NATIONAL TECHNICAL UNIVERSITY of ATHENS
Lab. Thermal Turbomachines
Parallel CFD & Optimization Unit

Design Optimization Tools & Applications

1. Introduction
2. Design of Matrix Turbines

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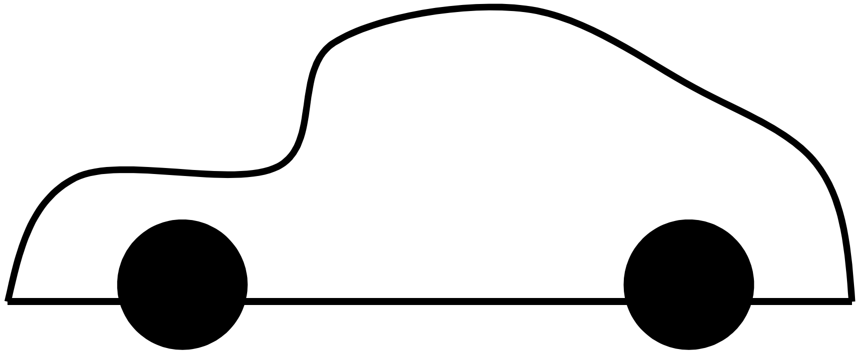
- From the Analysis to the Design-Optimization
- Single Objective Optimization, SOO
- Multi Objective Optimization, MOO
- Multi Disciplinary Optimization, MDO

TERMINOLOGY: Understand the difference:

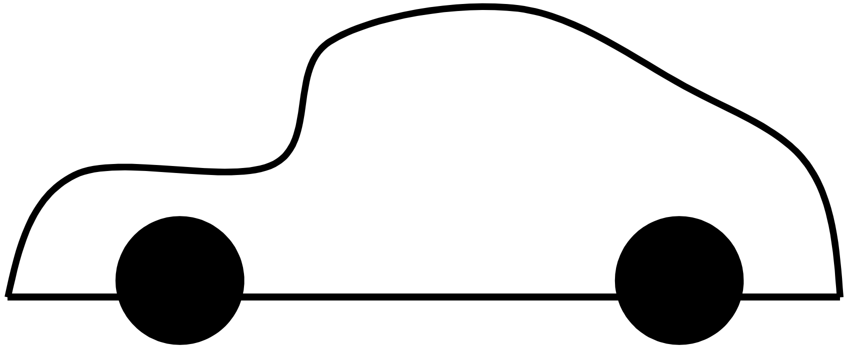


- Optimal Design of a Car
- Design of Optimal Car
- Optimal Design of an Optimal Car
- Optimal Design of an Optimal Car Shape

What is Optimal (Car)? – Optimal Function

- The one with max. speed
- The one with min. fuel consumption
- The most comfortable one
- The less expensive
- The one with min. emissions
- …

Optimality : an Objective function (min ή max F) must be carefully defined!!!

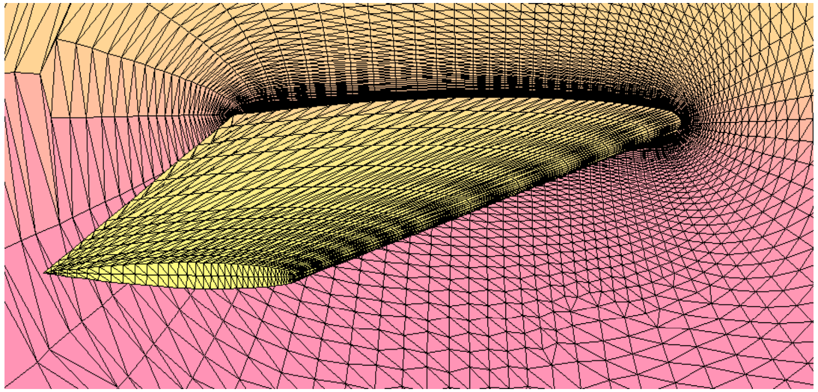


- Objective Function F
- Cost Function (min)
- Fitness Function (max)

But what if more than one objectives?

Transforming a MOO problem to a SOO one

<u>Example:</u> Design of Optimal Wing



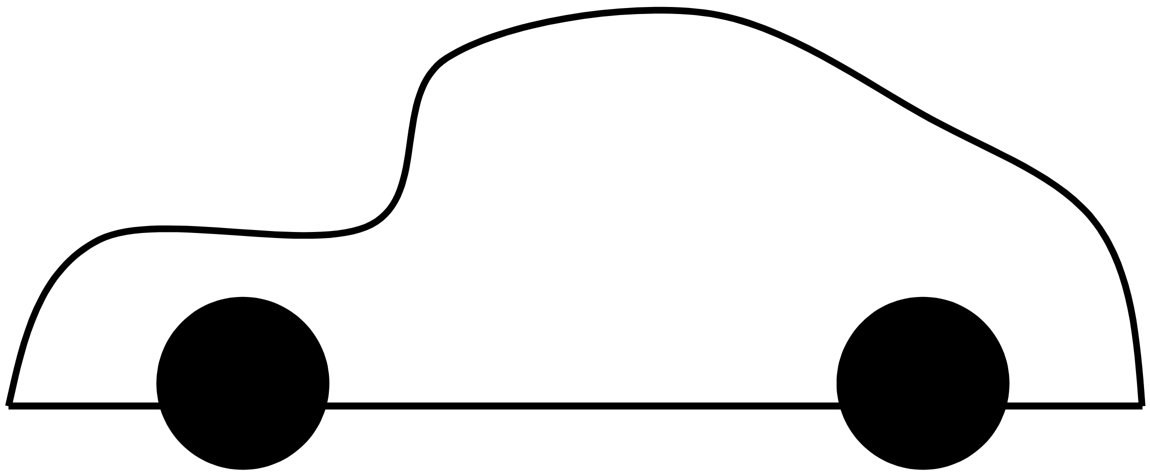
max C_L min C_D	min $-C_L$ min C_D	min $1/C_L$ min C_D	max C_L max $-C_D$

min $C_D + w/C_L$	min $C_D + 1/C_L$	min $C_D + 10/C_L$

min C_D subject to: $C_L=1.2$	min C_D subject to: $C_L>1.2$

Objective Function

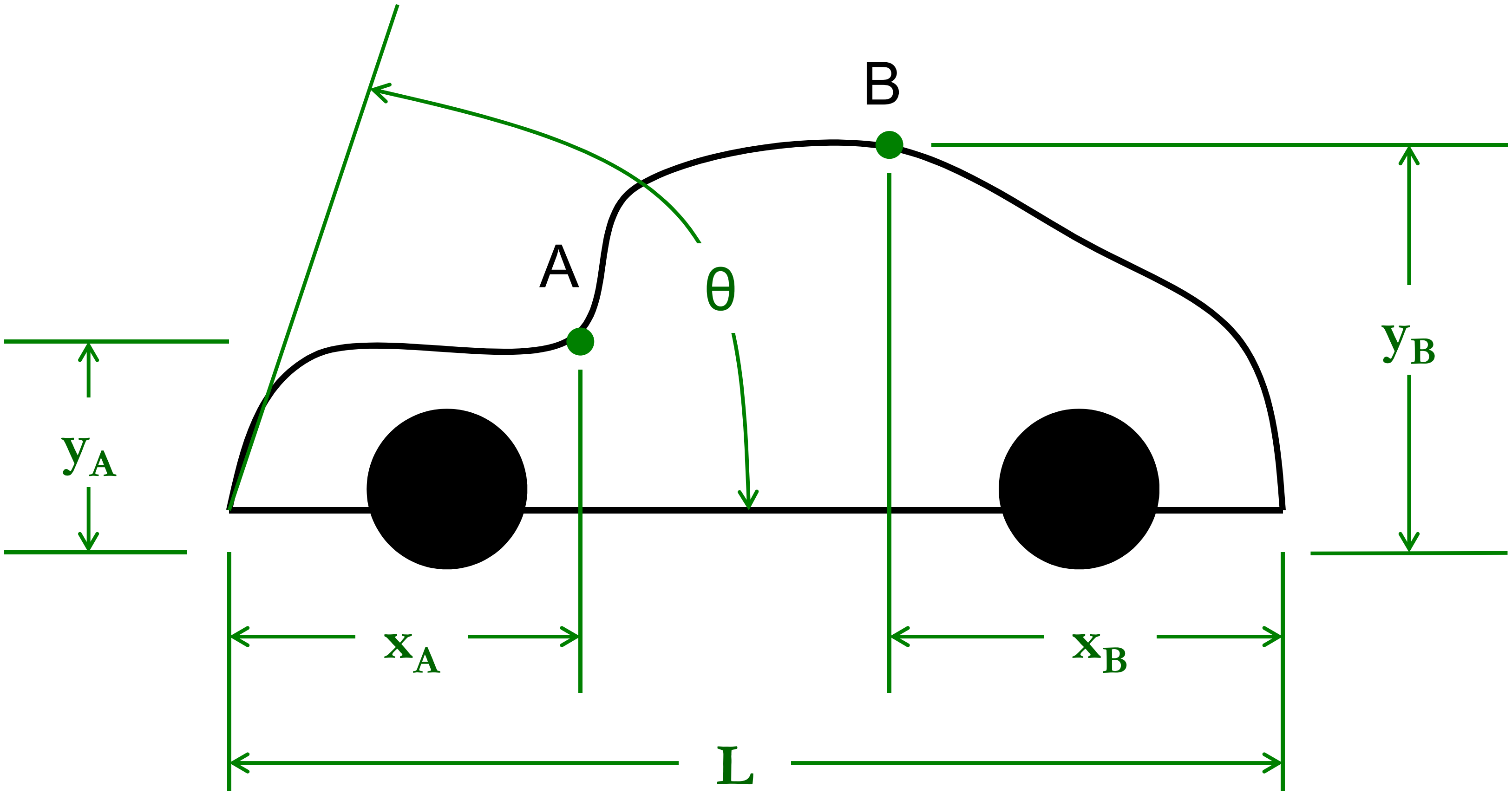
Objective: Minimum DRAG



Objective Function: DRAG Coefficient

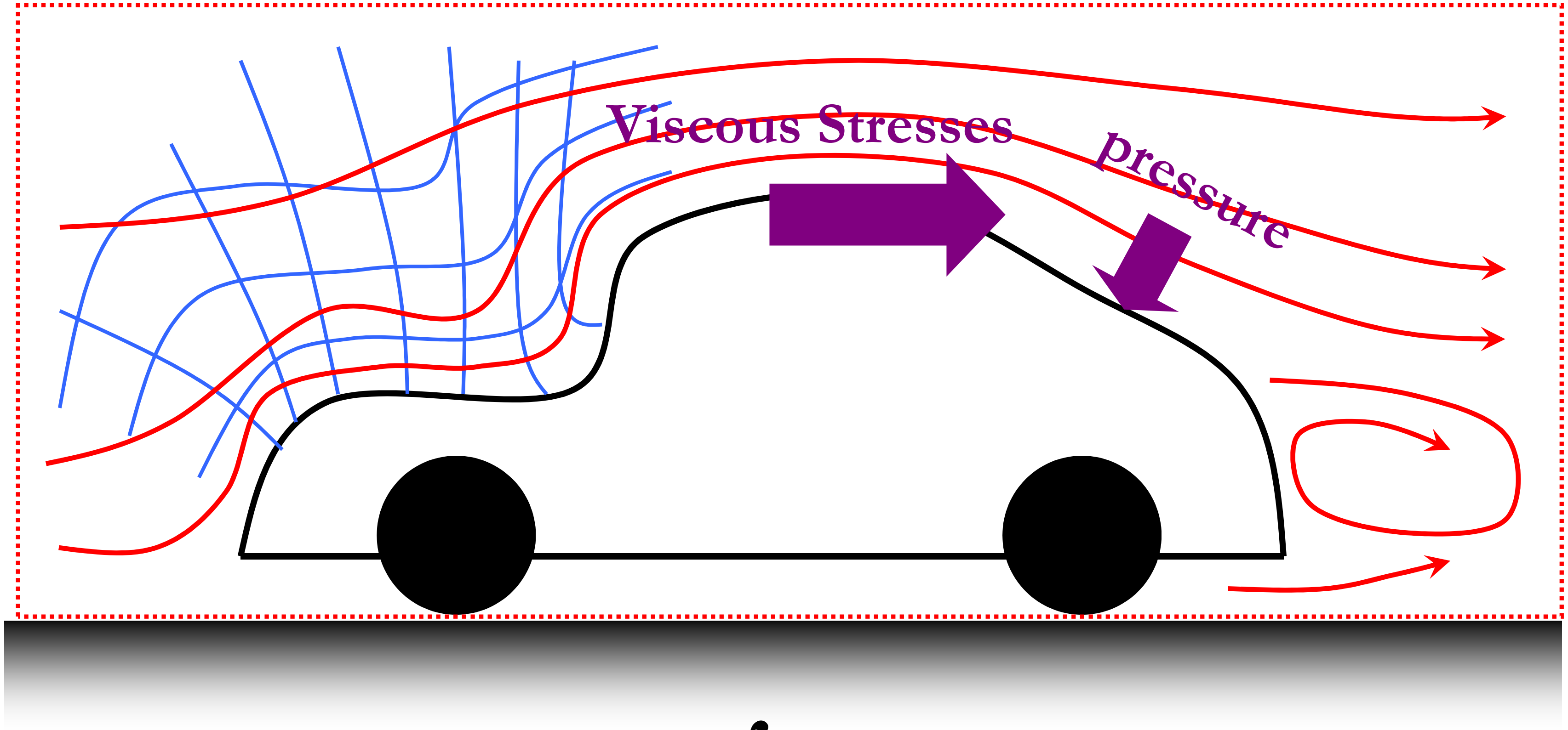
$$\min F = C_D$$

Shape Parametrization



N=6 degrees of freedom (dofs)

Evaluation Tool: Code for the numerical solution of the Navier-Stokes eqs.

