Numerical Optimization of Accelerators

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Contents:

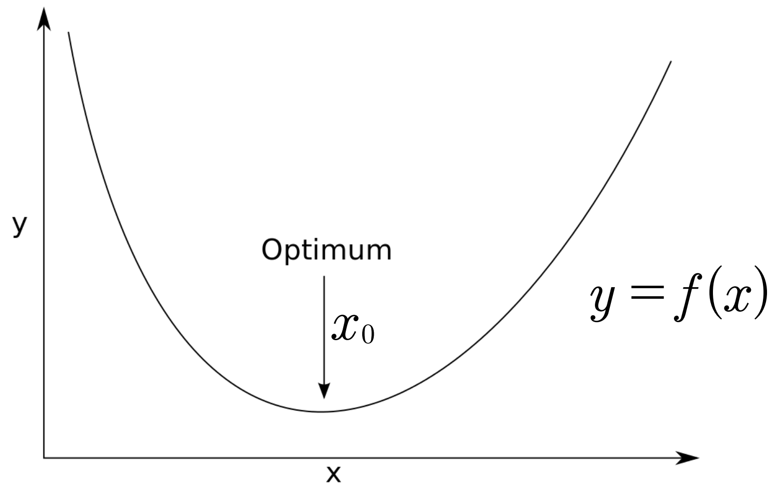
- Optimization: Basics
- Example problem: Injection in a synchrotron
- Beam physics codes and optimization schemes
- Genetic algorithms
- Applications in accelerator physics
- Conclusions

Optimization

Find $\mathbf{x}_0$ such that $f(\mathbf{x}_0) \le f(\mathbf{x})$

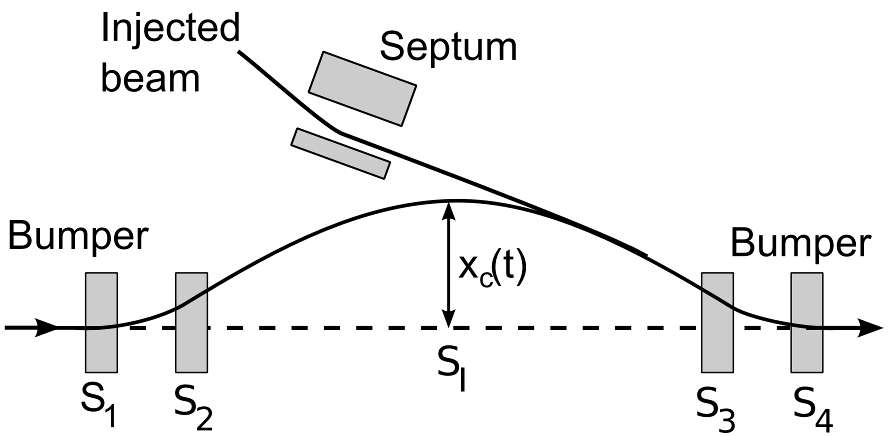
for all $a_j \le x_j \le b_j$

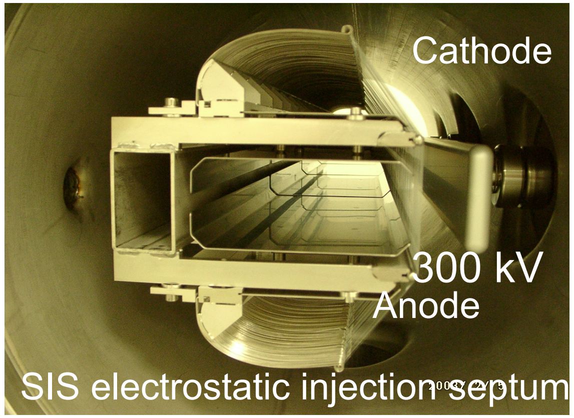
The function f(**x**) is called, variously,
an **objective function**,
fitness function (maximization),
cost function (minimization)



