 & \text{if } f_i \text{ should be minimized} \\ -1 & \text{if } f_i \text{ should be maximized} \end{cases}$$

An element $x^* \in \mathbb{X}$ is Pareto optimal (and hence, part of the optimal set X^*) if it is not dominated by any other element in the problem space \mathbb{X} . In terms of Pareto optimization, X^* is called the Pareto set or the Pareto Frontier.

$$x^* \in X^* \Leftrightarrow \nexists x \in \mathbb{X} : x \vdash x^*$$



- x_1
- △ elements dominated by x_1
- elements non-dominated by x_1

Multi-criteria optimization reduction (scalarized problem)

The most common method of reducing multi-criteria problems to single criterion is the **weighted sum method** (or linear scalarization). This method assumes the creation of a **metafunction** $g(x)$ on the basis of the function $f_i \in F$. Each optimization criterion f_i is multiplied by a weight w_i describing its importance. The use of signs (negative, positive) for weights allows us to combine the minimized and maximized criteria:

$$g(x) = \sum_{i=1}^n w_i f_i(x) = \sum_{\forall f_i \in F} w_i f_i(x)$$
$$x^* \in X^* \Leftrightarrow g(x^*) \geq g(x) \quad \forall x \in \mathbb{X}$$

In this method, the appropriate selection of weights is particularly important. Subjectivism may prove to be a problem. The main advantage of the method is its simplicity.

Examples of other methods:

- **method of hierarchical optimization** (the method involves ranking criteria),
- **ϵ -constraint method** (selecting the most important criterion and transforming the others into constraints),
- **achievement scalarizing problems of Wierzbicki** (using *nadir* and *utopian* vectors)

Constraints

In many scenarios, p inequality constraints g and q equality constraints h may be imposed additional to the objective functions. Then, a solution candidate x is feasible, if and only if $g_i(x) \geq 0 \quad \forall i = 1, 2, \dots, p$ and $h_i(x) = 0 \quad \forall i = 1, 2, \dots, q$ holds. Obviously, only a feasible individual can be a solution, i.e. an optimum, for a given optimization problem.

Approaches:

- death penalty

X

- penalty functions

- constant
- linear
- exponential

$$\text{e.g. } f'(x) = f(x) + v \sum_{i=1}^p [g_i(x)]^{-1}$$

- constraint as an additional objective

$$\text{e.g. } g(x) \geq 0 \quad \text{into} \quad f^*(x) = \min \{-g(x), 0\}$$

- and more...

Carroll, C. W. (1961). The created response surface technique for optimizing nonlinear, restrained systems. *Operations Research*, 9(2), 169-184.

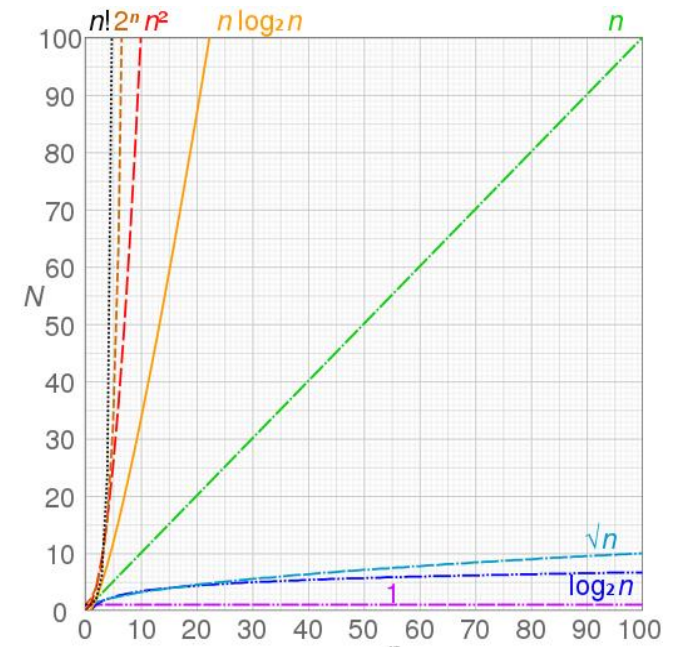
Weise, T. (2009). *Global optimisation algorithms-theory and application*. Self-Published., 25-26

Complexity

Practical problems in construction can be easily qualified as **NP-hard** (non-deterministic polynomial-time hard) problems. The time needed for solving these problems grows exponentially with the increase the problem's size.

At least $O(c^n)$ to find the solution.

At least $O(n^c)$ or $O(c^n)$ to check the solution.

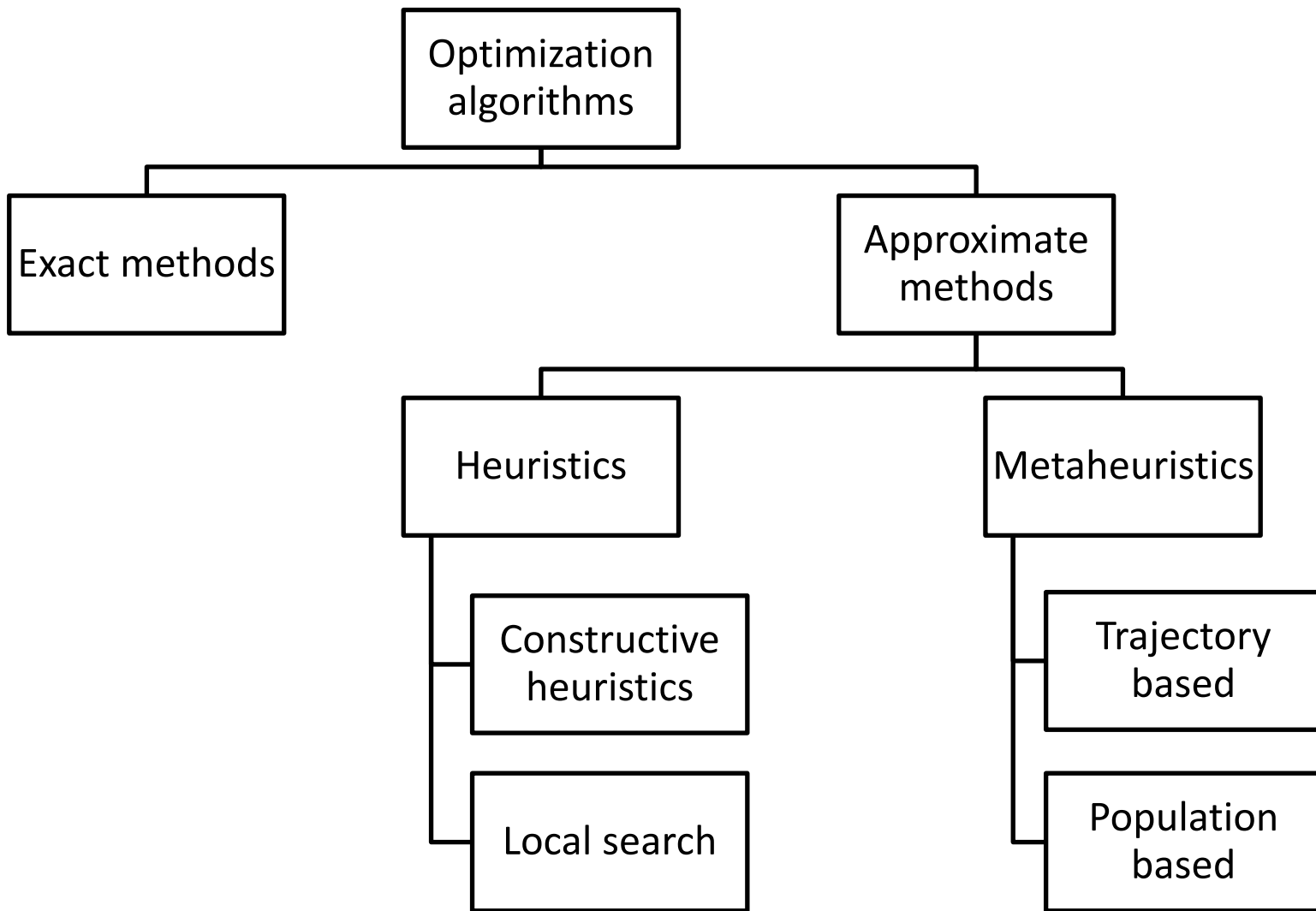


https://en.wikipedia.org/wiki/File:Comparison_computational_complexity.svg

Age of the universe $\approx 10^{10}$ years!

