/ Using evolutionary algorithms for placements problems solving /

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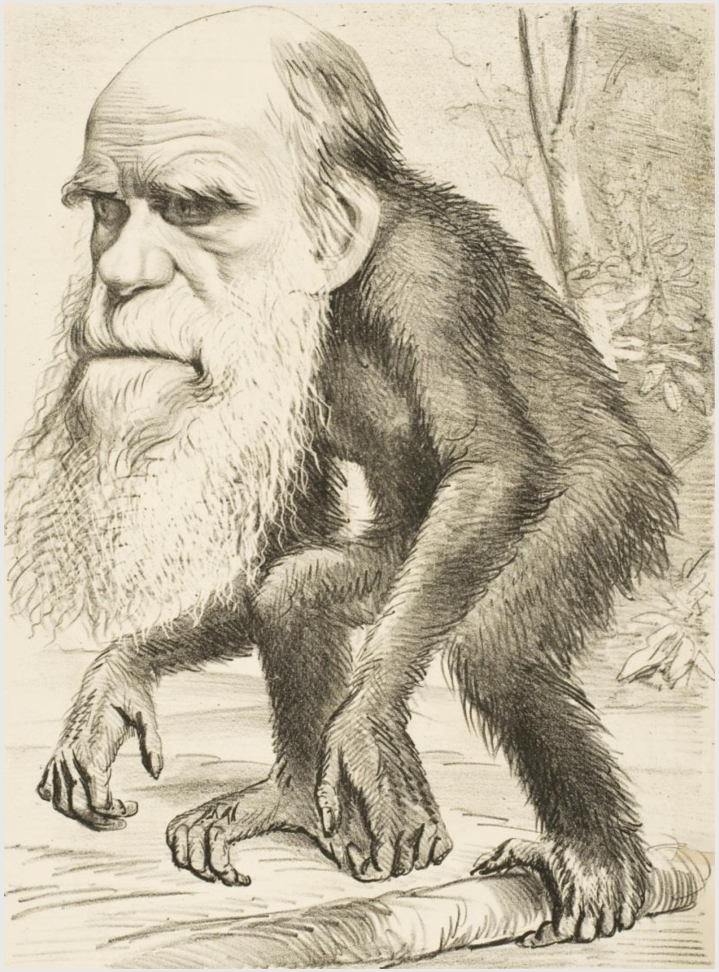
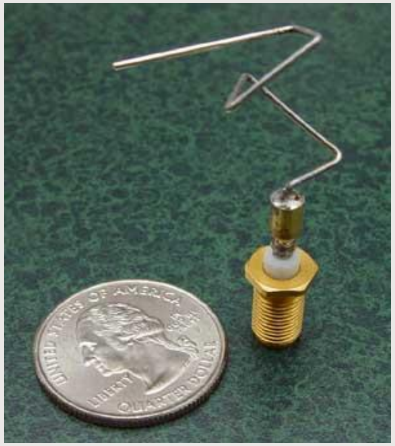
AGENDA

- Introduction to evolutionary algorithms
- A Multi-Objectives Evolutionary Algorithms typology
- Some examples
- Conclusion