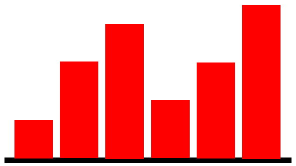


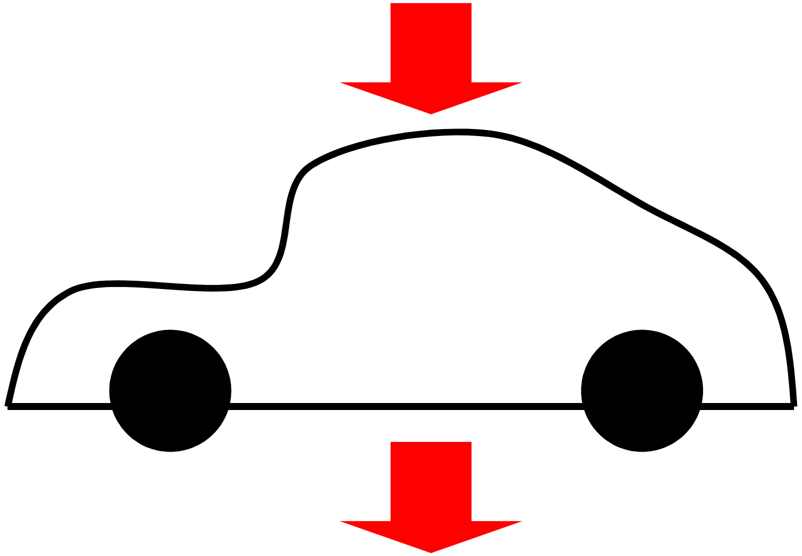
$$C_D = \oint_{carcontour} forces$$

Evaluation

$\vec{b}$ =

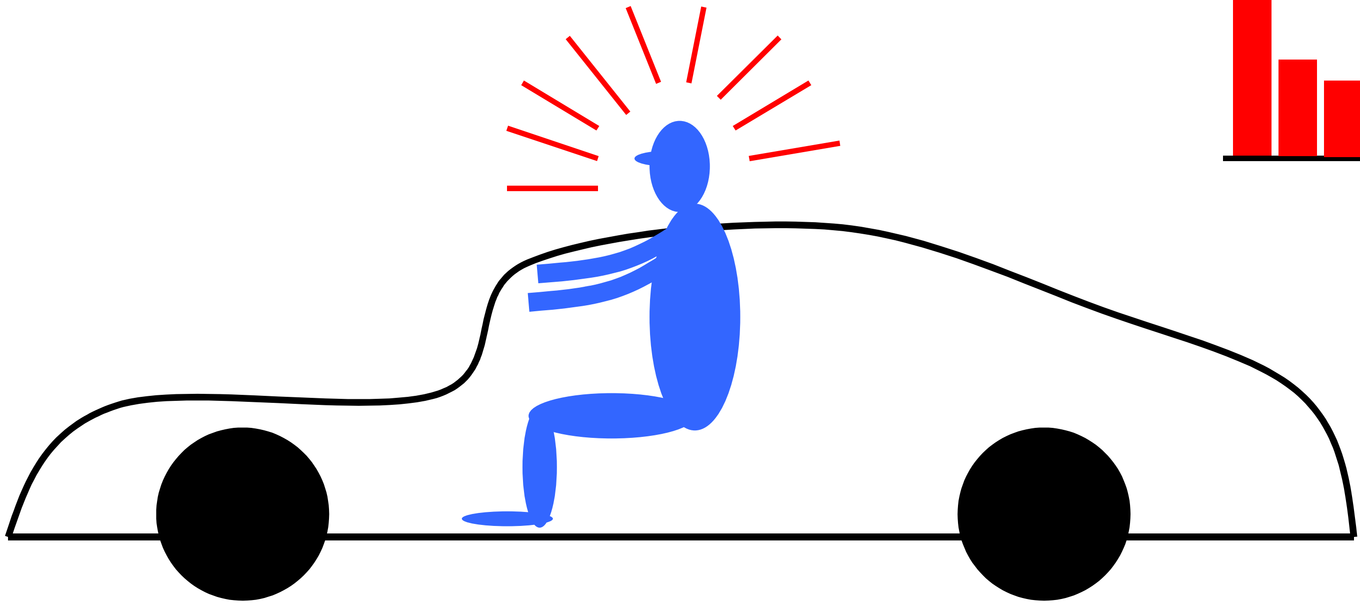
L	x_A	y_A	x_B	y_B	θ
b1=…	b2=…	b3=…	b4=…	b5=…	b6=…

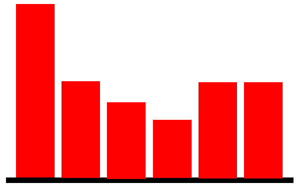




$F=C_D=\ldots$

Constraints:





Equality & Inequality Constraints!!!

Feasible & Infeasible Solutions to the problem

Classification of Optimization Methods

Gradient-Based Method

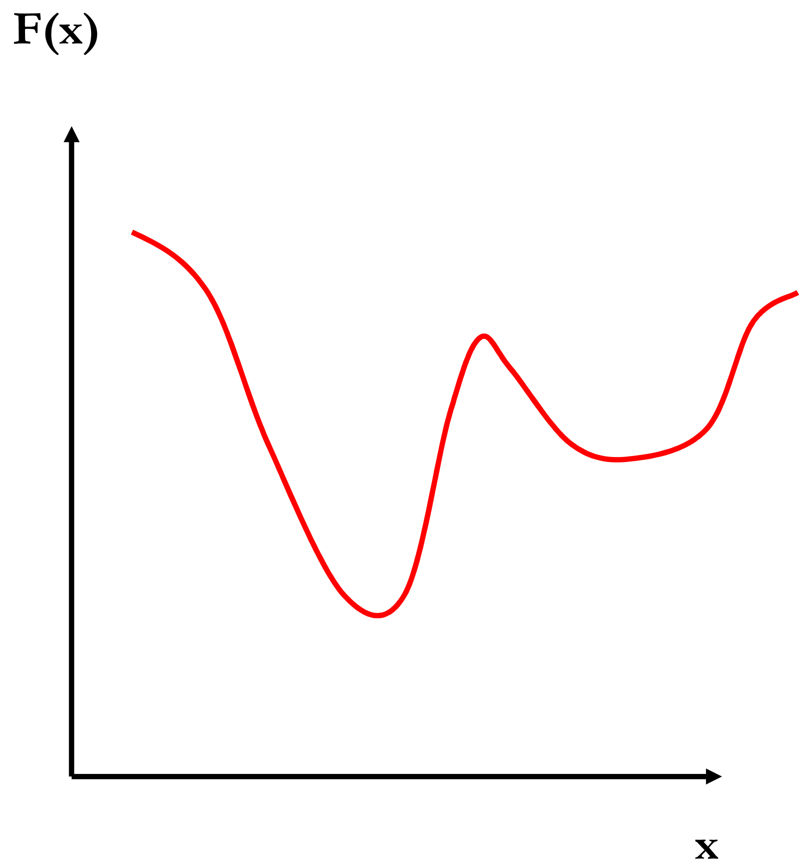
vs.

Stochastic Methods

Individual-based Methods

vs.

Population-based Methods

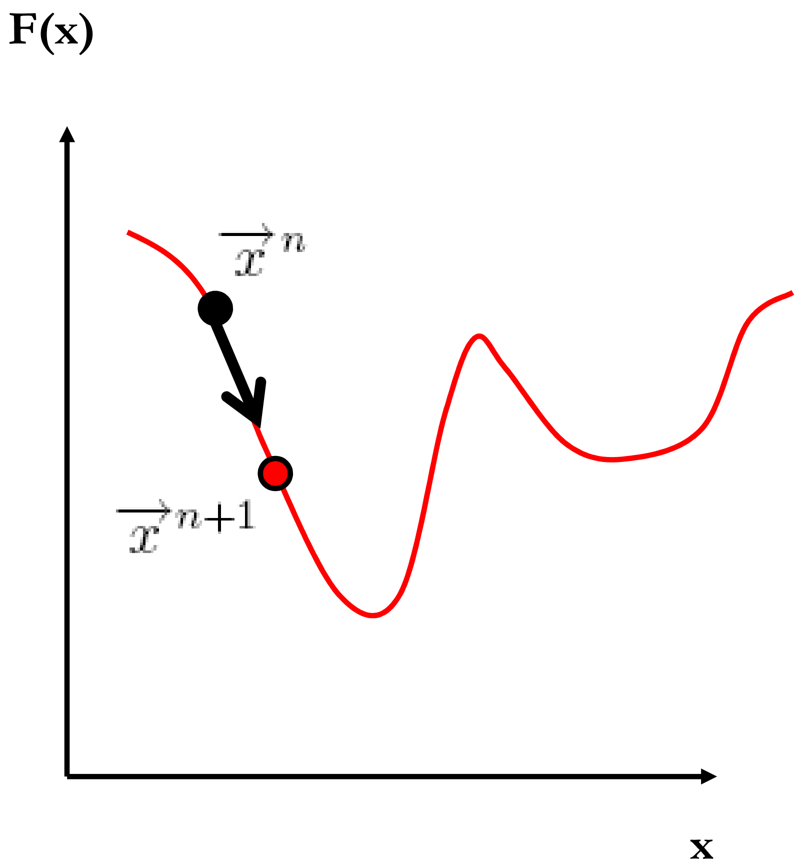


Deterministic (Gradient-Based) Optimization

$$\overrightarrow{x}^{n+1} = \overrightarrow{x}^{n} + \eta^n \, \overrightarrow{p}^{n}$$

$$\overrightarrow{p}^{n} = -\nabla F(\overrightarrow{x}^{n})$$

(if minimization)

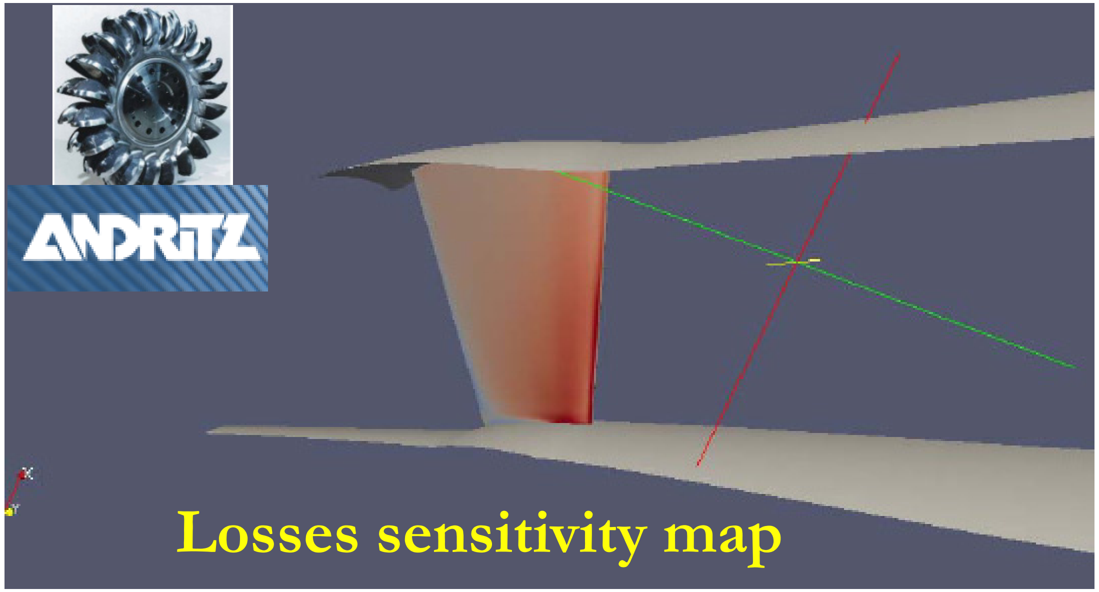


How to compute the *gradient* of F:

- Finite-Differences
- Complex Variable methods
- Automatic Differentiation
- Adjoint method