Computational Complexity O	Data size	10	20	50	100	200	1000
$\log n$		3,32 ns	4,23 ns	5,64 ns	6,64 ns	7,64 ns	9,97 ns
n		10 ns	20 ns	50 ns	100 ns	200 ns	1 μ s
$n \log n$		33,21 ns	86,44 ns	282,2 ns	664,4 ns	1,53 μ s	9,97 μ s
n^2		100 ns	400 ns	2,5 μ s	10 μ s	40 μ s	1 ms
2^n		1 μ s	1,05 ms	13 days	$4 \cdot 10^{13}$ years	$5,1 \cdot 10^{43}$ years	$3,4 \cdot 10^{284}$ years
$n!$		3,6 ms	77 years	$9,6 \cdot 10^{44}$ years	$3 \cdot 10^{141}$ years	$2,5 \cdot 10^{358}$ years	$1,27 \cdot 10^{2551}$ years

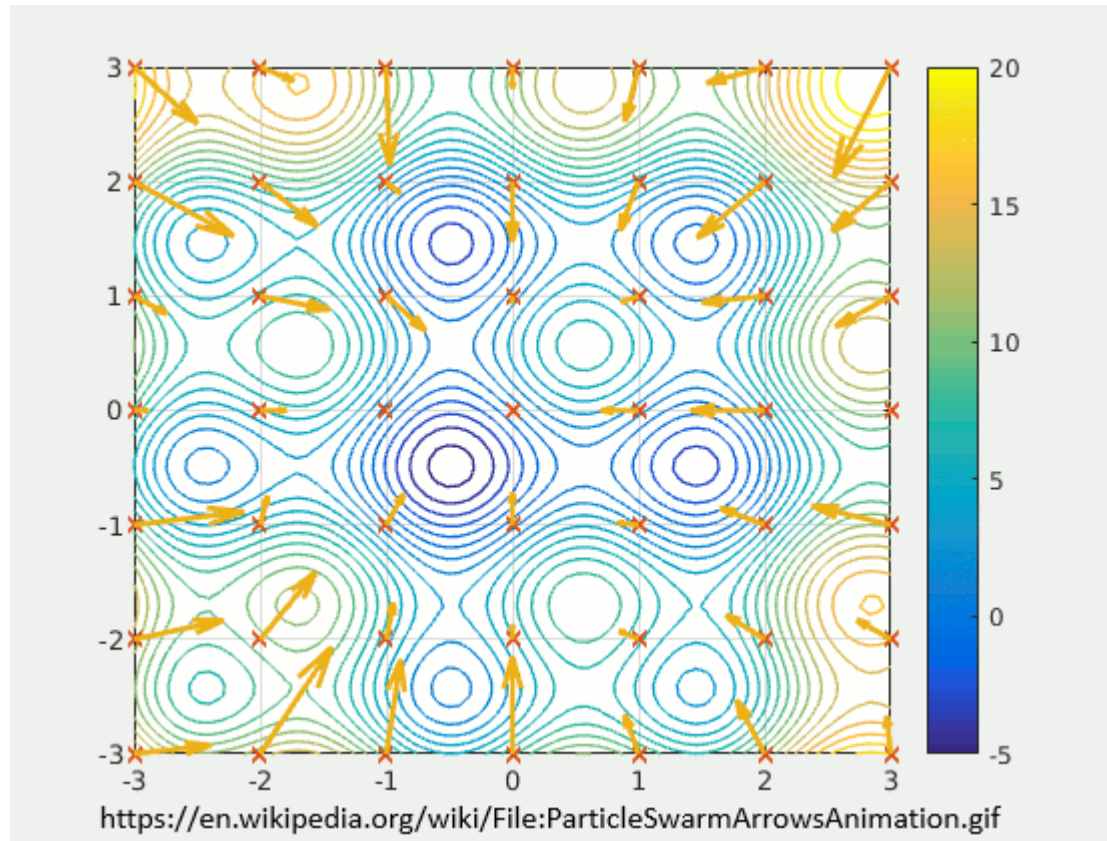
Optimization algorithms



Particle Swarm Optimization (PSO)

The algorithm keeps track of a series of global variables: target condition, global best (called: gBest) – value indicating which particle is currently closest to the target, and stopping value (which indicates when the algorithm should stop).

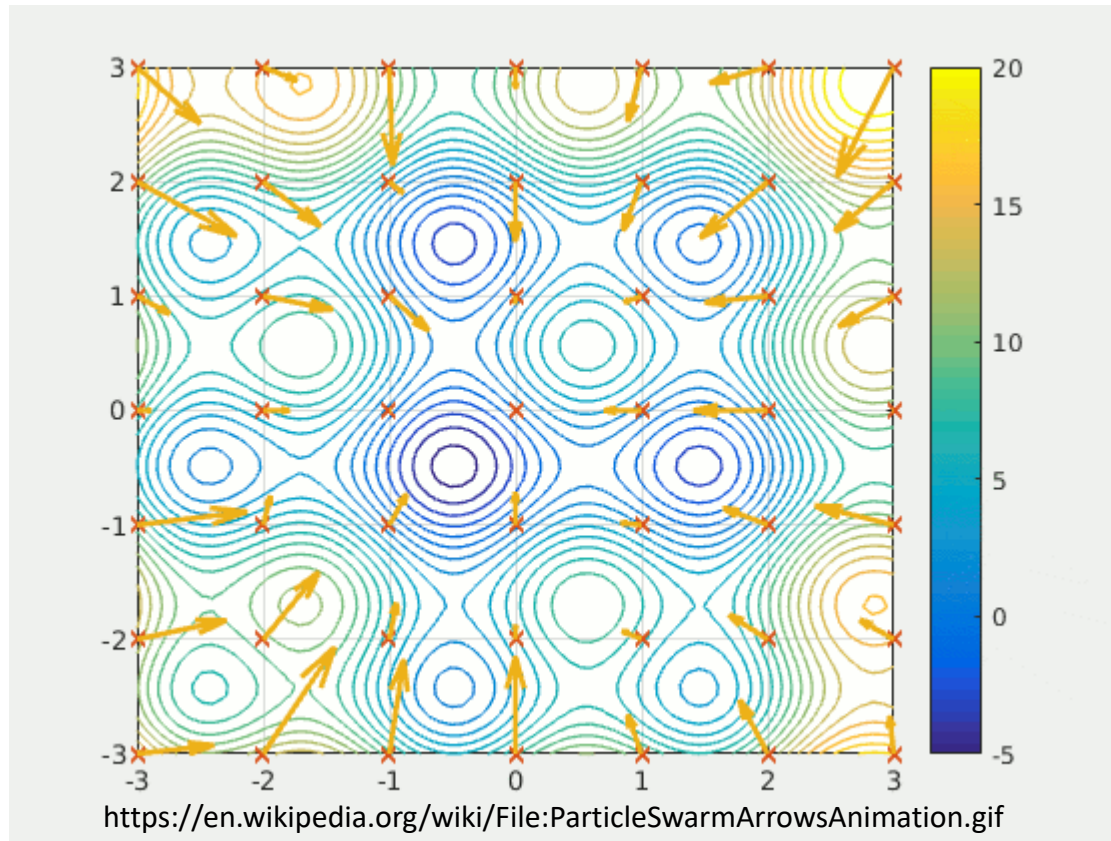
The individuals (particles) store following: position (data representing a possible solution), a personal best (called: pBest), and velocity (value indicating how much the data/ current position can be changed).