Introduction to EAs

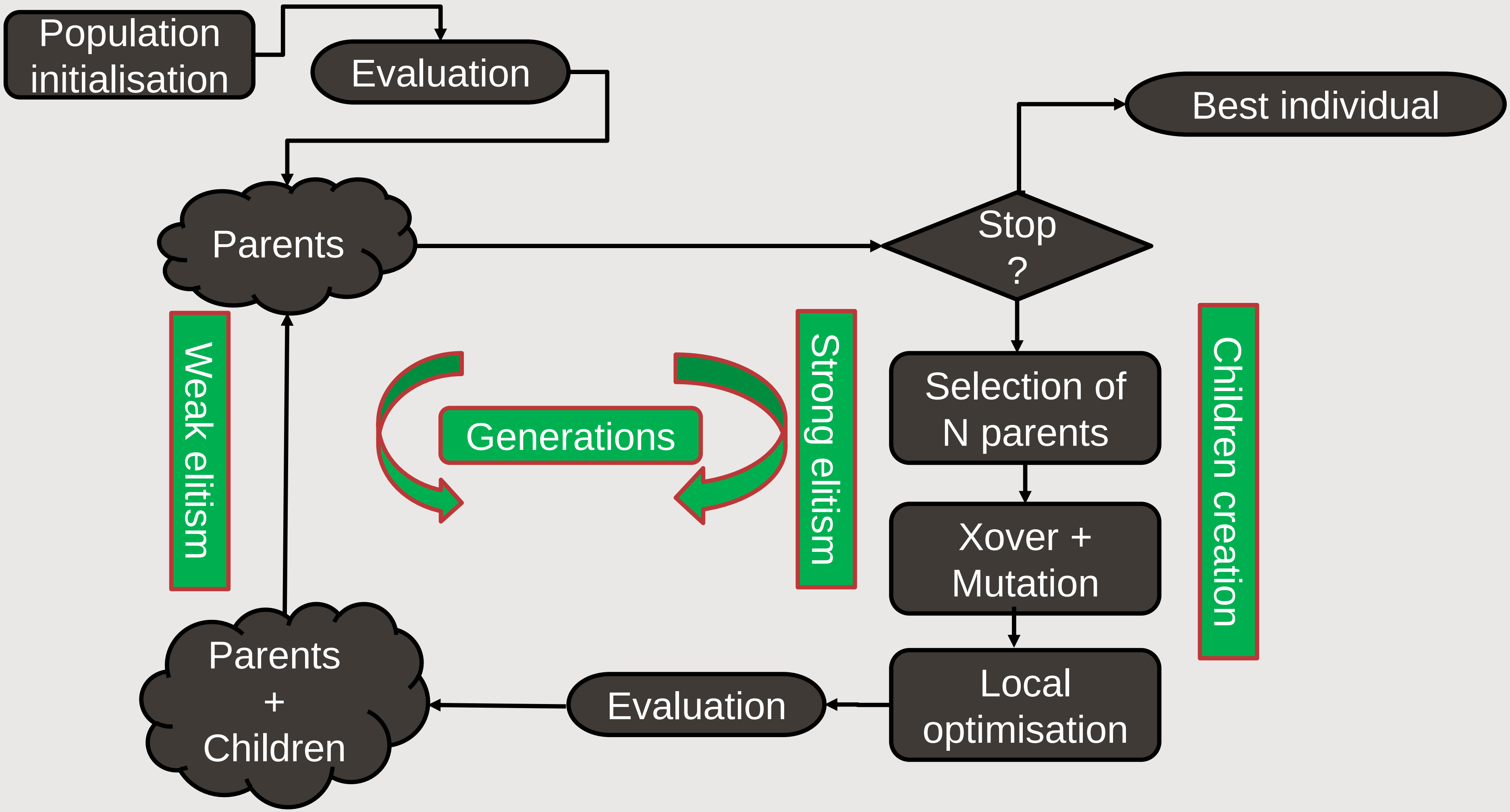
Caricature de Charles Darwin
Hornet, 1871





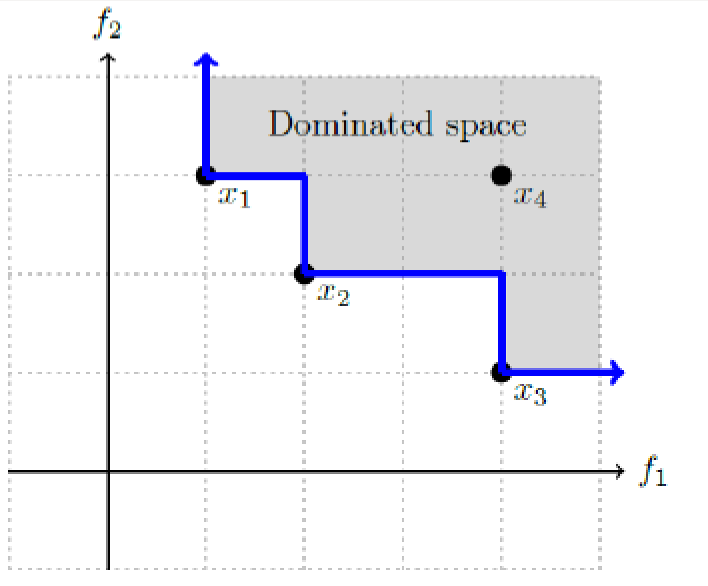
Mission ST-5 NASA -µSatellites, 2006:
Computation of very low and very directive antenna to reach satellite dishes.