Deterministic (Gradient-Based) Optimization

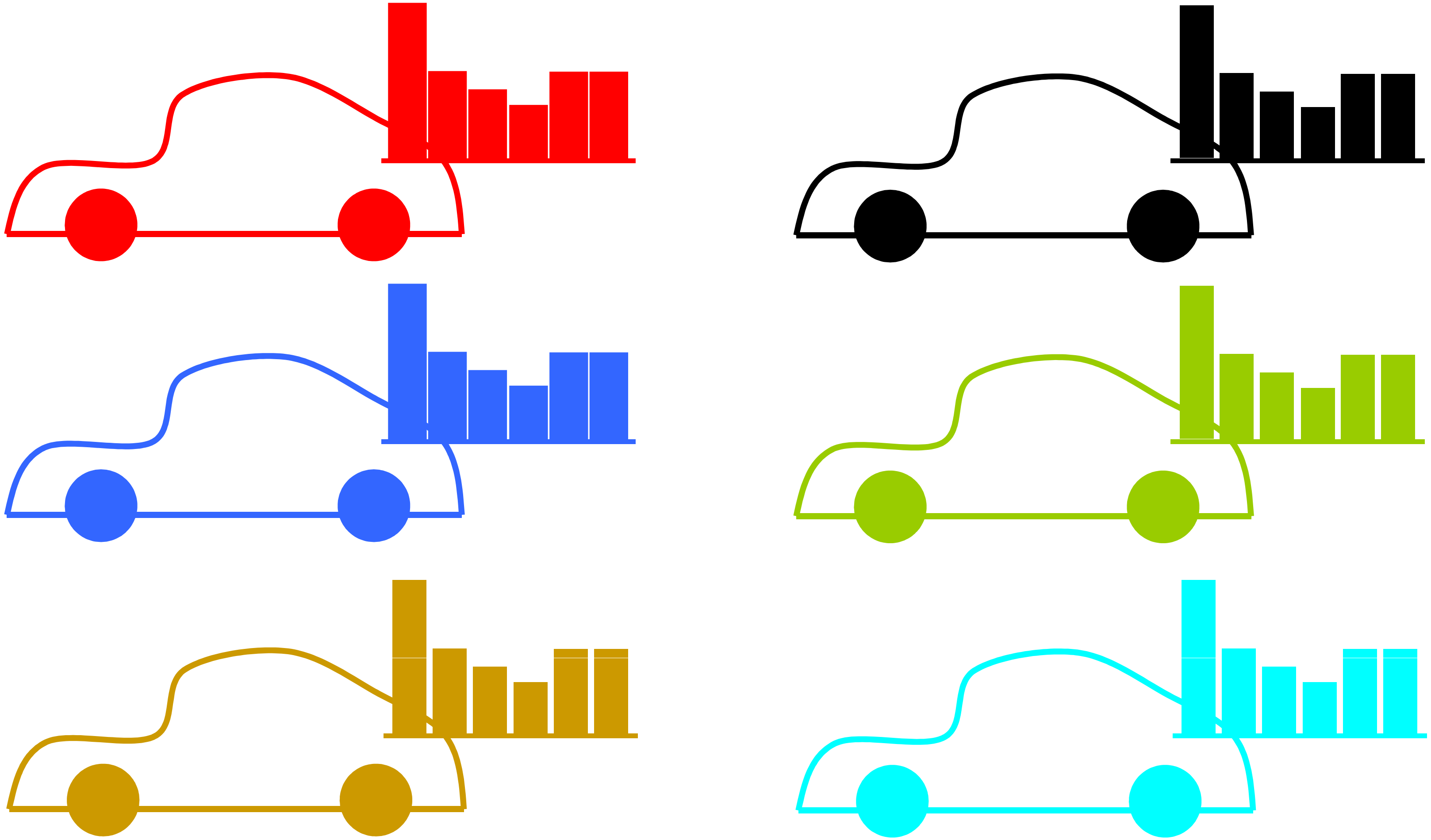
(a <u>by-product</u> of the adjoint method)



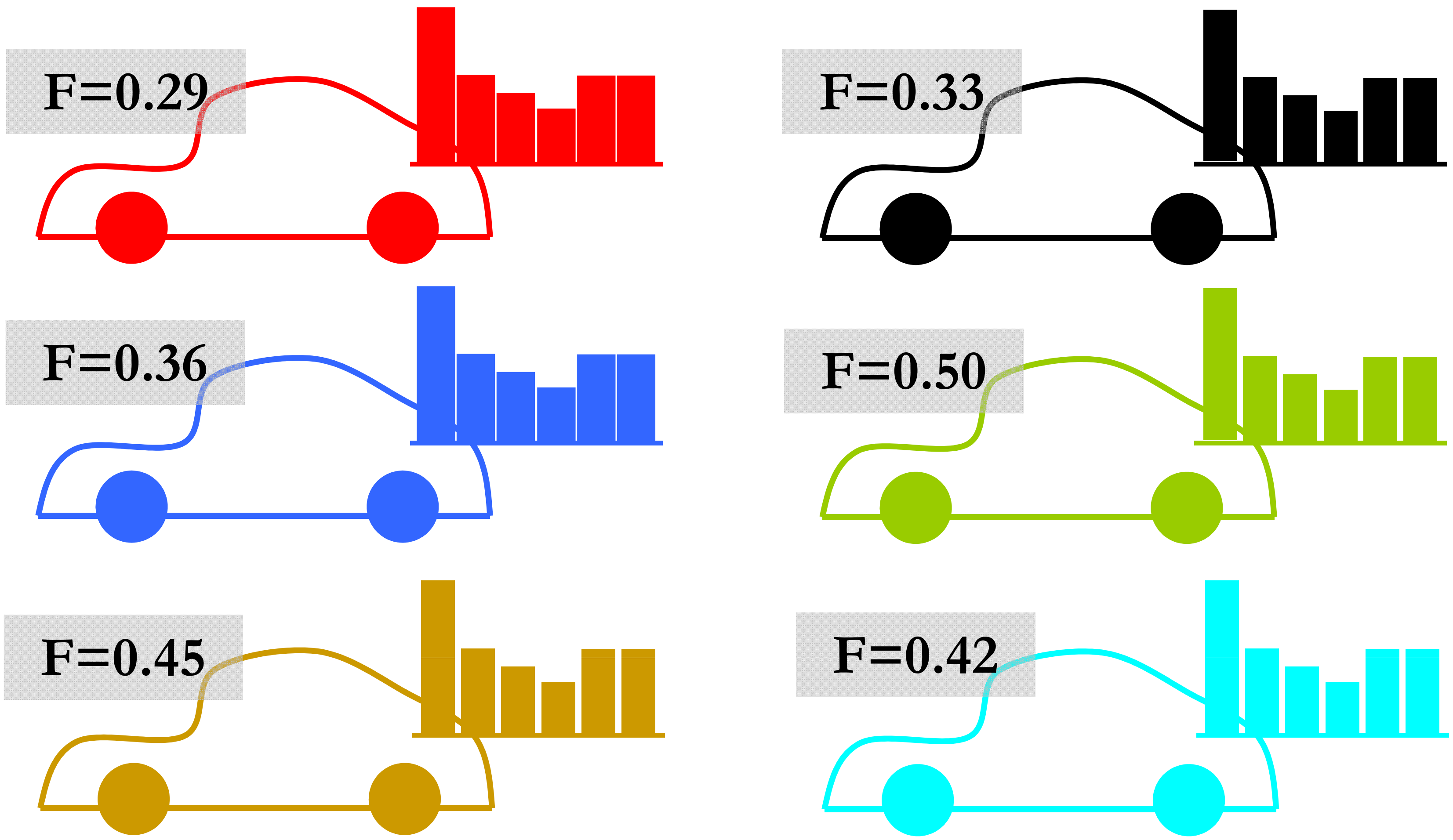
(a <u>by-product</u> of the adjoint method)

(<u>bridging the "gap" between modern design tools and an old-fashioned designer</u>)

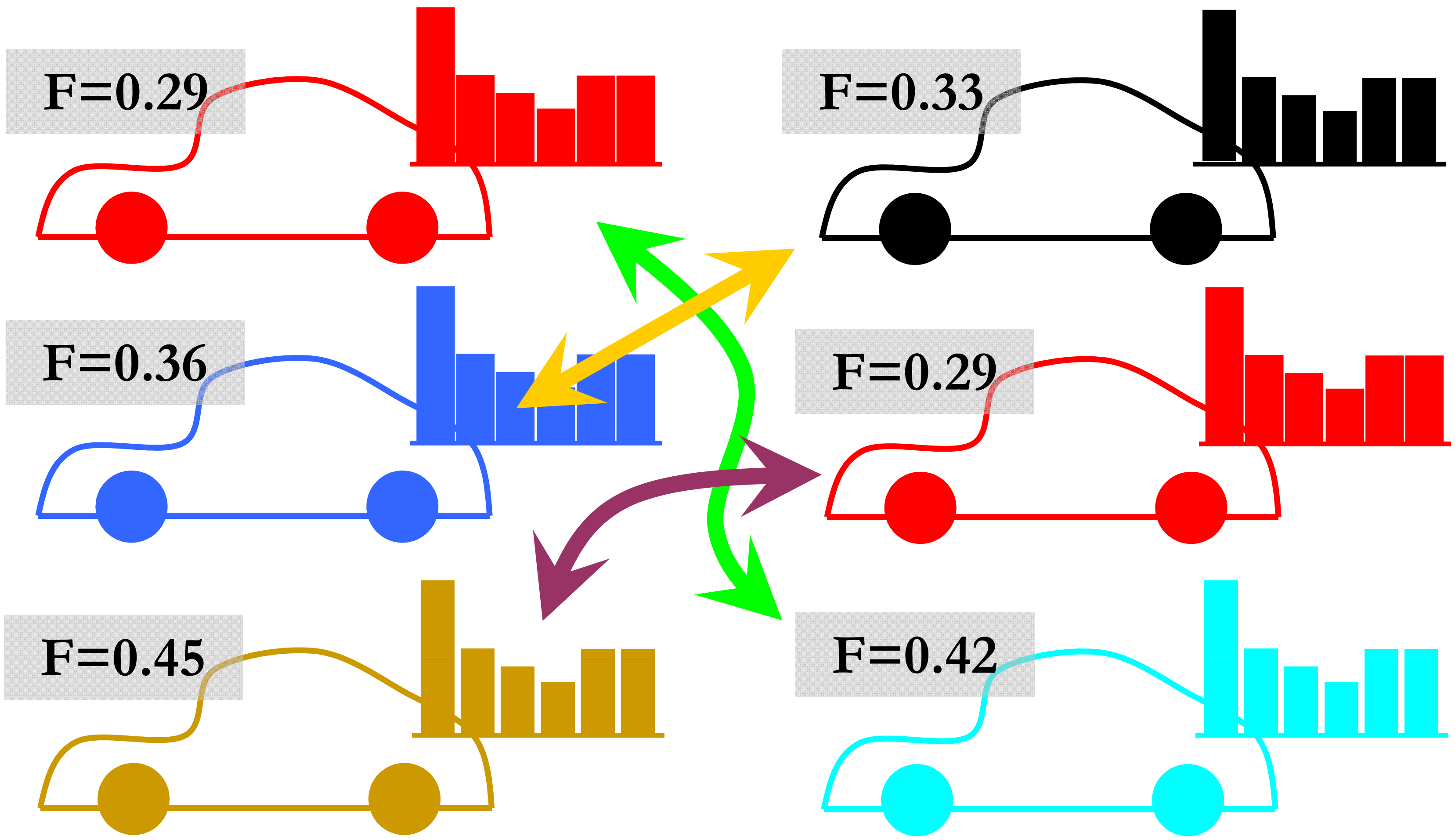
A Gradient-Free Population-based Algorithm:



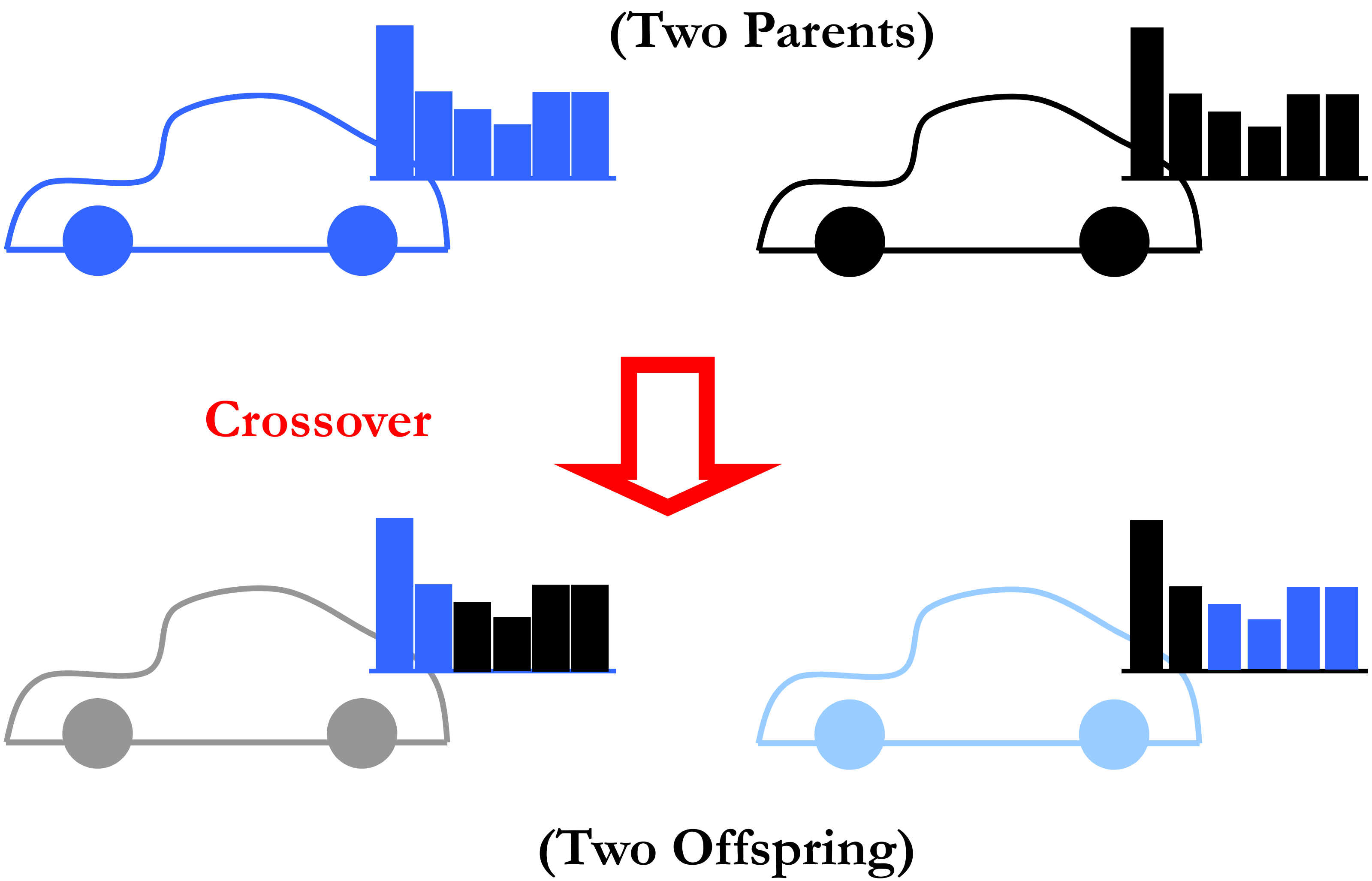
Evaluation of the Population:

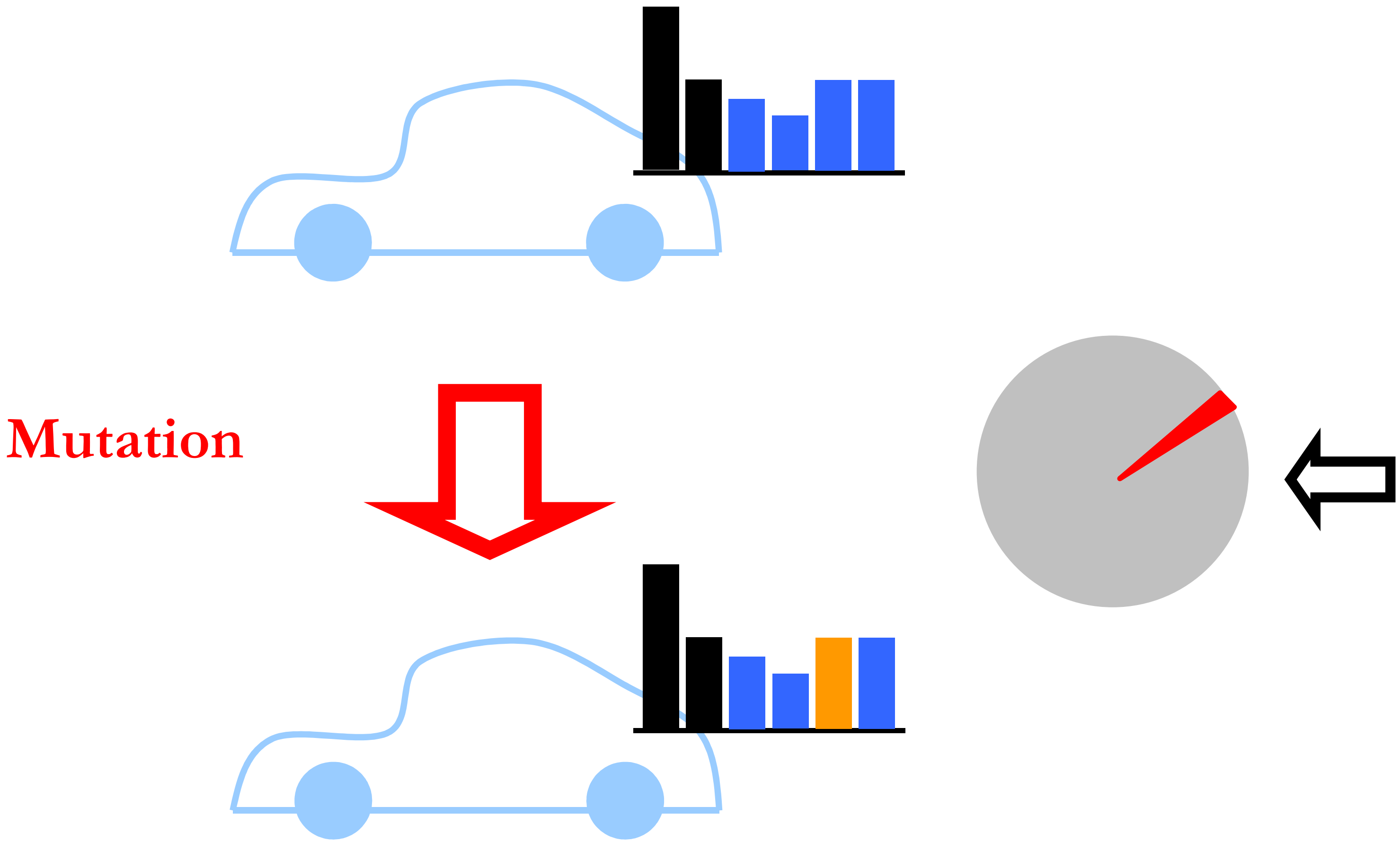


Parent Selection:

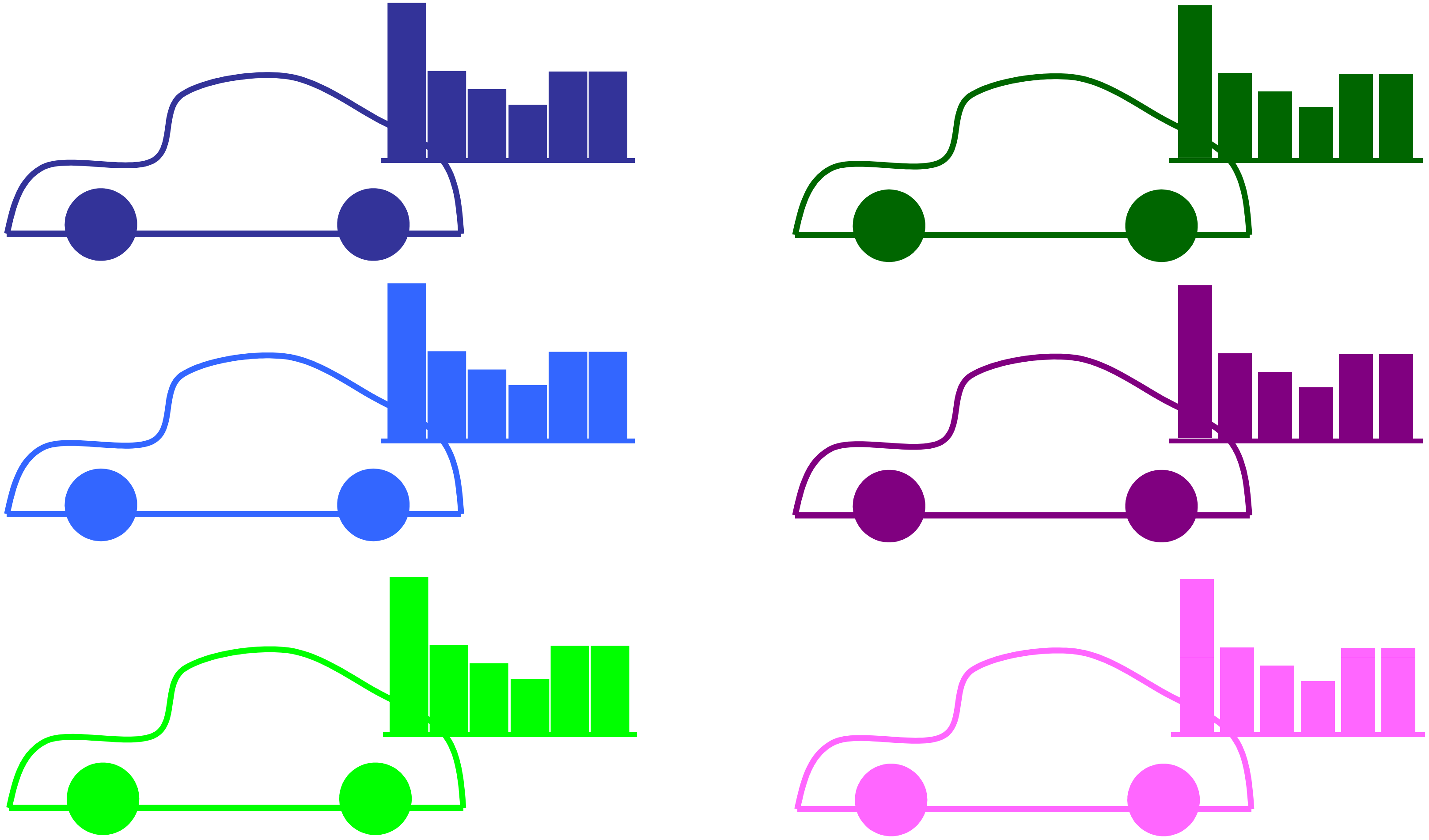


Evolutionary Algorithms

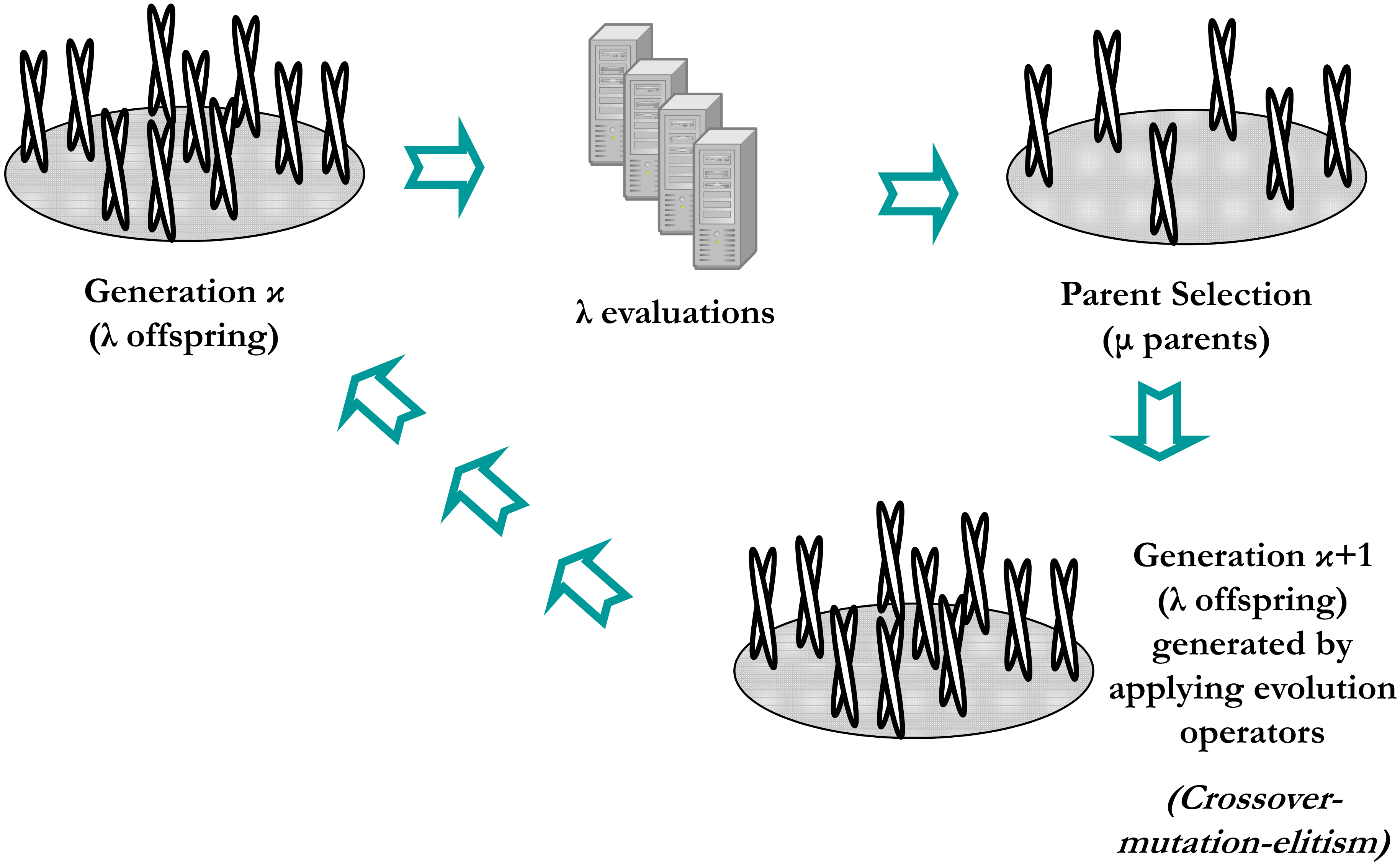



Mutation

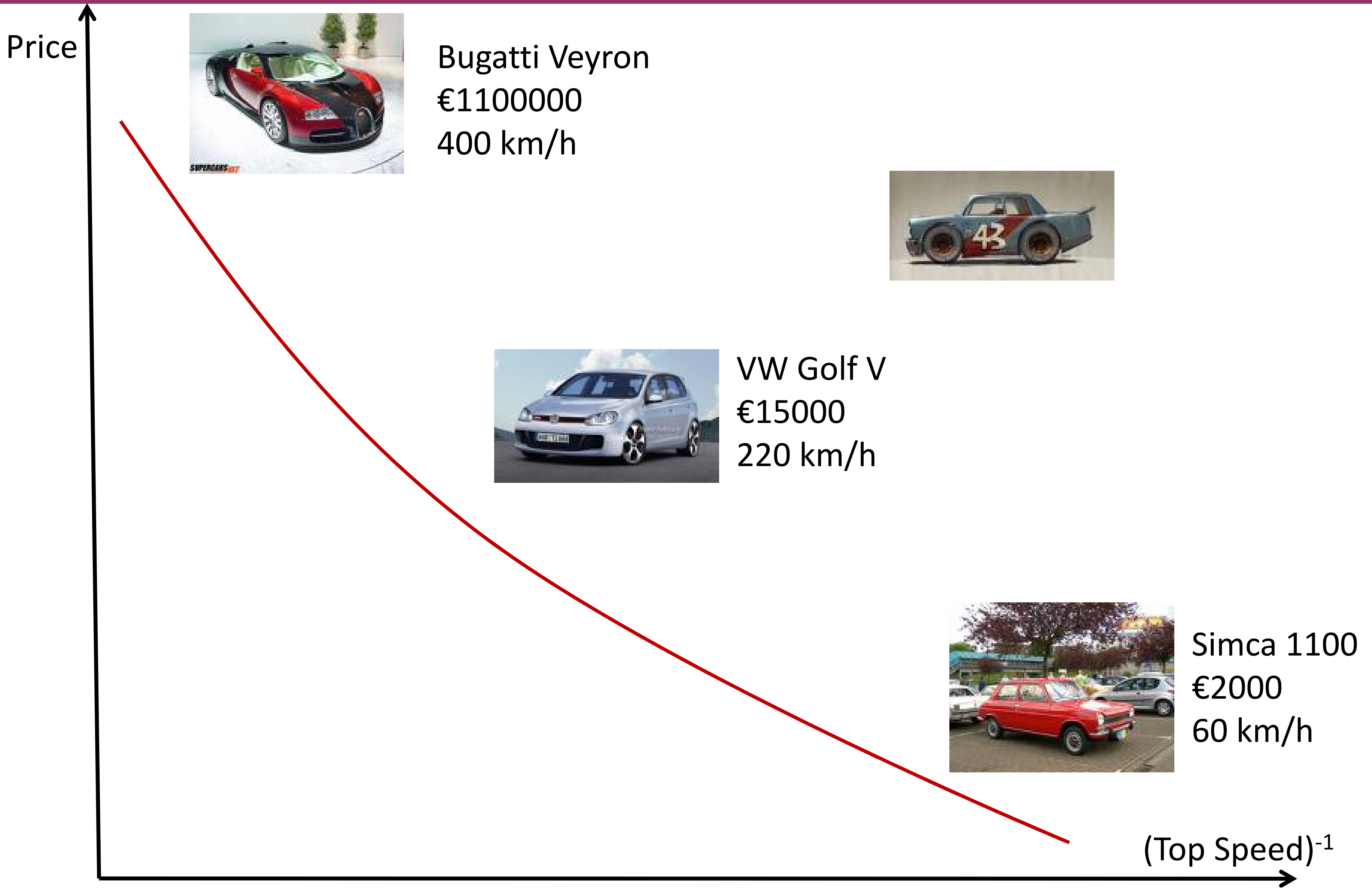
The New Offspring Population



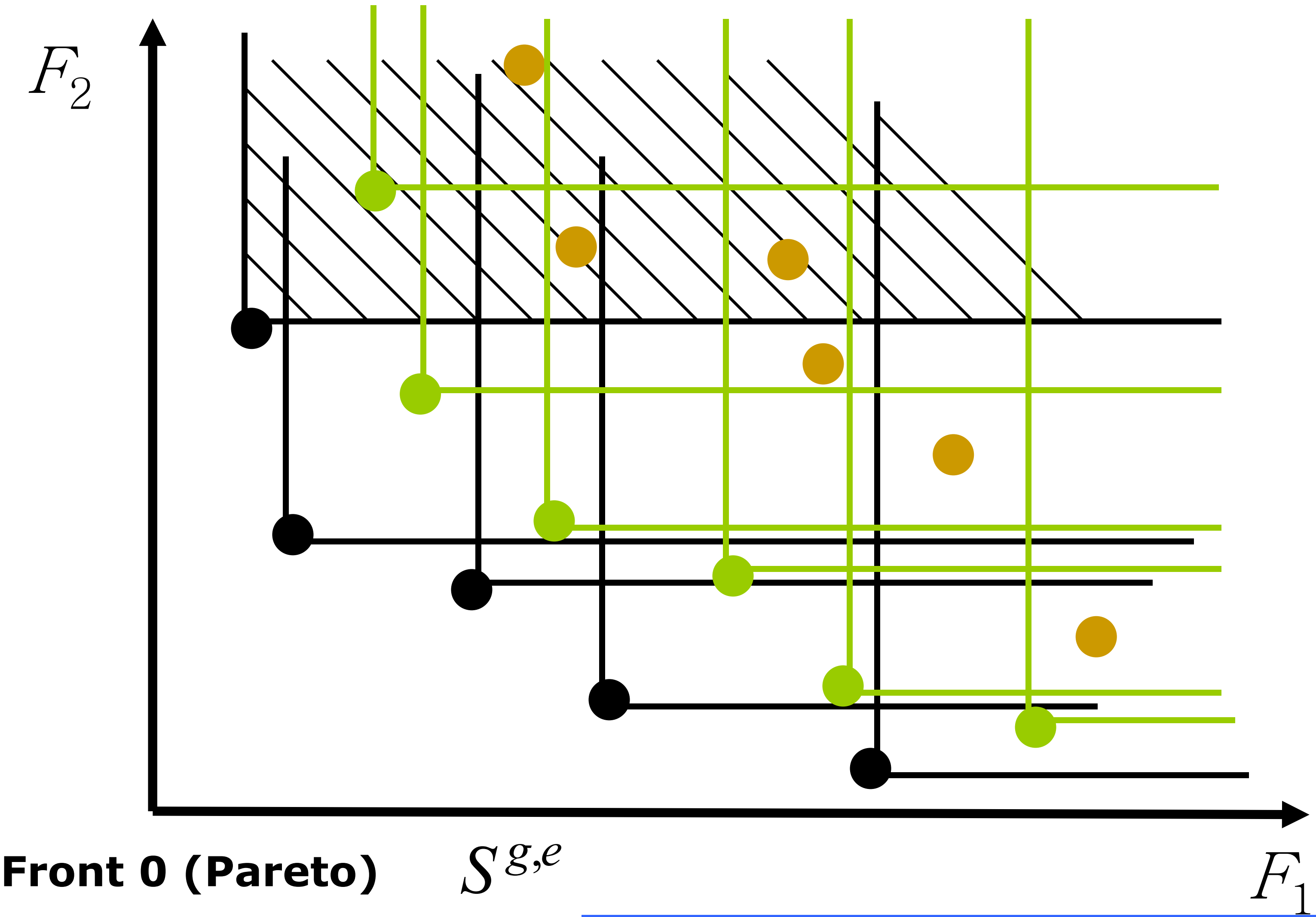
The Generalized (μ,λ) Evolutionary Algorithms



Multiobjective Optimization – The Pareto Front



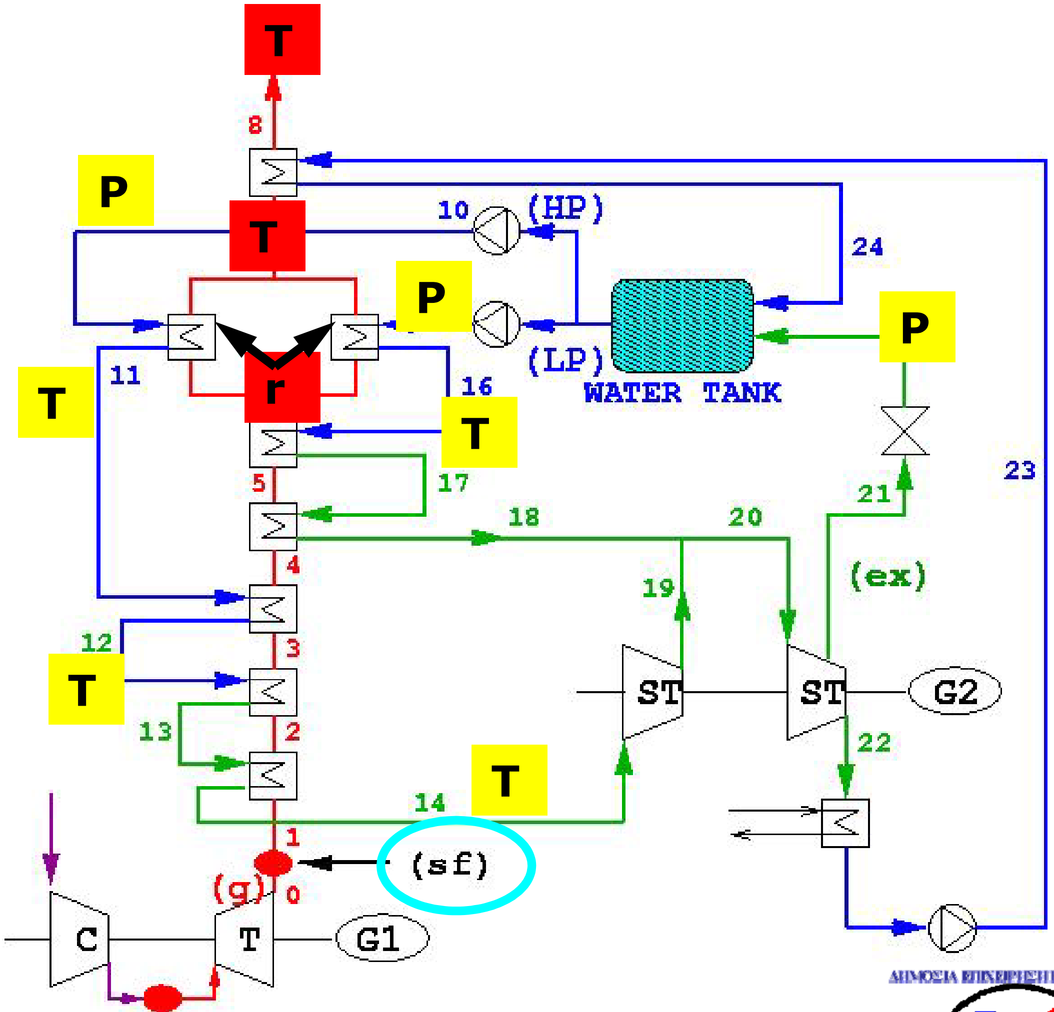
Multiobjective Optimization – The Pareto Front



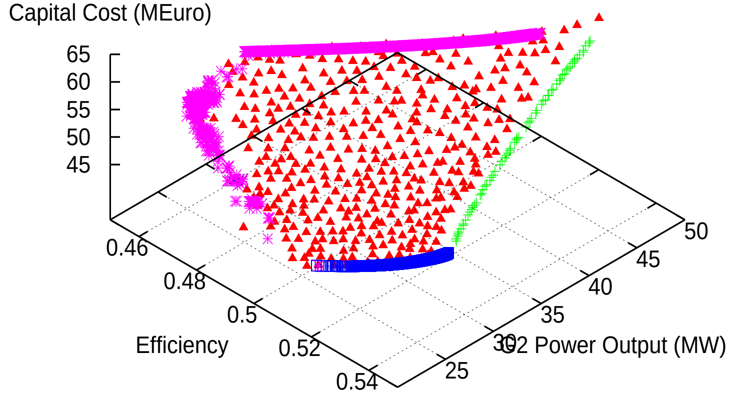
- Front 0 (Pareto)
- Front 1
- Front 2

Two-objective Example: min F_1, min F_2

Example: Design of Optimal Power Plants



Three Objectives:
(a) Max. efficiency,
(b) Max. power output,
(c) minimum investment



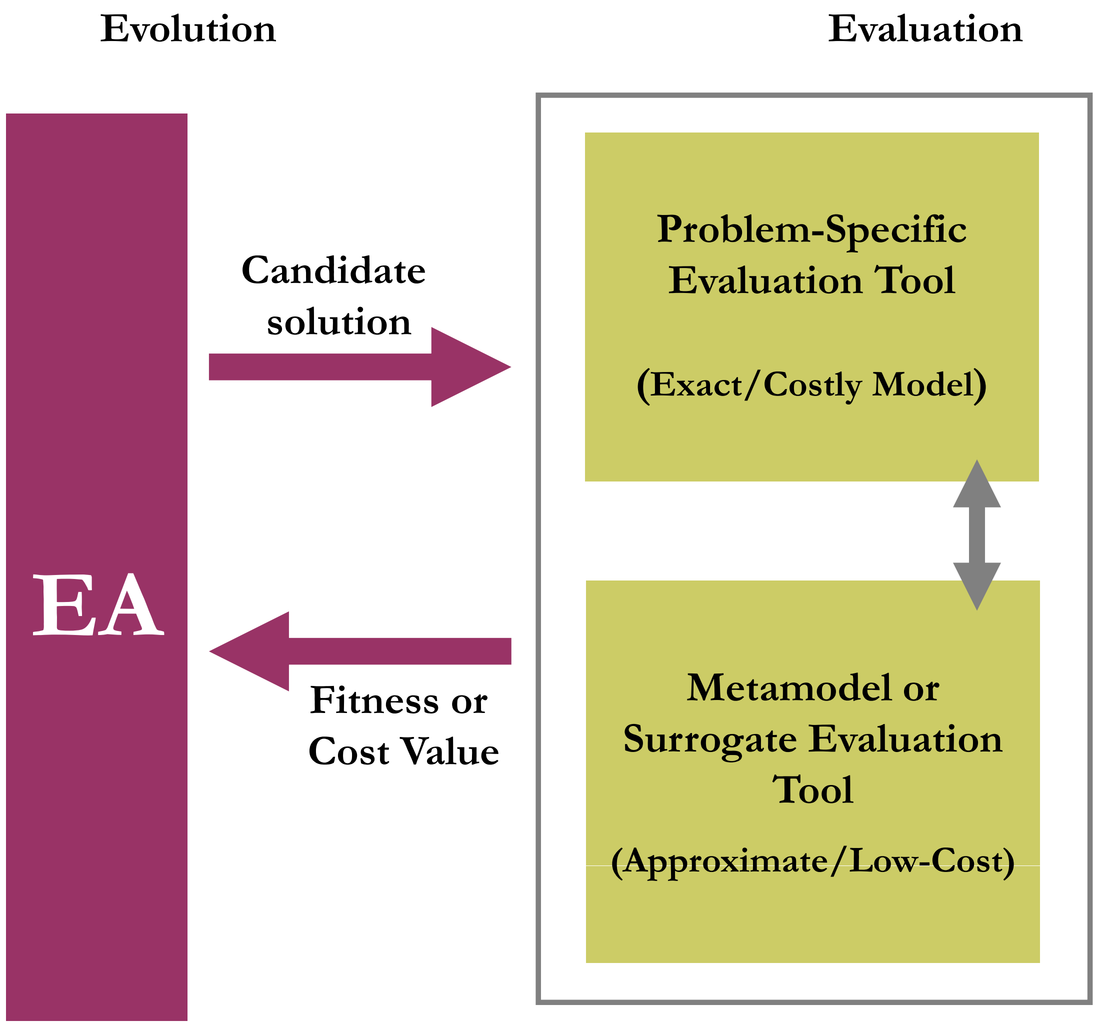
Research funded by

Unfortunately:

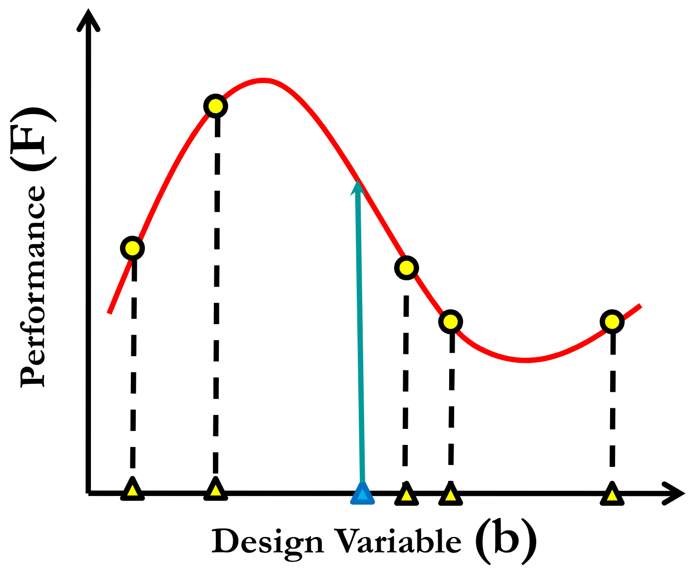
Conventional EA/ACO/PSO/BFO etc are computationally expensive, even on parallel platforms!

This is where research is focusing during the last decade!!!!!!!!!

Metamodel-Assisted Evolutionary Algorithms (MAEAs)

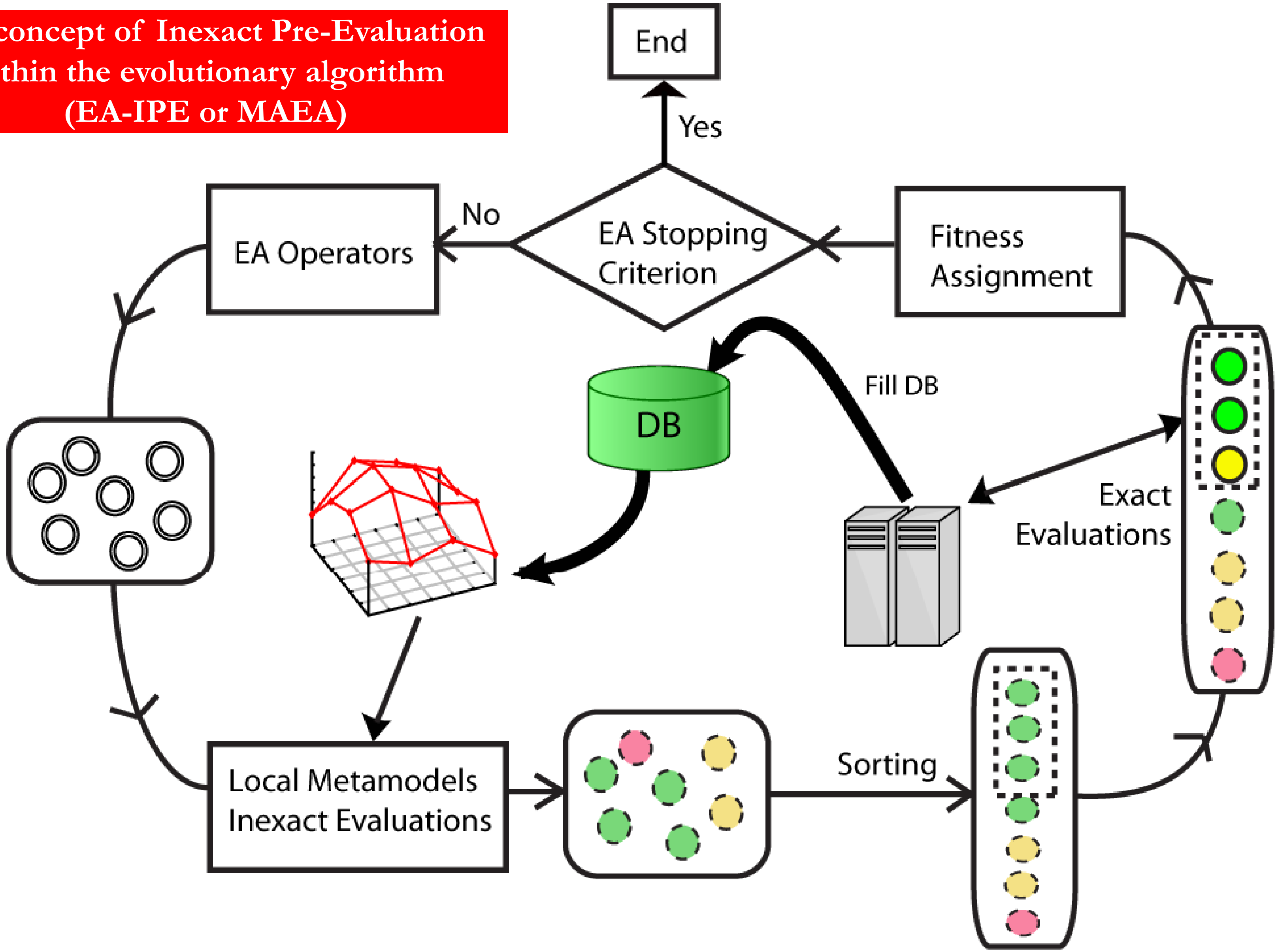


The role or metamodels during the evolution is, practically, to interpolate previously evaluated individuals (generated during the EA) for saving CPU cost.

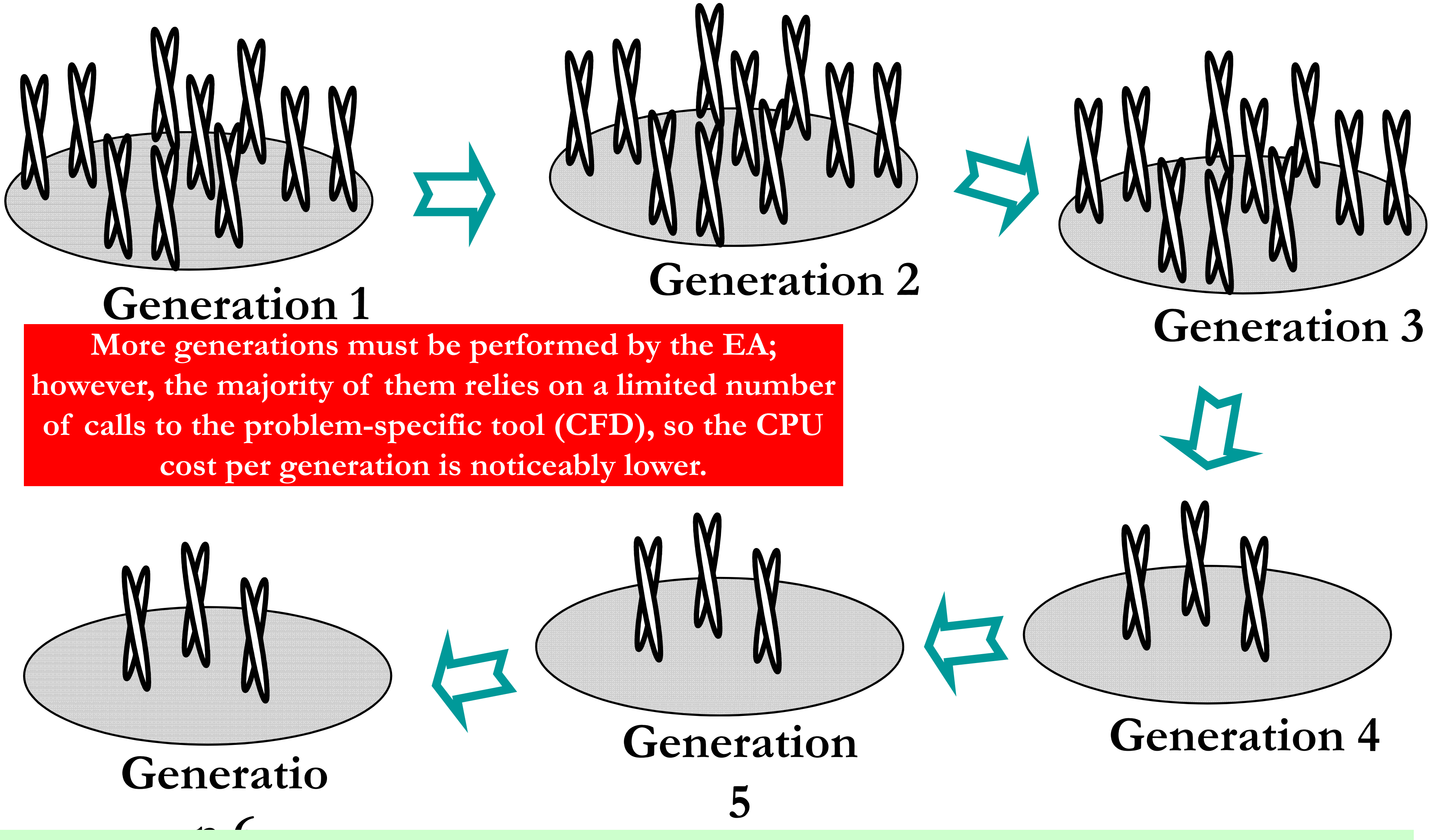


MAEAs with On-Line Trained Metamodels

The concept of Inexact Pre-Evaluation within the evolutionary algorithm (EA-IPE or MAEA)

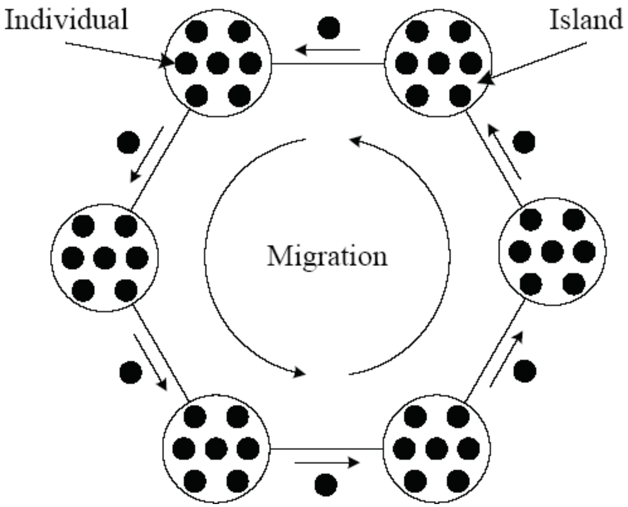


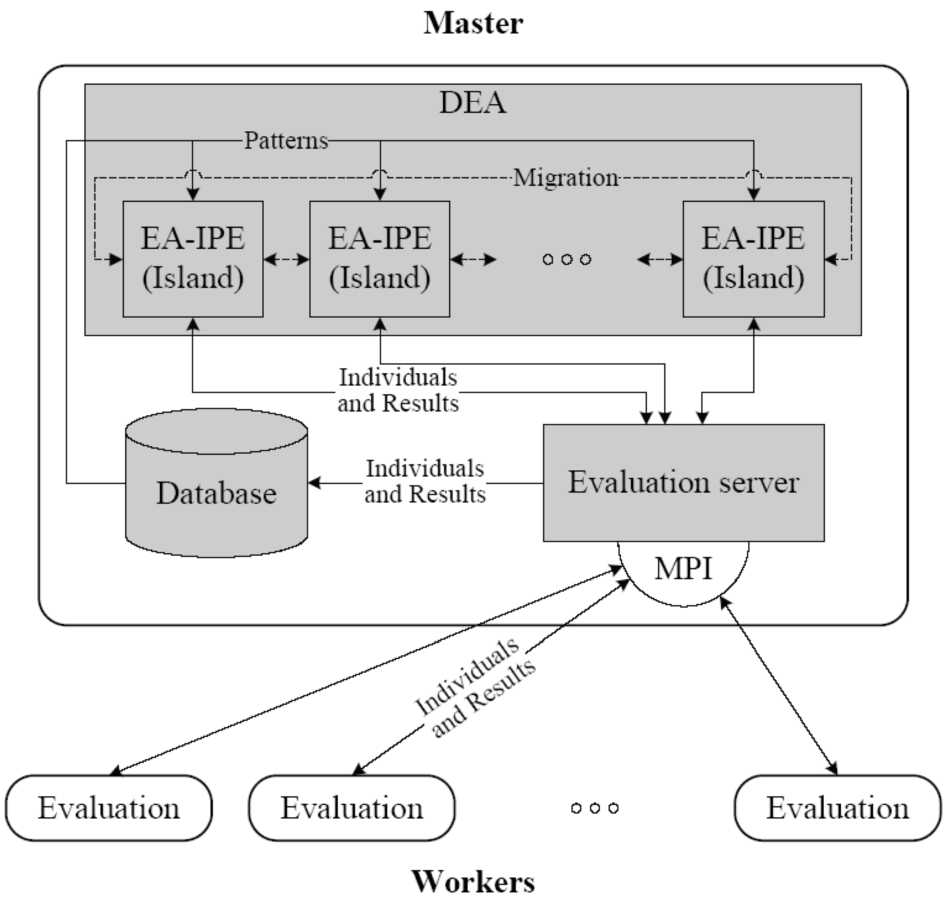
MAEAs with On-Line Trained Metamodels



More generations must be performed by the EA; however, the majority of them relies on a limited number of calls to the problem-specific tool (CFD), so the CPU cost per generation is noticeably lower.