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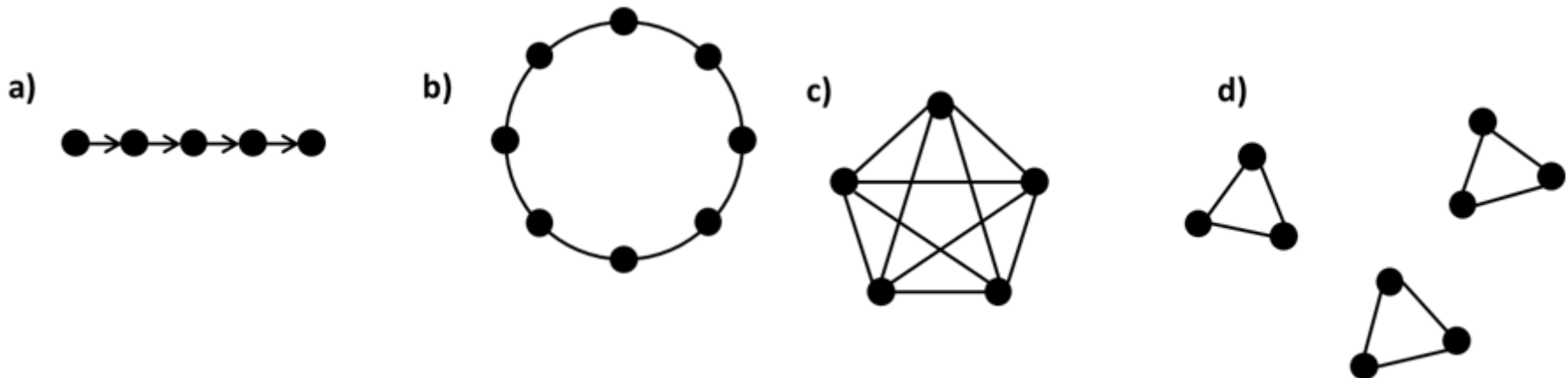
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Particle Swarm Optimization (PSO)

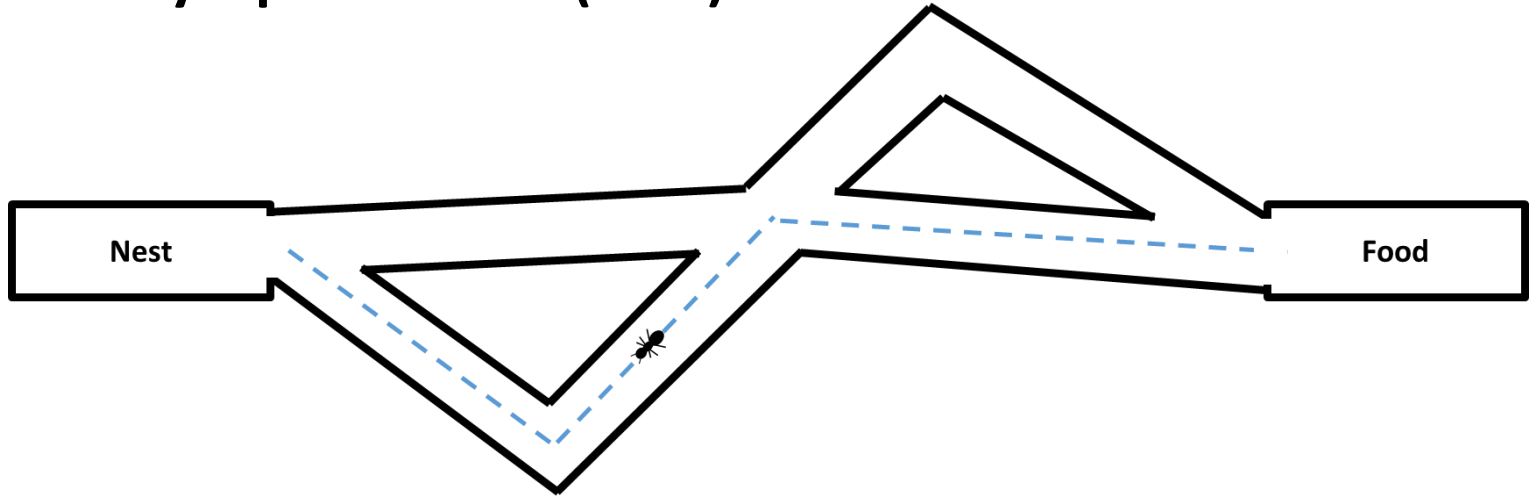
In order to avoid getting stuck at local optimums, several population topologies (neighborhoods) can be used. These neighborhoods can involve a group of particles which act together (communicate between each other) or subsets of the search space that particles happen into during testing. Some of the popular topologies include:

- a) Single-sighted – individuals only compare themselves to the next best
- b) Ring topology – each particle compares only to those to the right and left
- c) Fully connected topology – every individual compares to each other
- d) Isolated – particles only compare to those within previously established groups

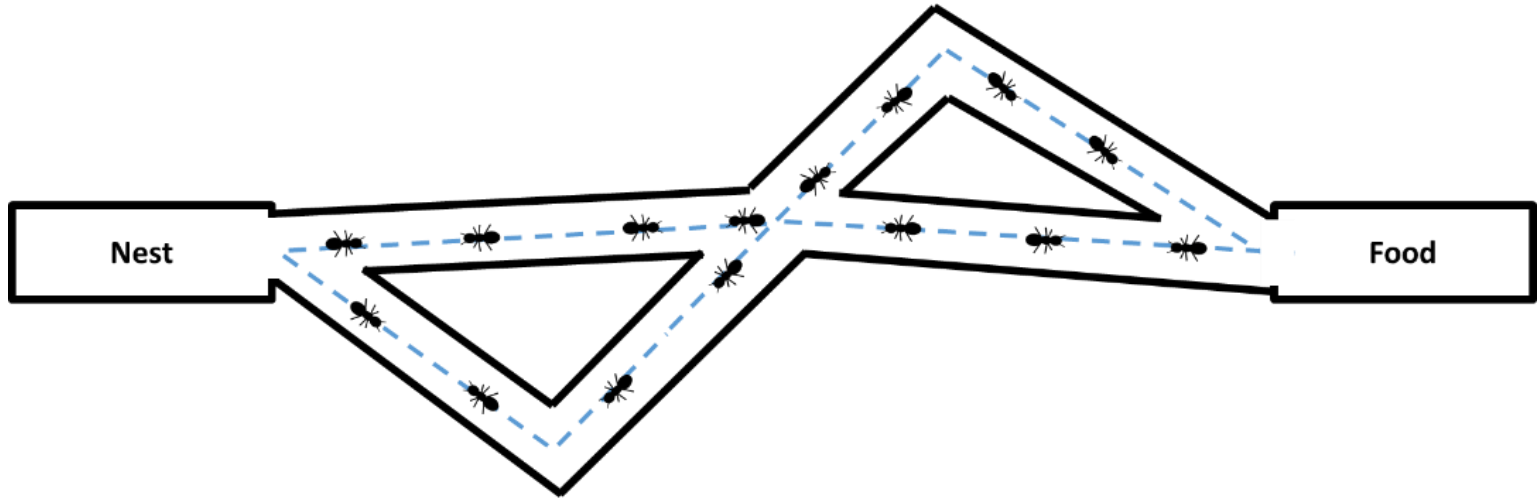


Ant Colony Optimization (ACO)

1)