Basic structure of an EA



MOOC FUN: Optimisation Stochastique Evolutionnaire, Pierre Colle: 2016

Pareto Front & Pareto dominance

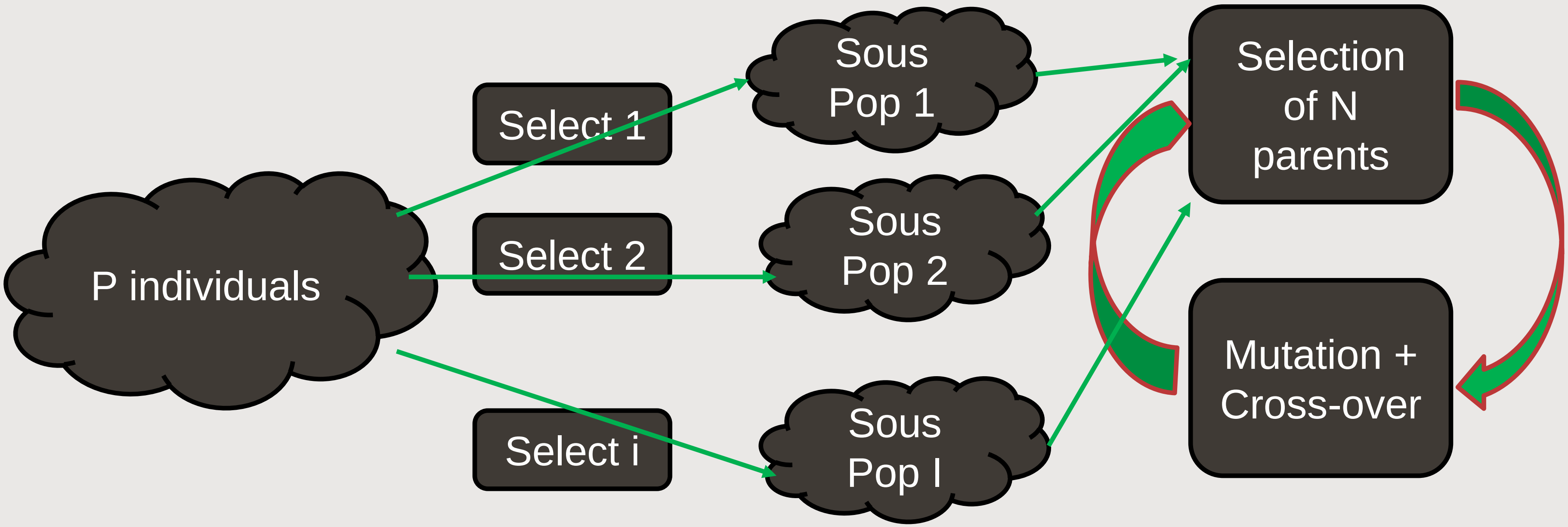


x dominates y ($x \prec y$) if : $\forall i \in [1..m], x_i \leq y_i$ and $\exists i \in [1..m], x_i < y_i$

Multi-criteria optimization and decision making: Michael Emmrich & André Deutz:

- Why using EA for solving MO problems ?
  - EAs can provide a good approximation in a limited time.
  - EAs work on a population of solutions, and a single run is enough, to provide a Pareto front,
  - An MOEA can make a set of Pareto points to evolve,
  - MOEA are less sensitive to various Pareto front shapes, concave shapes or more complex shapes,
  - They are difficult to trap in local minima thank to the sampling of the space state,
  - Evolutionary Algorithms are embarrassingly parallel,

- Vector Evaluated Genetic Algorithm
  - Non Pareto approach



Multi-objective Optimization with Vector Evaluated Genetic Algorithm Schaefer: 1985

MOEAs based on Pareto dominance

- To approach well the Pareto Front -> Convergence
- To have a uniformly distributed Pareto Front -> Diversity

- Non dominated sorting, niching and non niching technics, elitism,

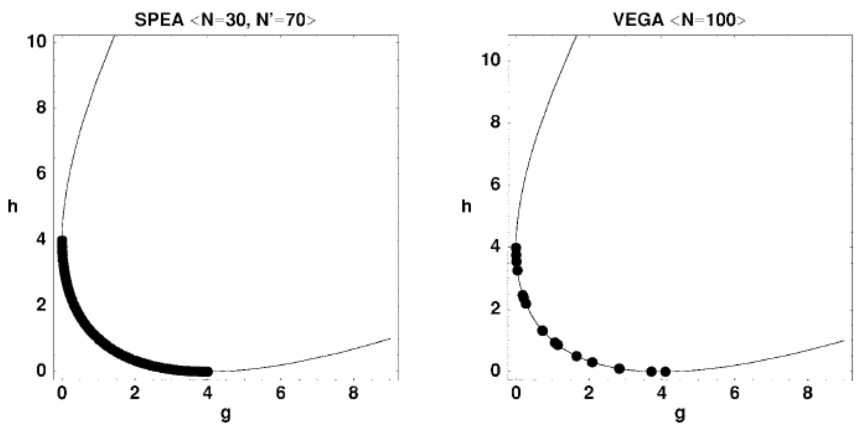


Fig. 5. Performance of SPEA and VEGA on Schaffer's f_2.