K.C. GIANNAKOGLOU: 'Design of Optimal Aerodynamic Shapes using Stochastic Optimization Methods and Computational Intelligence', Int. Review Journal Progress in Aerospace Sciences, Vol. 38, pp. 43-76, 2002.





Basic issues:

- Number of demes or islands
- Communication topology
- Communication frequency
- Migration algorithm
- EA set-up per deme

M.K. KARAKASIS, A.P. GIOTIS and K.C. GIANNAKOGLOU: 'Inexact Information Aided, Low-cost, Distributed Genetic Algorithms for Aerodynamic Shape Optimization', Int. J. for Numerical Methods in Fluids, Vol. 43, pp. 1149-1166, 2003.

Expected Gain in CPU Cost (EA/MAEA/DEA/DMAEA)

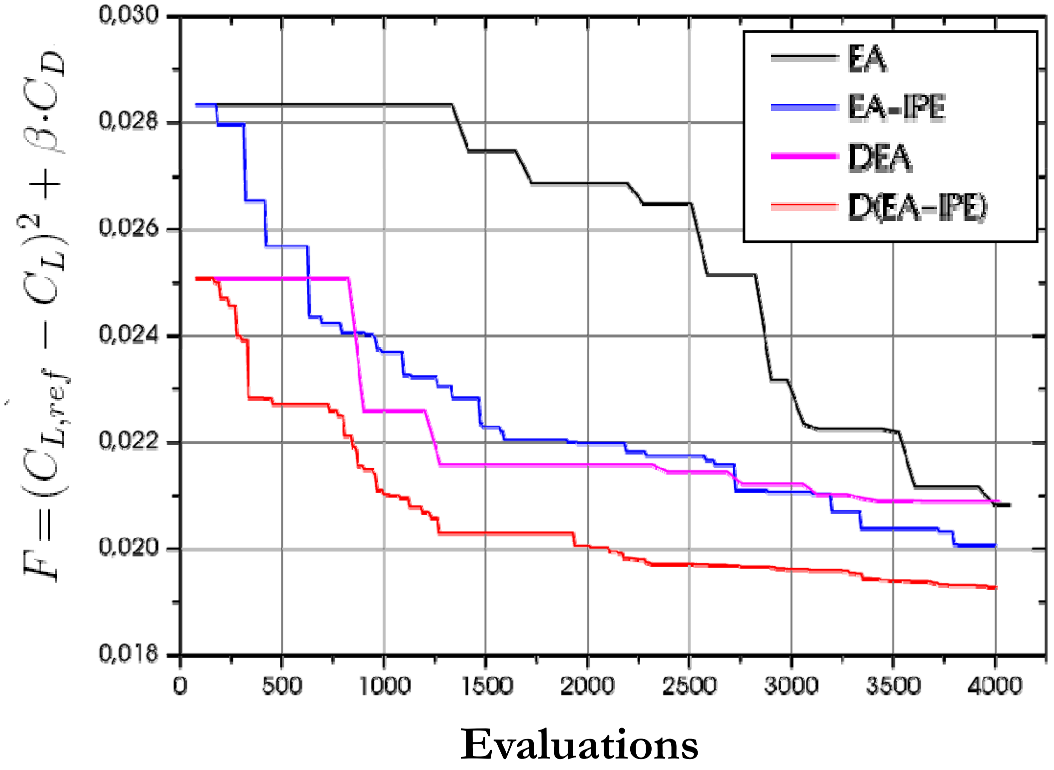
Airfoil Shape Optimization (min. C_D, fixed C_L)

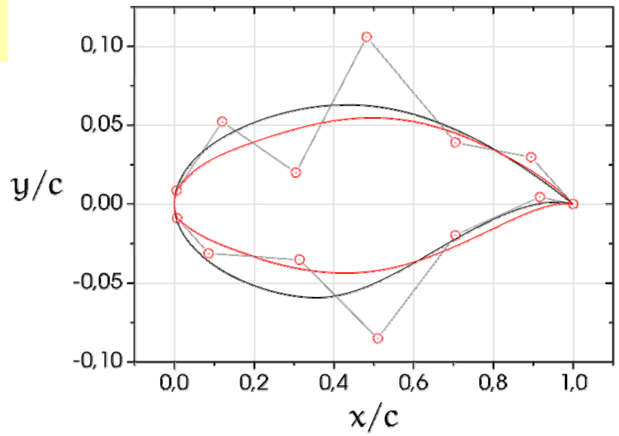
Flow Conditions M_∞=0.75, α_∞=2.734°, Re=6.2 10^6

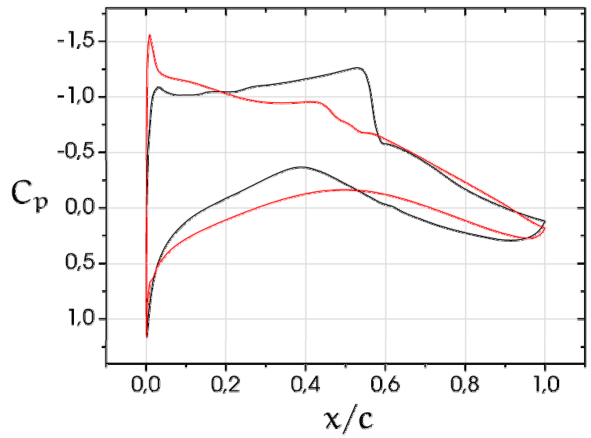
$C_{L,ref}$=0.749, $C_{D,ref}$=0.0235, β=2

Optimal Solution (SOO): $C_{L,opt}$=0.744, $C_{D,opt}$=0.00963

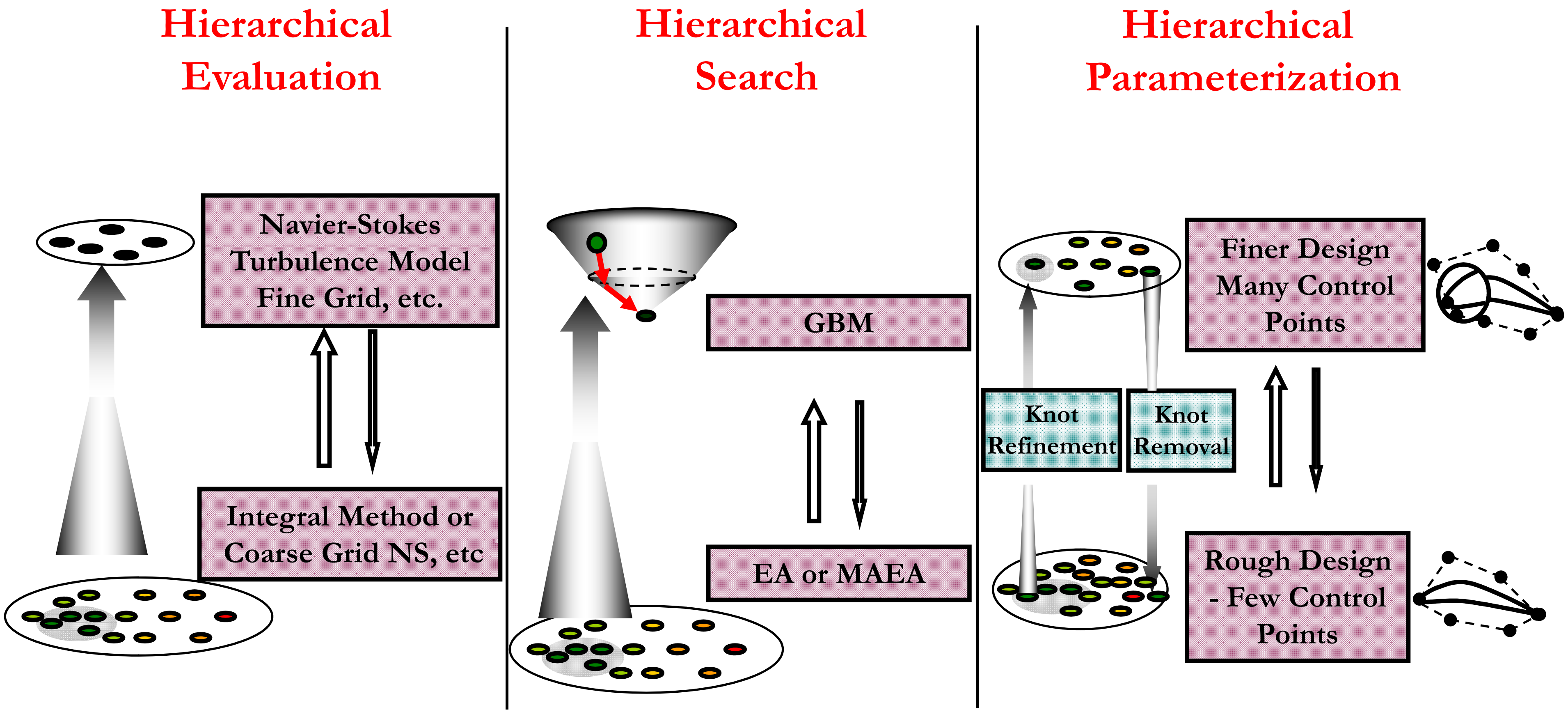
EA-IPE = MAEA







Hierachical EAs or MAEAs



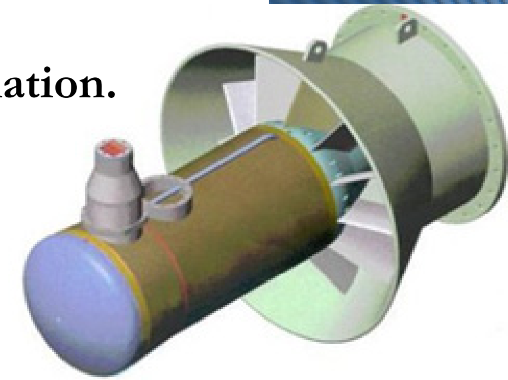
K.C. GIANNAKOGLOU and I.C. KAMPOLIS, '*Multilevel Optimization Algorithms based on Metamodel- and Fitness Inheritance-Assisted Evolutionary Algorithms*', in Computational Intelligence in Expensive Optimization Problems, Editors: Y. Tenne, C.-K. Goh, Springer-Verlag Series in Evolutionary Learning and Optimization, 2009.

Design-Optimization of Matrix Hydraulic Turbines

- Hydromatrix®: a number of "small", axial flow turbine generator units assembled in a grid or "matrix".

Advantages compared to conventional designs (lower cost to power ratio):

1. Minimization of the required civil construction works.
2. Minimum time for project schedules, construction and installation.
3. Small geological and hydrological risks.
4. Minimum environmental inflict .



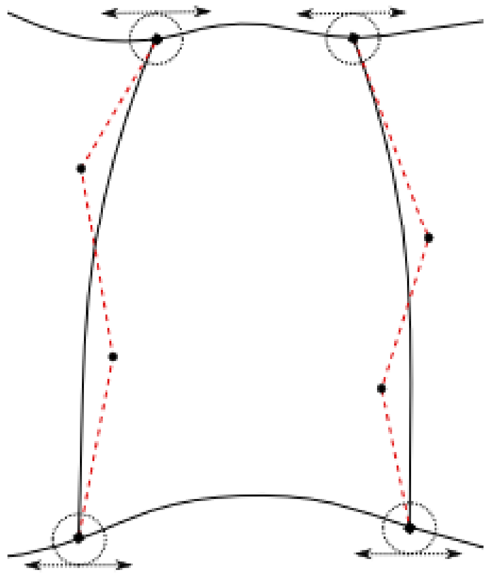
Design-Optimization of Matrix Hydraulic Turbines

Parametrization:

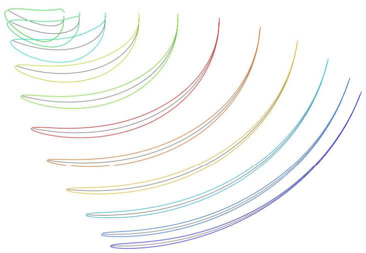
Bezier curves are used to parameterize the spanwise distribution of:

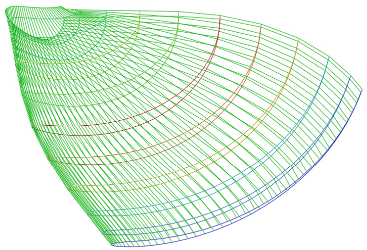
- **mean camber surface angles at LE & TE.**
- **circumferential position of the blade LE & TE.**
- **mean camber surface curvature.**

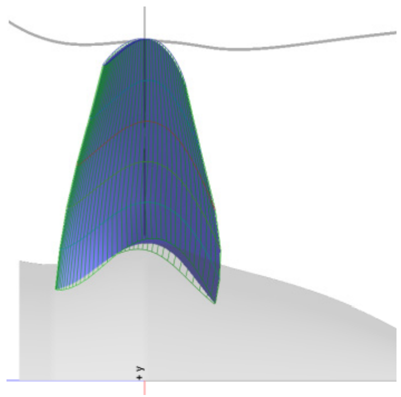
Blade thickness distribution.