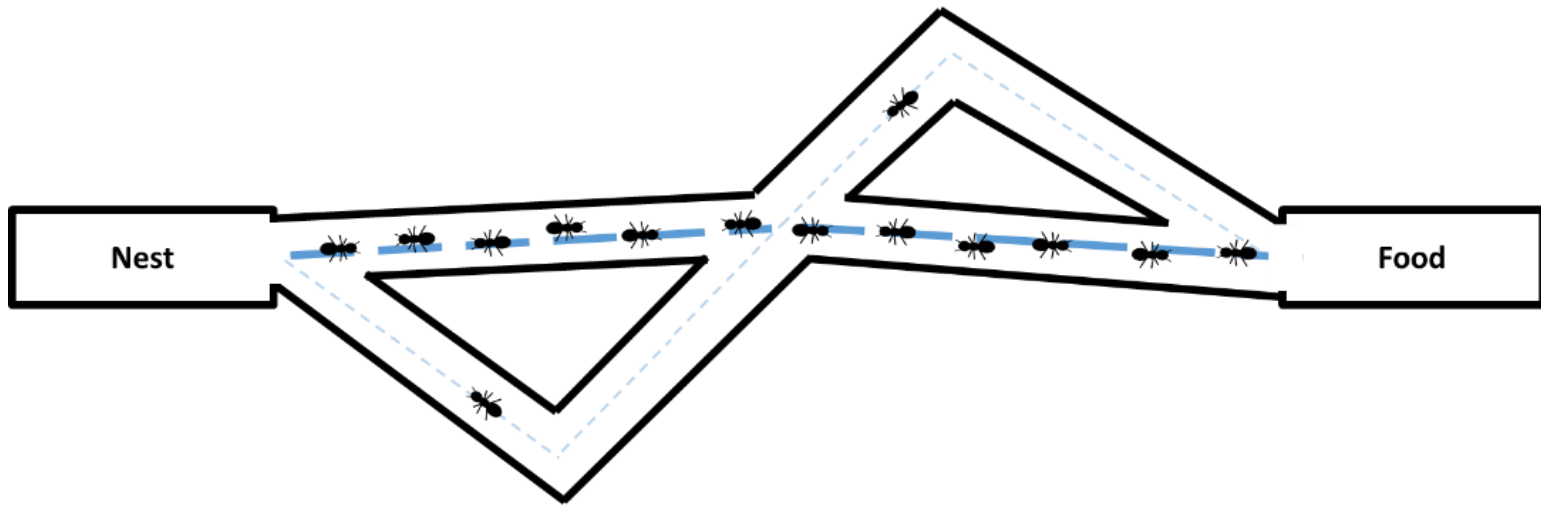


2)

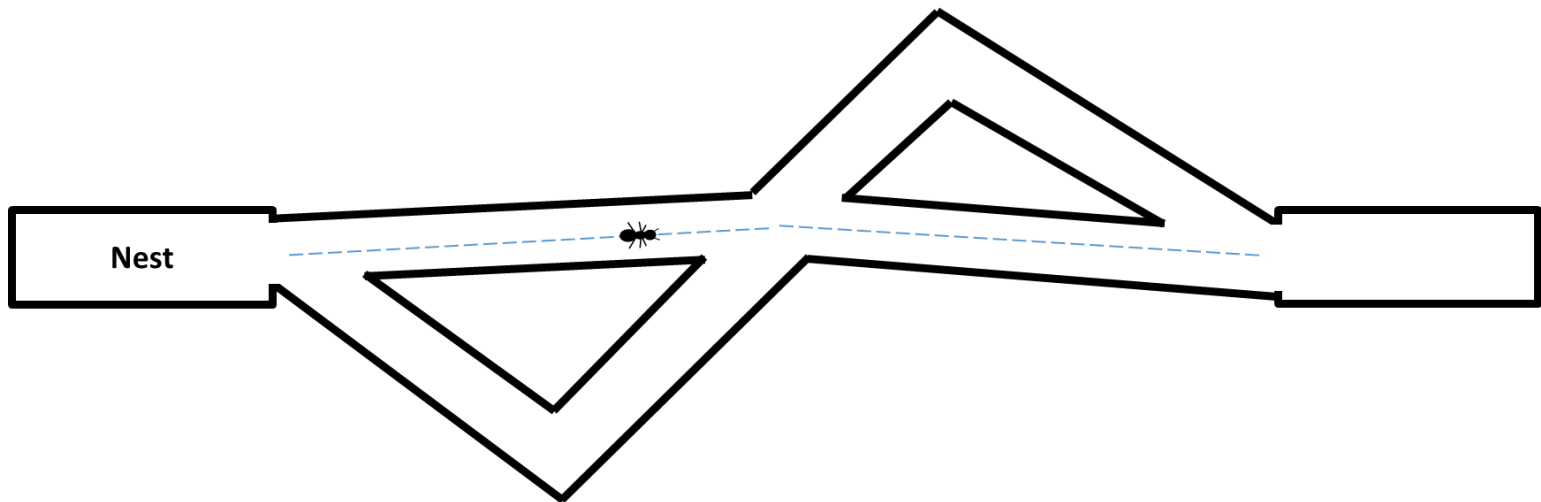


Ant Colony Optimization (ACO)

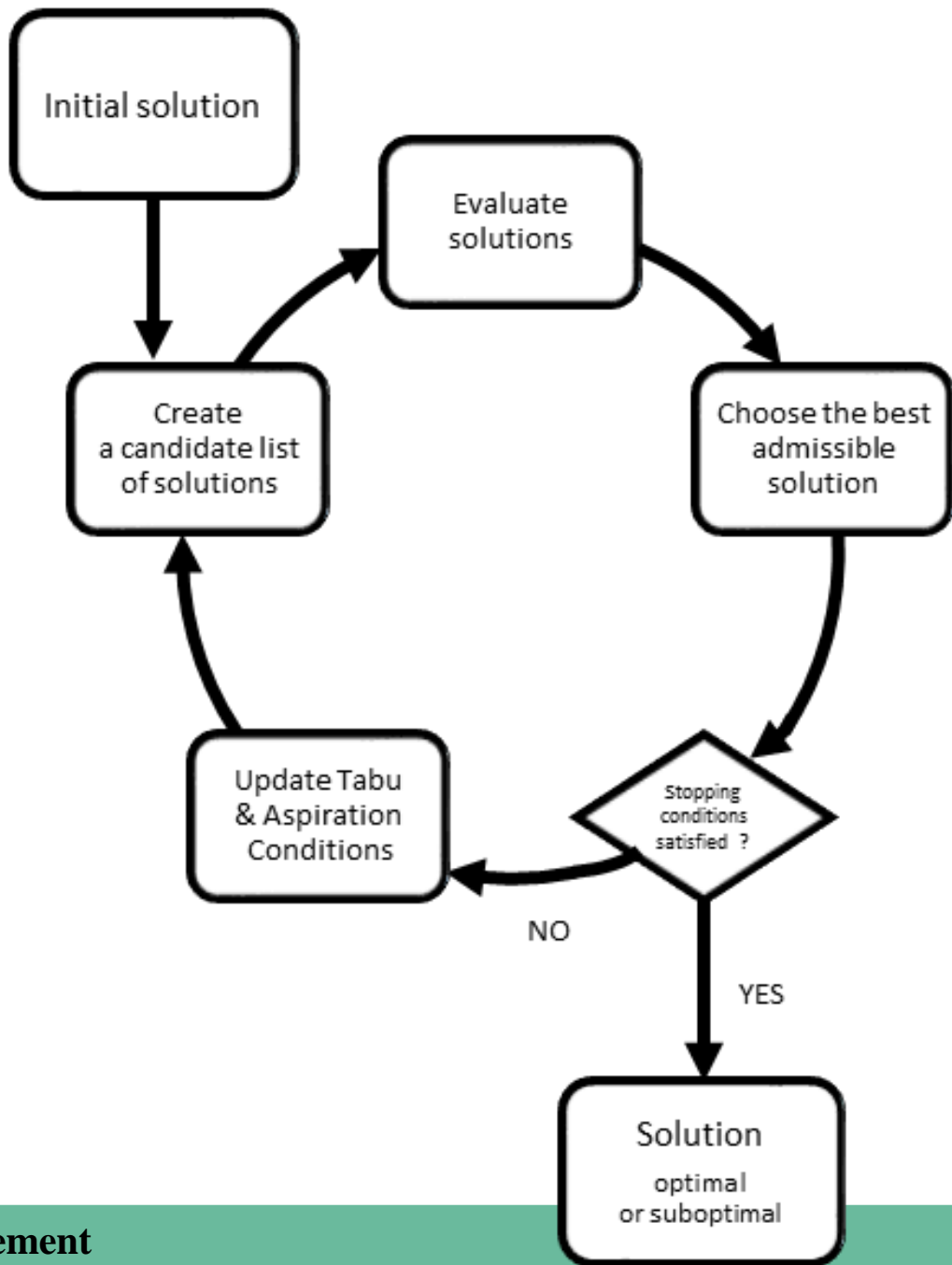
3)