Multi-objective Evolutionary Algorithms: A comparative Case study and the strength Pareto Approach : Eckart Zitzler and Lotar Thiele 1999

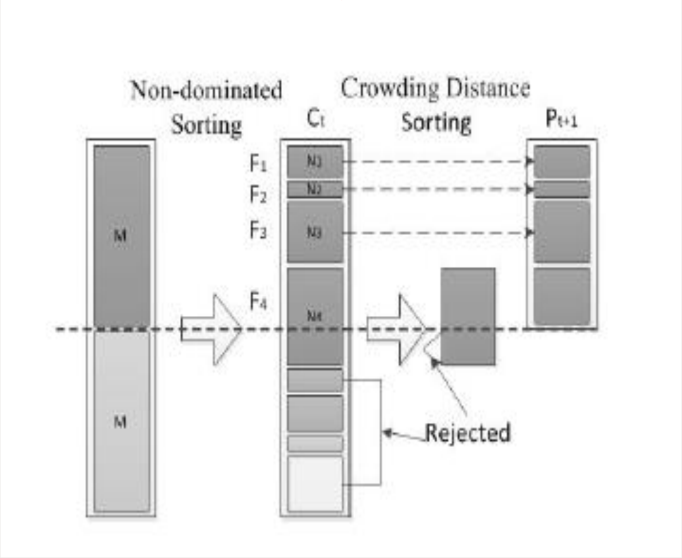
MOEAs based on Pareto dominance

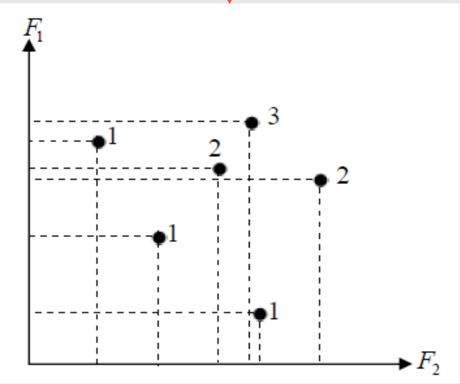
- NSGA II: Non dominated Sorting Genetic Algorithm

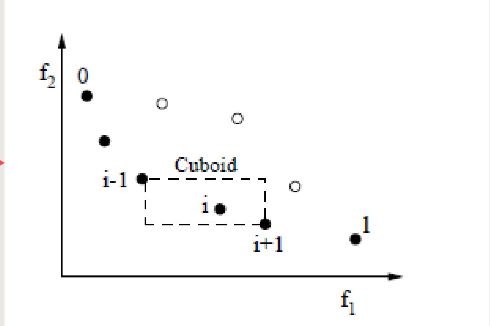
  Fast non dominating sorting approach

  Crowding distance

  Elitism



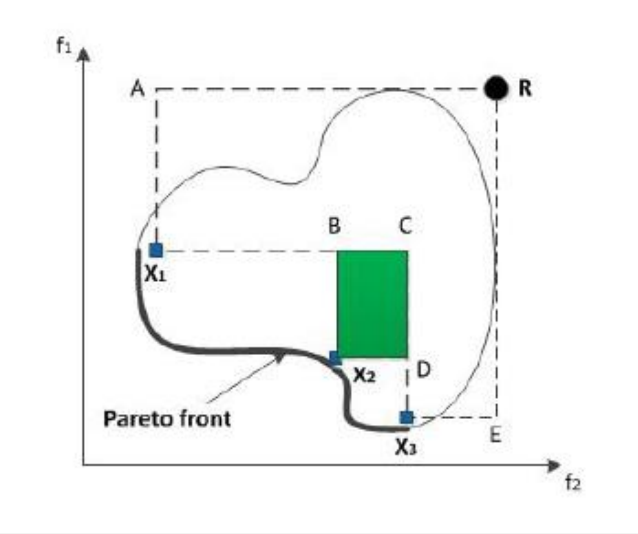




A fast elitist non dominated genetic algorithm for Multi-Objective Evolutionary optimizations: NSGA II, Kalynamoy Deb, Samir Agrawal: 2002

MOEA Based on performances indicator

- The hyper-volume indicator,
  - Evaluate conveniently convergence and diversity of the Pareto front,
  - High computational complexity, but one can use estimations (Monte Carlo method).



Source: A survey of Multi-objective Evolutionary Algorithms: Jiawei Zhang, Lining Xin: 2017g

MOEA Based on performances indicator

- An example, SMS-EMOA: S Metric Selection EMOA,
- Maximize the hyper-volume,
- Steady state algorithm.