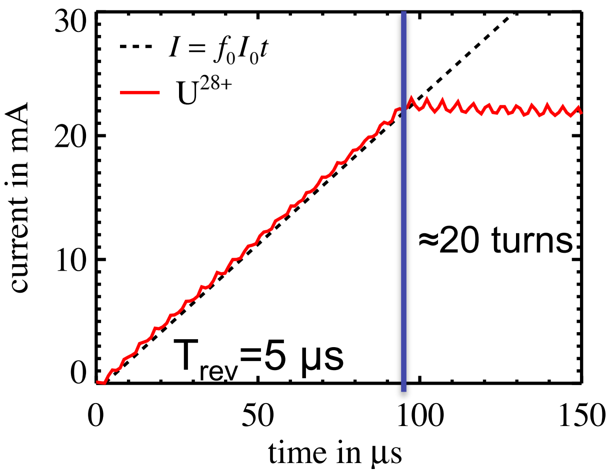
Multi-objective optimization: $\min(f_1(\mathbf{x}),\ f_2(\mathbf{x}), \ldots)$ -> Pareto front

Example: Multi-turn injection (into the GSI SIS)





Measured current evolution in SIS18



- The beam from the linac is injected in horizontal phase space until the machine acceptance is reached

- Loss (at the septum) should be as low as possible -> activation, damage, vacuum

(Multi-) objectives:
- stacked current (maximize)
- beam loss (minimize)

Example: Multi-turn injection

Parameters:

injected turns: n

current from linac: I_0

horizontal emittance: ε_x

horizontal tune: Q_x

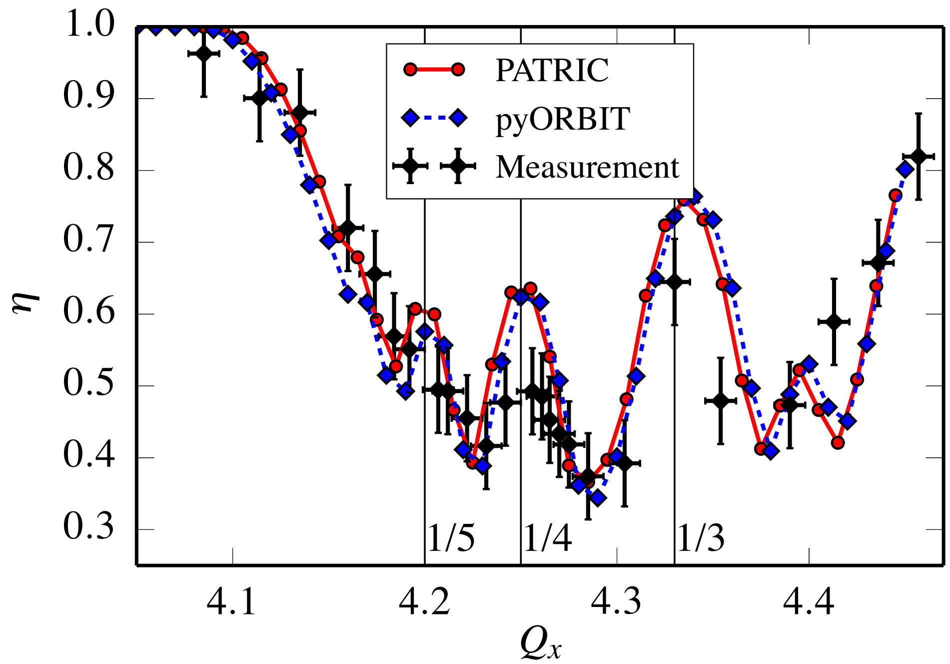
bumper ramp: τ

Objectives:

$$I(Q_{x,} n, \varepsilon_x, \tau, \ldots)$$

$$\eta\,(Q_{x,} n, \varepsilon_x, \tau, \ldots)$$

Measured vs. simulated MTI efficiency



MTI efficiency: $\eta = \frac{I_{loss}}{nI_0}$

Sabrina Appel, http://arxiv.org/abs/1403.5972

Numerical models and codes (for intense hadron beams)

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Tracking codes: ELEGANT, MADX, ….