4)



Tabu Search (TS)



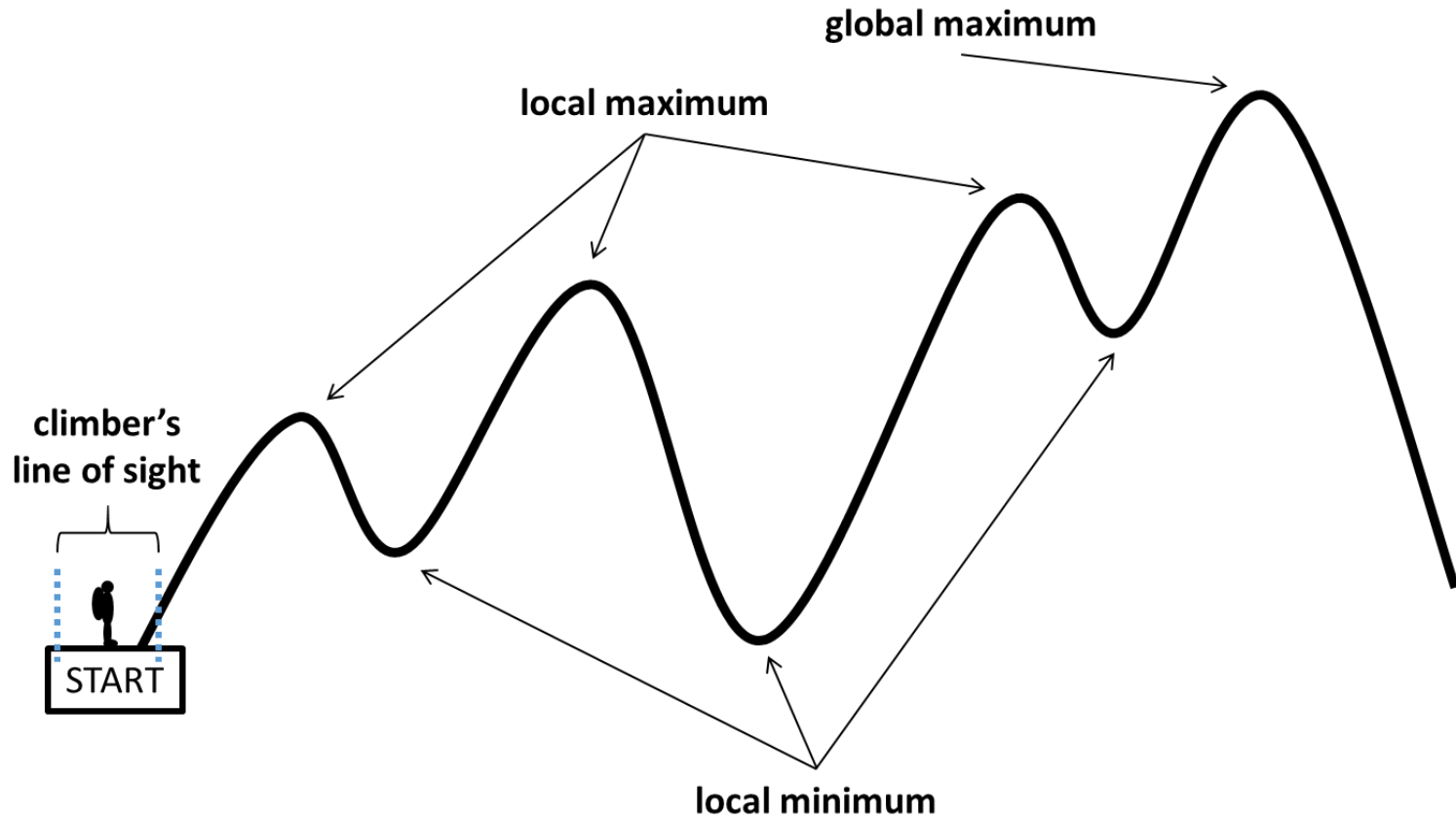
Simulated Annealing (SA)

The simulated annealing algorithm (SA) was developed by Kirkpatrick on the base of Metropolis works.

Relation between annealing in metallurgy and simulated annealing optimisation algorithm

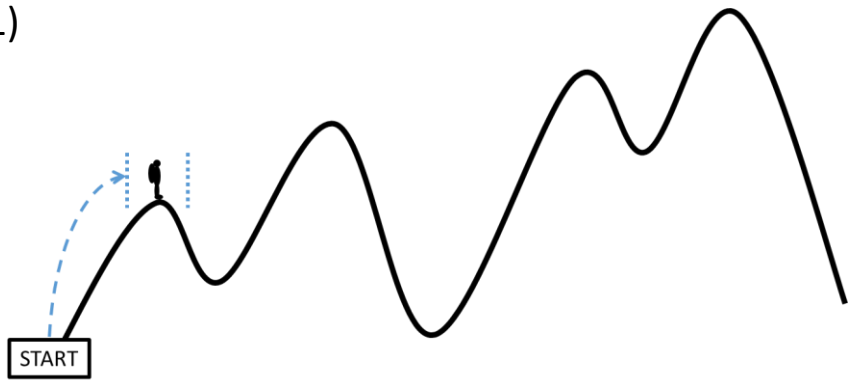
Metallurgy	Optimisation algorithm
System states	Solutions
Energy	Optimisation goal (e.g. time or cost)
Change of state	Neighbouring solutions
Temperature	Artificial temperature parameter
Frozen state	Obtained solution

Simulated Annealing (SA)

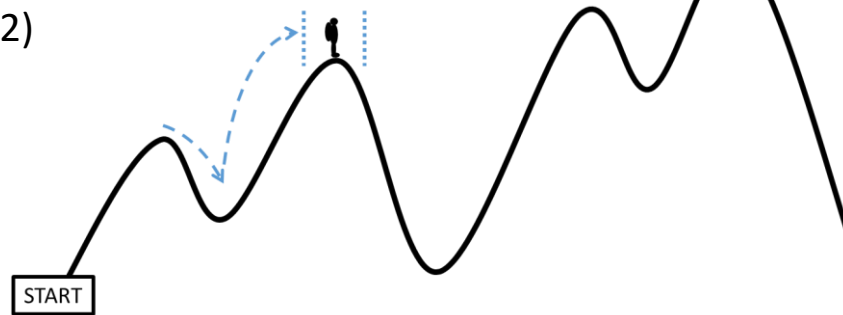


Simulated Annealing (SA)

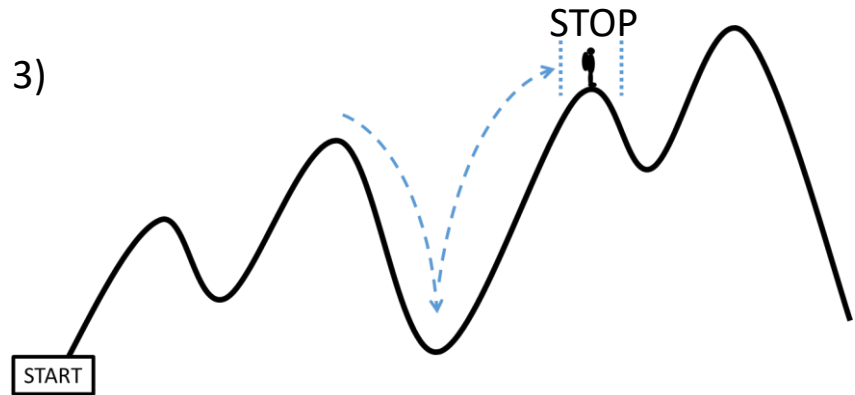
1)