- **Total: 52 to 74 design variables**

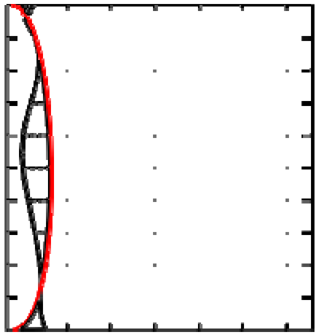


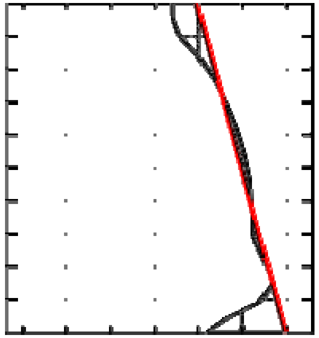




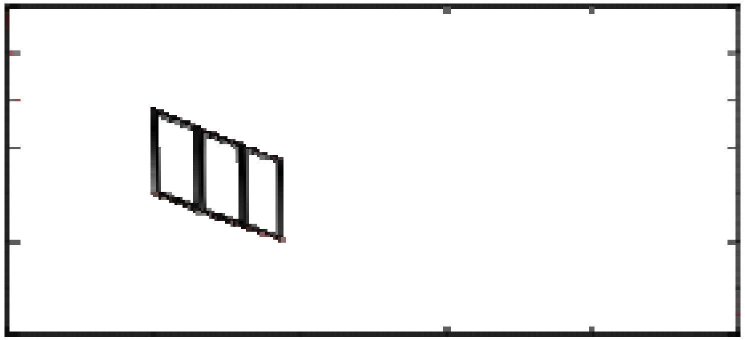
Design-Optimization of Matrix Hydraulic Turbines

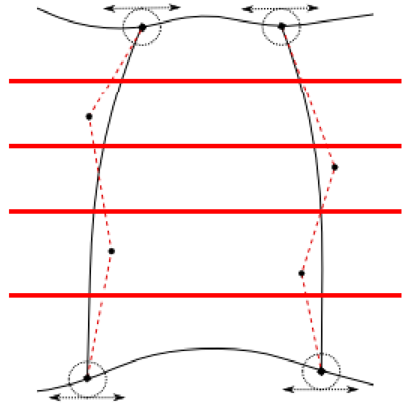
- **Objective 1 (G$_1$) : Minimization of the weighted sum of the deviations of the outlet swirl and axial velocity distributions from target curves**





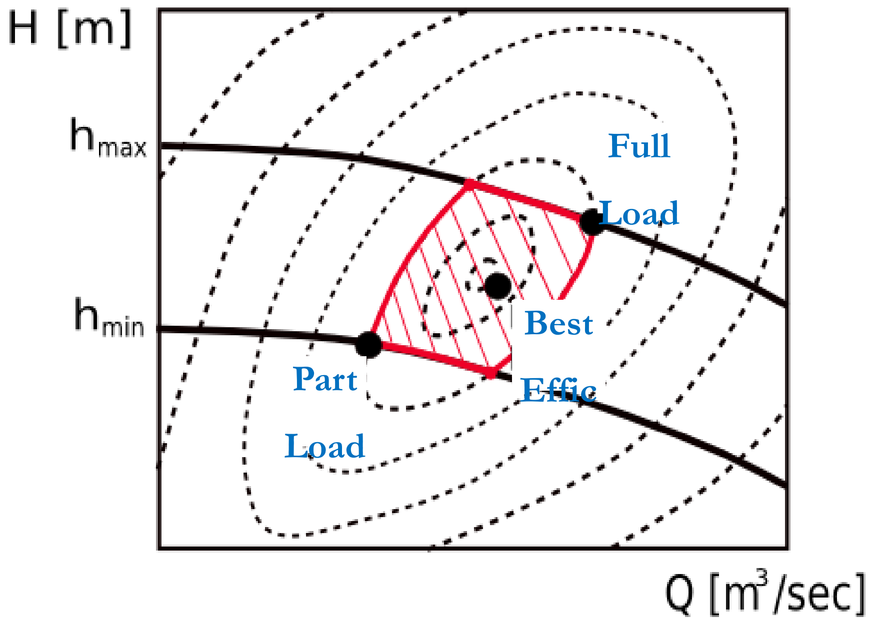
- **Objective 2 (G$_2$): the standard deviation of the pressure distribution along the chordwise direction, at eleven equidistant spanwise locations**





- **Objective 3 (G$_3$): cavitation index**

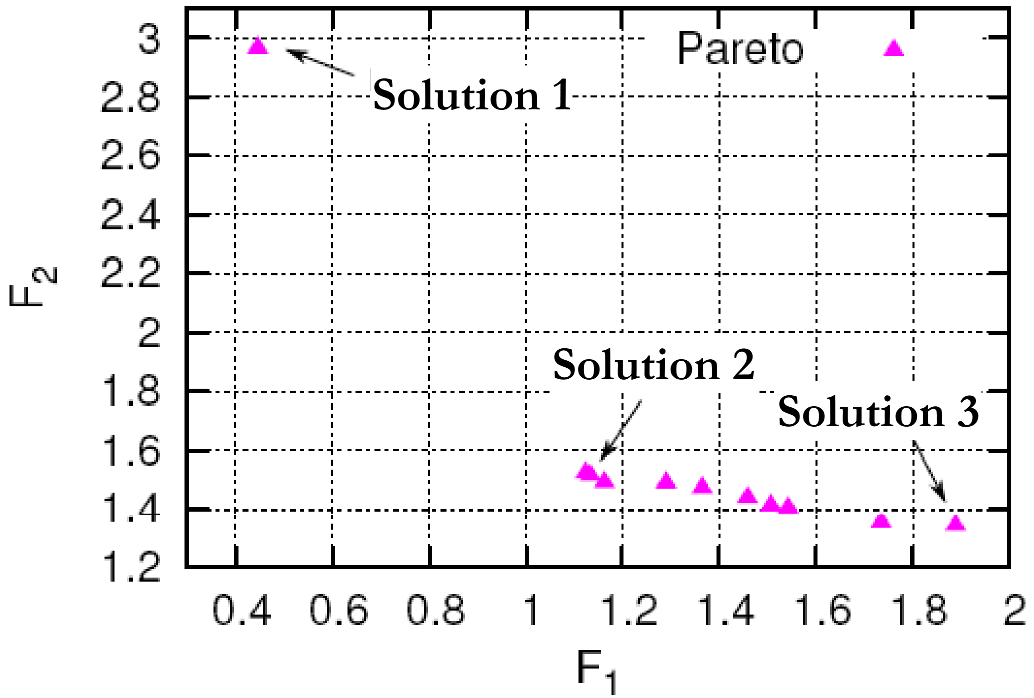
Design-Optimization of Matrix Hydraulic Turbines



	H [m]	Q[m³/sec]
Part Load	3.9	9.9
Best Efficiency	7.35	11.4
Full Load	9.8	12.1

(3 objectives) x (3 operating points) = 9 objectives in total

$F_2 = f(G_3)$ at the three operating points

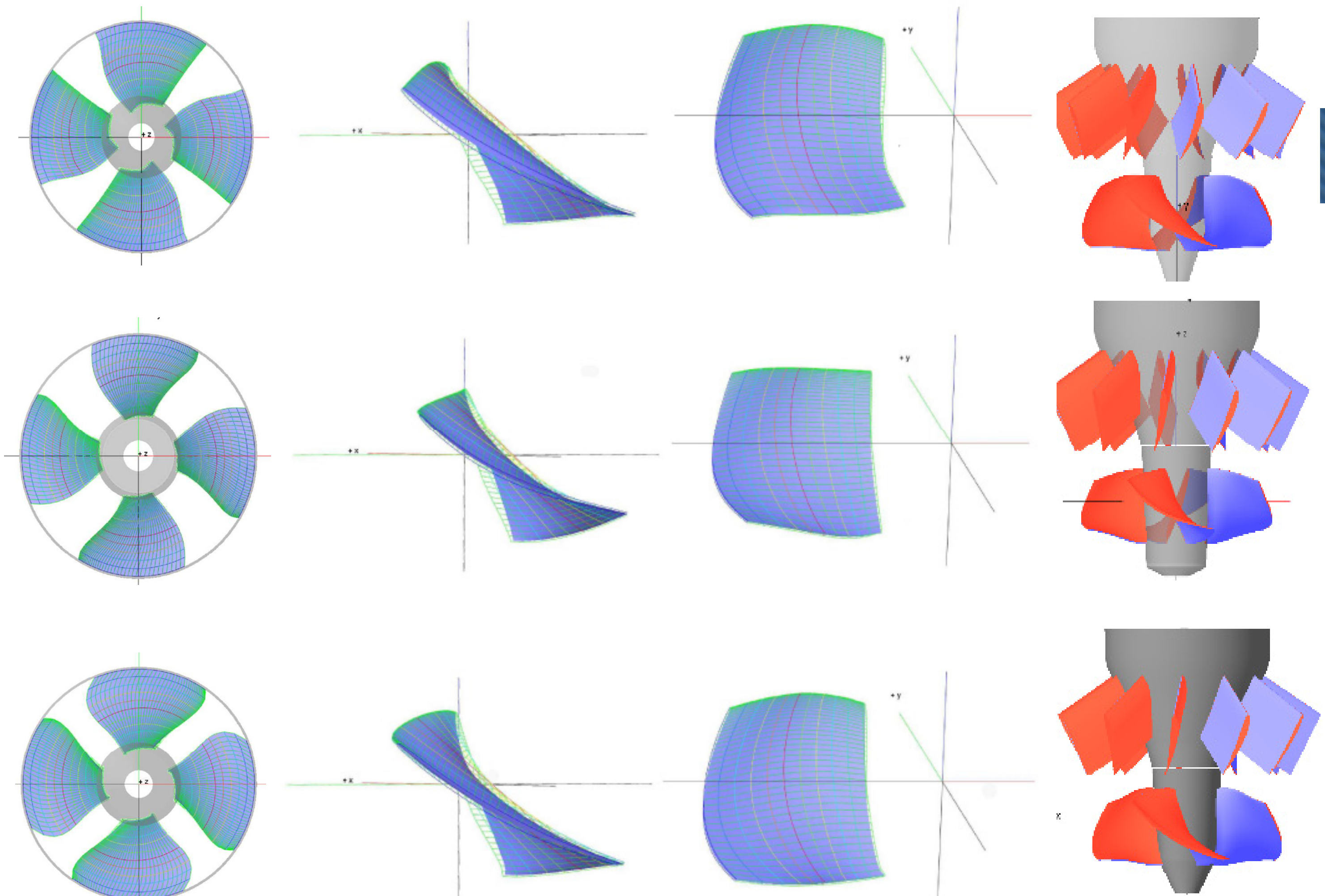


$F_1 = f(G_1,G_2)$ at the three operating points

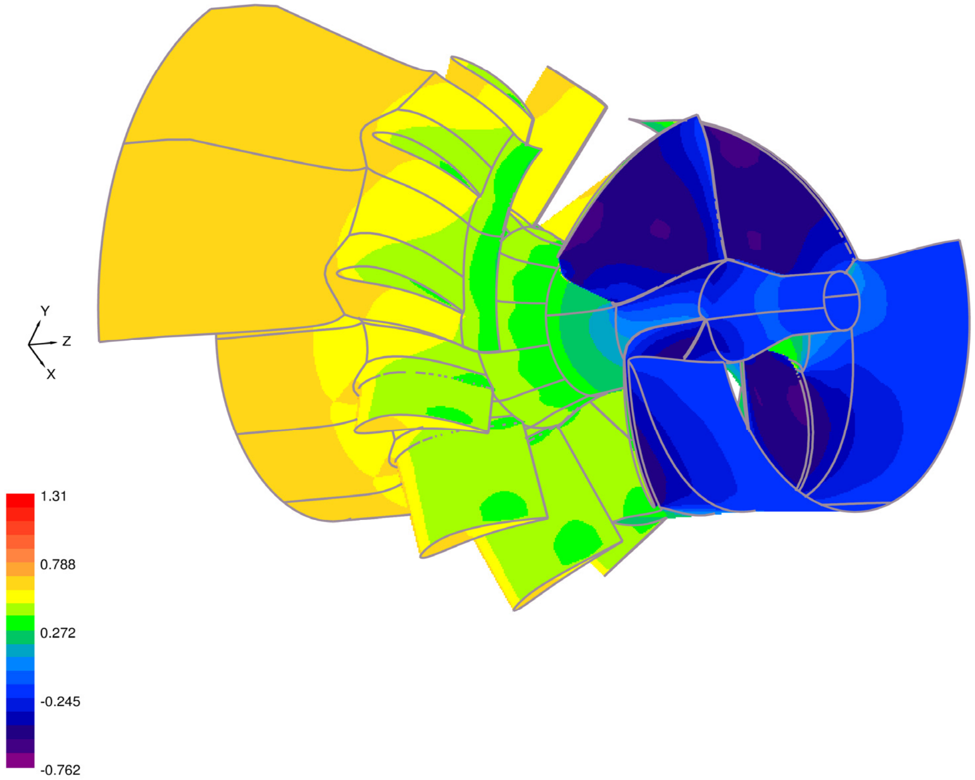
(1)

(2)

(3)



Design-Optimization of Matrix Hydraulic Turbines



NTUA

The Evolutionary Algorithm SYstem

http://velos0.ltt.mech.ntua.gr/EASY
http://147.102.55.162/EASY