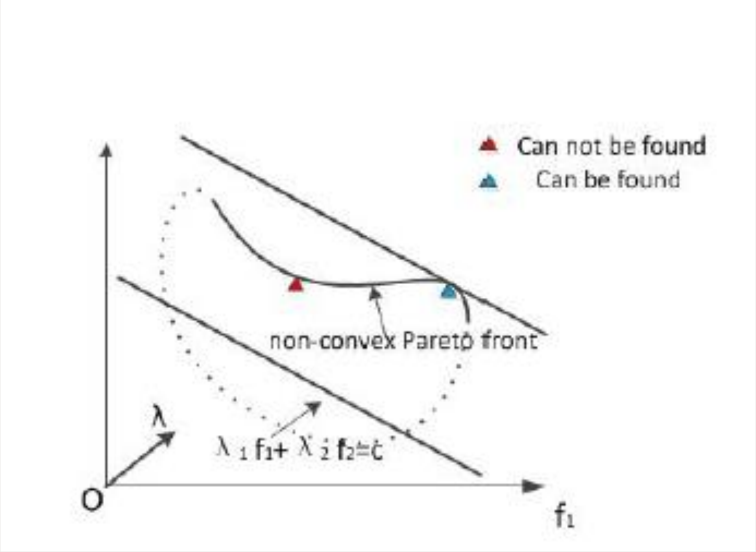
Algorithm 1 SMS-EMOA

$S_0 \leftarrow init()$
$t \leftarrow 0$
repeat
  $q_{t+1} \leftarrow generate(S_t)$
  $\{P_0, \cdots, P_n\} \leftarrow fast\ nondominated\ sort(S_t + \{q_{t+1}\})$
  $r \leftarrow argmin_{x \in P_n}[\triangle Hv(x, P_n)]$
  $S_{t+1} \leftarrow (S_t + \{q_{t+1}\} - \{r\})$
  $t \leftarrow t + 1$
until $termination\ condition\ fulfilled$

A survey of Multi-objective Evolutionary Algorithms: Jiawei Zhang, Lining Xing: 2017

› An example: Weighted sum approach

- Several linear combination of the objectives to find the Pareto Front
- Using a set of weight vectors: λ_i $i \in [1..N]$
- Minimize $g^{ws}(x \backslash \lambda_i) = \sum_{j=1}^{m} \lambda_{ij} * f_j(x), x \in \Omega$



A survey of Multi-objective Evolutionary Algorithms: Jiawei Zhang, Lining Xing: 2017

ASREA (Archive Based Stochastic Ranking Evolutionary Algorithm)

- NSGA II is a very good but sequential algorithm,
- ASREA -> Compute the dominance from a small archive,
- Complexity: O(m*a*n), a: archive size,
- Rank of an individual: number of individuals who dominate it + 1,
- If Rank = 1, replace an individual in the archive (except those at the extremity of the Pareto front),
- Half of the population composed of archives individuals, other half composed from a tournament selection.

  - GPU ASREA / NSGA II

Pop size :	100	1000	10,000	100,000	1M
NSGA-II :	0.0005s	0.03s	4.53s	19.2h	-
G-ASREA:	0.0001s	0.0001	0.0008	0.007	0.06s

GPGU based compatible archived based stochastic ranking evolutionary genetic algorithm: Pierre Collet - 2010

Examples

- Network flows placement
  - Path Computation Element context
  - “Solving Multicommodity Capacited Network Design Problems using a MOEA: Mark P. Kleeman, 2007)

- Controllers placement problem
  - « Genetic algorithm with particule swarm optimisation based mutation for distributed controllers placement in SDN »: Linxia Liao 2017
  - « An evolutionary controllers placement algorithm for reliable SDN networks »: Sanner, Ouzzif, Hadjaj-Aoul 2017
- NVFs Placement
  - Analog to resources management in data-centers
  - “A power efficient genetic algorithm for resource allocation in cloud computing data centers” :Guiseppe Portaluri, 2014

- VNFs chains placement
  - Mapping of a VNF chain on a networks resources graph
  - “Application of evolutionary Mechanism to Dynamic Virtual Network Function Placement” : Mari Otokura: 2016

Conclusion

- **Can be a generic solver for placements problems in SDN and NFV context.**

- The basic frame of a GA is flexible and easy to adapt to placements problems, the main point is to define what is an individual, number of objectives can be extended,

- Common model structure can be designed for all NFV & SDN placement problems

- They are easy to customize to have a better tuning to a specific problem through local cross-over optimization (Lamarckism, Baldwinism, hybridation…)

- Evolutionary Algorithms can also be parallelised, there is an opportunity today due the parallelisation of computers

- They are adapted to dynamic approaches…

Merci / Thanks