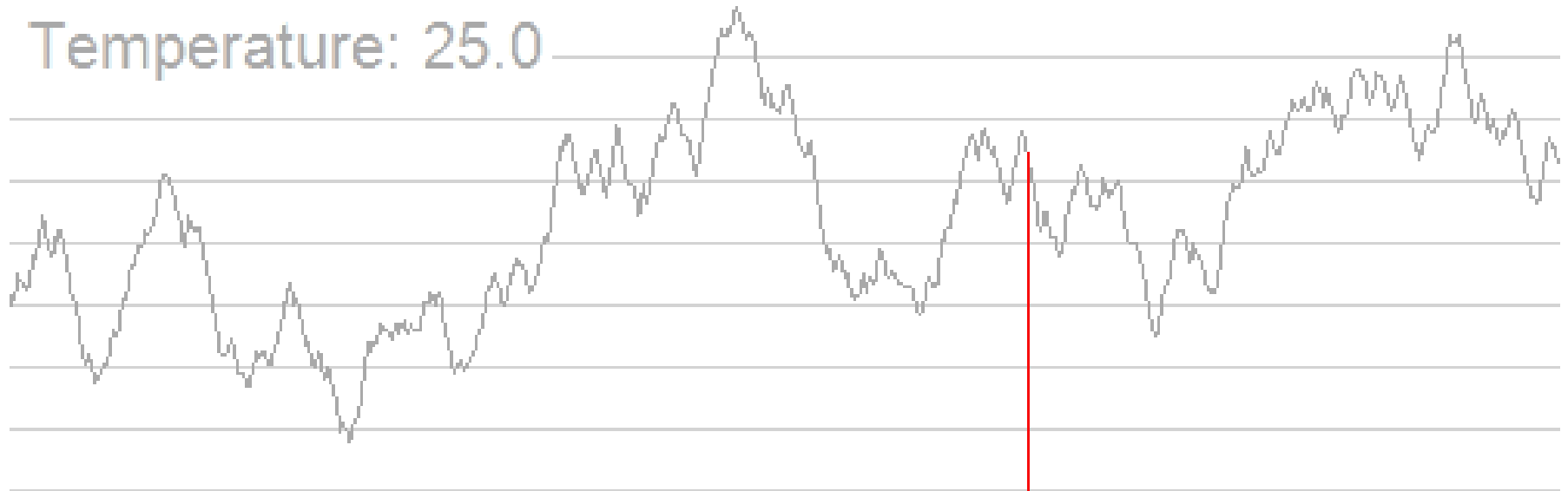
2)



3)



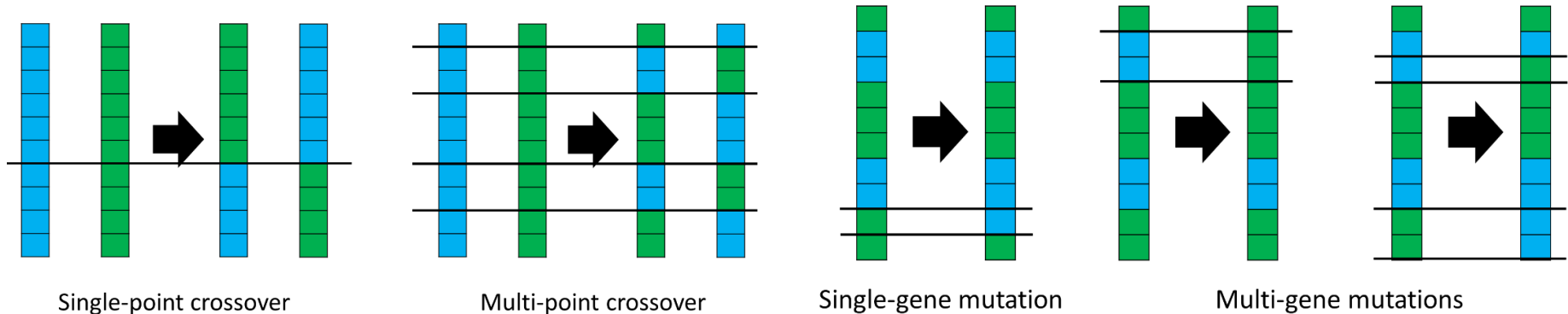
Simulated Annealing (SA)



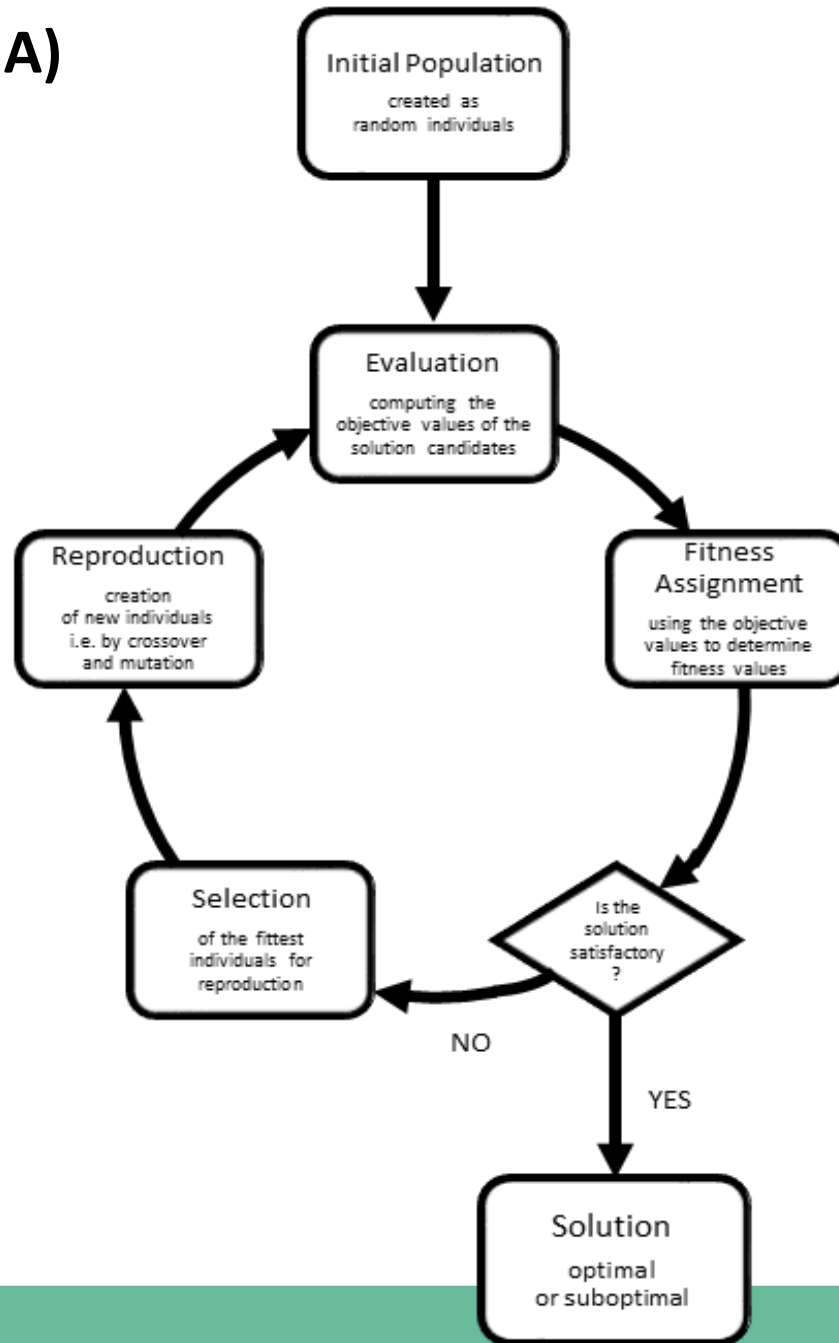
https://en.wikipedia.org/wiki/File:Hill_Climbing_with_Simulated_Annealing.gif

Genetic Algorithms (GA)

- **Individuals** (candidate solutions) – these are the basic specimen subject to evolution. In biology, these individuals are living in the environment.
- **Population** – a set of individuals subject to evolution.
- **Fitness** – a function that allows to rate given individual (according to the optimization problem)
- **Phenotype** – features of specimen determining its fitness (adaptation to the given environment).
- **Genotype** – a structural representation of the phenotype. It is a complete description of an individual. A genotype may be represented by a single chromosome. In terms of optimization problem, it may be description of the construction schedule.
- **Chromosome** – a sequence of genes, it stores genotype of an individual.

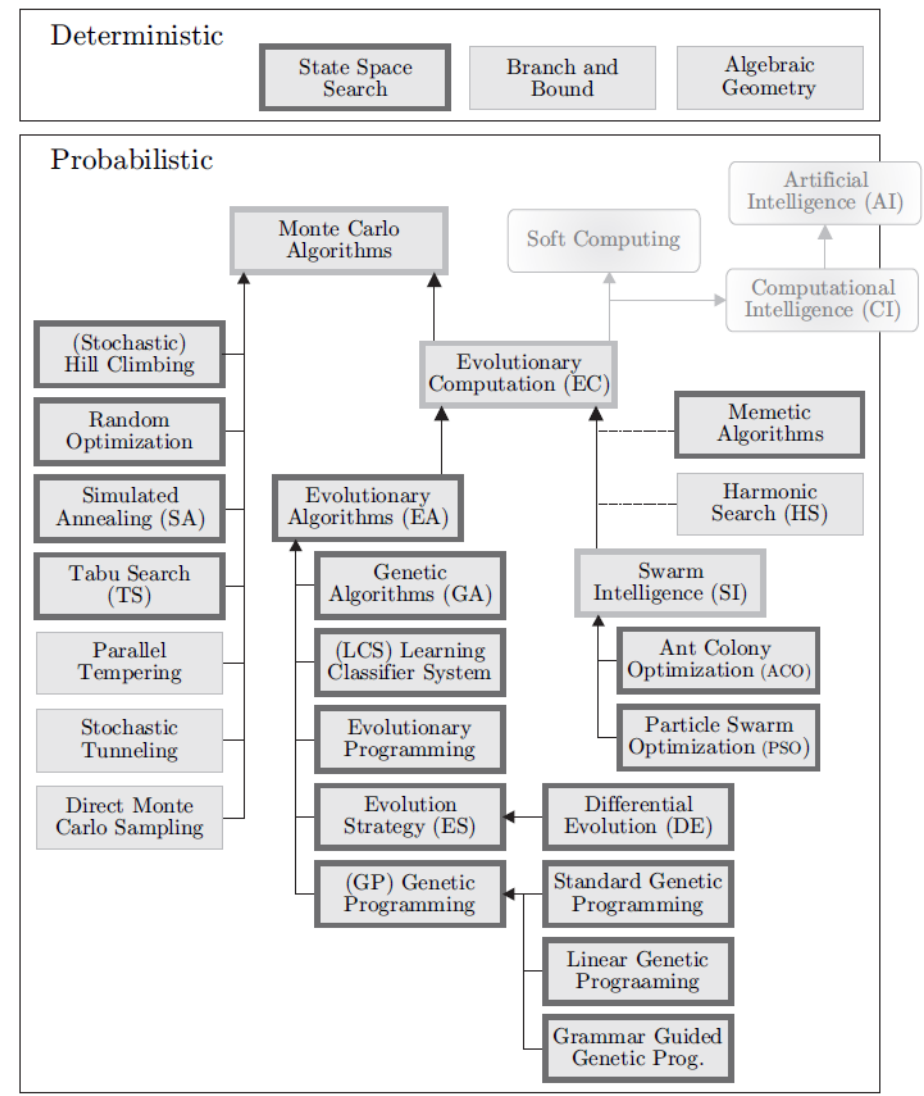


Genetic Algorithms (GA)



Some of the other algorithms

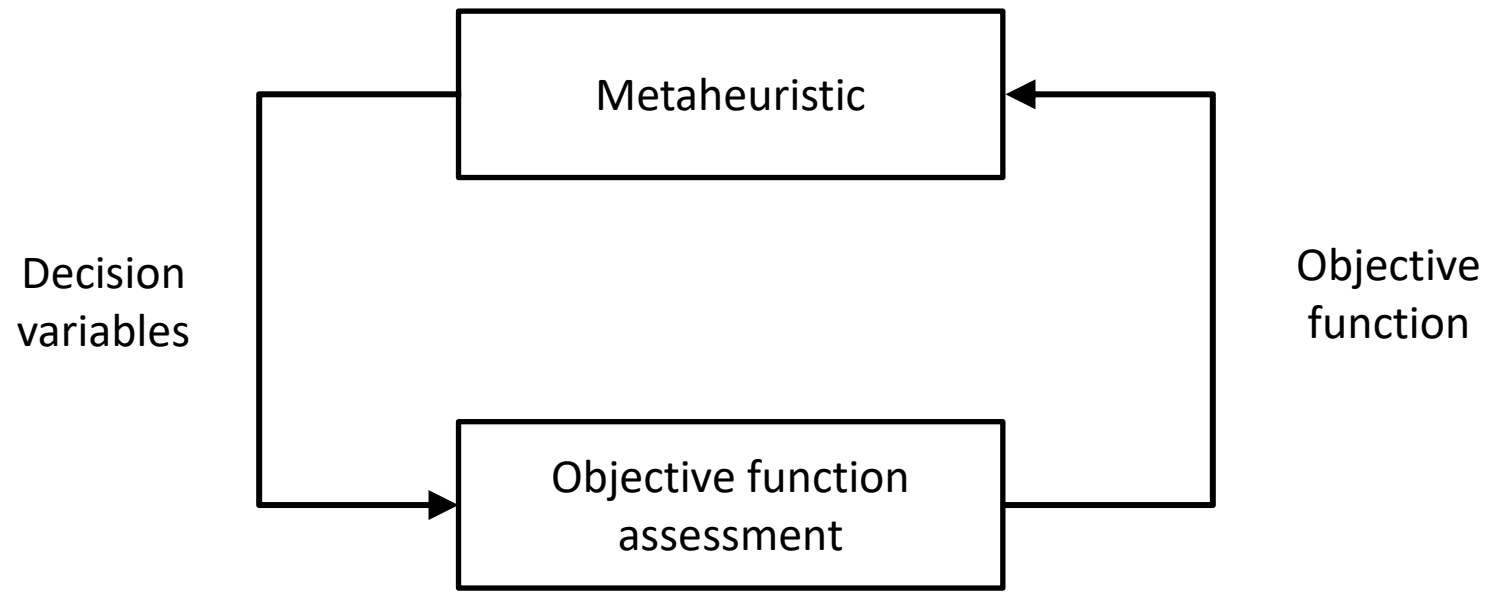
- Variable Neighborhood Search (VNS)
- Local Search (LS)
- Iterated Local Search (ILS)
- Monte-Carlo Tree Search (MCTS)
- Harmony Search (HS)
- Artificial Immune System (AIS)
- Frog-Leaping Algorithm (FLA)
- Artificial Bee Colony (ABC)
- Bee Colony Optimization (BCO)
- Marriage in honey-Bee Optimization (MBO)
- Social Cognitive Optimization (SCO)
- Differential Evolution (DE)
- Scatter Search (SS)
- Estimation of Distribution Algorithm (EDA)
- Rider Optimization Algorithm (ROA)
- NSGA-II (and other GA variants)
- hybrid algorithms
- memetic algorithms
- parallel metaheuristics
- ...



Weise, T. (2009). Global optimisation algorithms-theory and application.

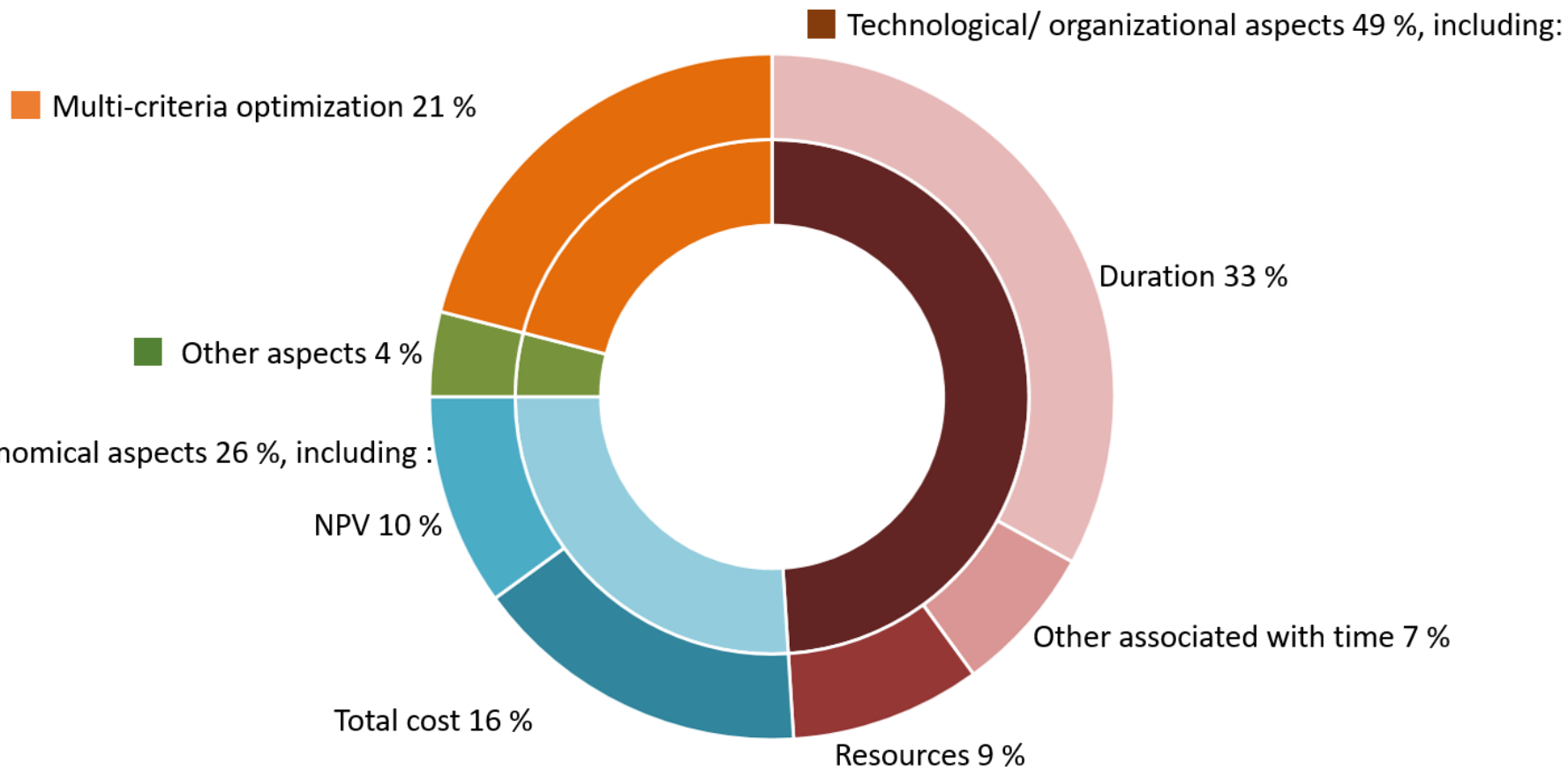
So which one is the best?

Black box



Construction schedules – optimization aspects

Frequency of RCPSP aspects – objective function:



Based on: Habibi, F., Barzinpour, F., & Sadjadi, S. (2018). Resource-constrained project scheduling problem: review of past and recent developments. *Journal of project management*, 3(2), 55-88.

Construction schedules – optimization aspects

- cost / total cost / outcome / total cash demand
- profit = income - outcome
- maximum monthly cash demand
- Future Value, FV
- Present Value, PV
- Weighted Average Cost of Capital, WACC
- Net Present Value, NPV
- Internal Rate of Return, IRR
- Modified Net Present Value, MNPV
- Net Present Value Ratio, NPVR
- Profitability Index, PI
- Modified Profitability Index, MPI
- Modified Internal Rate of Return, MIRR
- duration / makespan / total makespan
- Total Project Delay – TPD
- quality
- schedule robustness
- value
- continuity of work
- work brigades delay
- cost of moving brigades
- resource supply
- holding cost
- maximum employment
- employment deviations
- resource quality level
- durability
- LCC – Life Cycle Cost
- CO₂ emission
- demand for energy
- waste generation
- safety
- reputation
- customer satisfaction
- employees satisfaction
- environmental nuisances

Objective function / constraints

Further reading:

- Weise, T. (2009). Global optimisation algorithms-theory and application. Self-Published,, 25-26.
- CLOEMC - Construction Manager's Library - www.cloemcv.il.pw.edu.pl
- Neumann, K., Schwindt, C., Zimmermann, J. (2012). Project scheduling with time windows and scarce resources: temporal and resource-constrained project scheduling with regular and nonregular objective functions. Springer Science & Business Media.
- Sprecher, A., Kolisch, R., & Drexel, A. (1993). Semi-active, active and non-delay schedules for the resource-constrained project scheduling problem (No. 307). Manuskripte aus den Instituten für Betriebswirtschaftslehre der Universität Kiel.
- Kostrubiec, A. (2003). Harmonogramowanie realizacji projektów-przegląd modeli. W: Inżynieria zarządzania przedsiębiorstwami. Red. L. Zawadzka. Gdańsk, 2003.
- Google scholar

Partnership:

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COMMON LEARNING OUTCOMES FOR EUROPEAN MANAGERS IN CONSTRUCTION V

CLOEMC I:

M1: PROJECT MANAGEMENT IN CONSTRUCTION,
M2: HUMAN RESOURCE MANAGEMENT IN CONSTRUCTION,
M3: PARTNERING IN CONSTRUCTION,
M4: BUSINESS MANAGEMENT IN CONSTRUCTION ENTERPRISE
M5: REAL ESTATE MANAGEMENT,
M6: ECONOMY AND FINANCIAL MANAGEMENT IN CONSTRUCTION,
M7: CONSTRUCTION MANAGEMENT.

CLOEMC II:

M8: RISK MANAGEMENT,
M9: PROCESS MANAGEMENT – LEAN CONSTRUCTION,
M10: COMPUTER METHODS IN CONSTRUCTION,
M11: PPP PROJECTS IN CONSTRUCTION,
M12: VALUE MANAGEMENT IN CONSTRUCTION,
M13: CONSTRUCTION PROJECTS – GOOD PRACTICE.

CLOEMC III:

M14: DUE-DILIGENCE IN CONSTRUCTION,
M15: MOTIVATION AND PSYCHOLOGY ASPECTS IN CONSTRUCTION INDUSTRY,
M16: PROFESSIONALISM AND ETHICS IN CONSTRUCTION,
M17: SUSTAINABILITY IN CONSTRUCTION,
M18: HEALTH AND SAFETY IN CONSTRUCTION,
M19: MANAGING BUILDING PATHOLOGY AND MAINTENANCE.

CLOEMC IV:

M20. REVITALISATION AND REFURBISHMENT IN CONSTRUCTION,
M21. BUILDING INFORMATION MODELLING – BIM,
M22. OPTIMISATION OF CONSTRUCTION PROCESSES,
M23. DIVERSITY MANAGEMENT IN CONSTRUCTION,
M24. MECHANICS OF MATERIALS AND STRUCTURES FOR CONSTRUCTION

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COMMON LEARNING OUTCOMES FOR EUROPEAN MANAGERS IN CONSTRUCTION V

CLOEMC V:

M26: MENTORING AND COACHING IN CONSTRUCTION,

M27: ARCHEOLOGICAL AND HERITAGE PROTECTION ASPECTS IN CONSTRUCTION,

M28: DISRUPTIVE INNOVATION IN CONSTRUCTION MANAGEMENT,

M29: CIRCULAR ECONOMY IN CONSTRUCTION,

M30: AFFORDABLE HOUSING,

M31: SOCIAL SUSTAINABILITY IN CONSTRUCTION.



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