Tracking + Beam-Beam codes: BEAMBEAM3D, ….

Tracking + space charge/wakefields: pyORBIT, PATRIC

For MTI simulations we use pyORBIT and PATRIC at GSI.

Challenges for employing tracking codes in optimization schemes:
Model reduction, Performance !!!!! -> Parallel processing, GPUs

PATRIC (O. Boine-F., S. Appel, V. Kornilov, et al.):
- 3D particle tracking with self-consistent 2.5D space charge solver and wake fields
- MADX maps, arbitrary rf bucket forms
- Implemented for multi-core CPUs using MPI.

pyorbit (A. Shishlo, S. Cousineau, J. Holmes, et al.)
- https://code.google.com/p/py-orbit/
- Teapot tracking
- 2D/3D space charge models
- MPI

Numerical accelerator optimization

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Traditional, gradient-based methods:
- may get stuck in a local minimum/maximum (and never come out).
- require local gradients
- work if initial guess is already close to the optimum

Parameter scans:
- only applicable for 1D or 2D parameter spaces

Optimization problem:

Find $\mathbf{x}_0$ such that $f(\mathbf{x}_0) \leq f(\mathbf{x})$

for all $a_j \leq x_j \leq b_j$

f(**x**) evaluated by simulation code (or measured in the machine)

Accelerator problems: Multi-dimensional, Nonlinear, Multi-objective, Several 'optimum' solutions (choice of the accelerator designer is required)

Genetic algorithms: Search for solutions using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover. In between fast converging gradient methods and slow converging random search methods.

Can be combined with gradient-based methods (for refinement).

Genetic Algorithms (GA)

Analogy:

Gene		Variable
Individual		Set of variables
Population		Set of points
Mutation	⟷	Changing variable values
Recombination		Exchange of variable values
Generation		Iteration
Fitness		Value of objective function

The 2006 NASA ST5 spacecraft antenna. This complicated shape was found by an evolutionary computer design program to create the best radiation pattern (from Wikipedia).

A practical example: travel cost minimization

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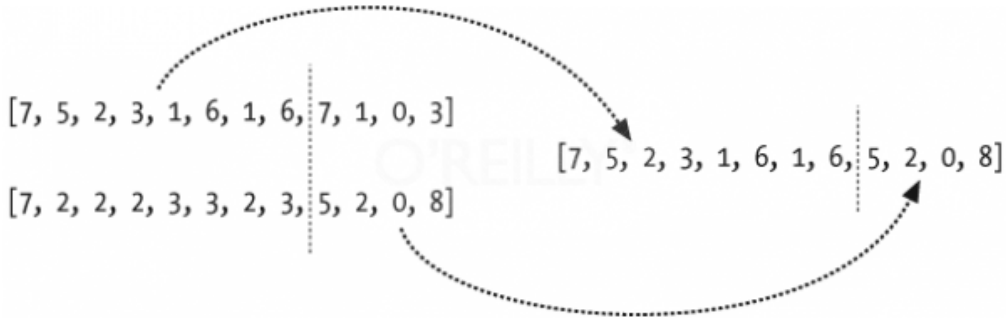
Travel solutions	Cost
[7, 5, 2, 3, 1, 6, 1, 6, 7, 1, 0, 3]	4394
[7, 2, 2, 2, 3, 3, 2, 3, 5, 2, 0, 8]	4661
...	...
...	...
[0, 4, 0, 3, 8, 8, 4, 4, 8, 5, 6, 1]	7845
[5, 8, 0, 2, 8, 8, 8, 2, 1, 6, 6, 8]	8088

Mutation:

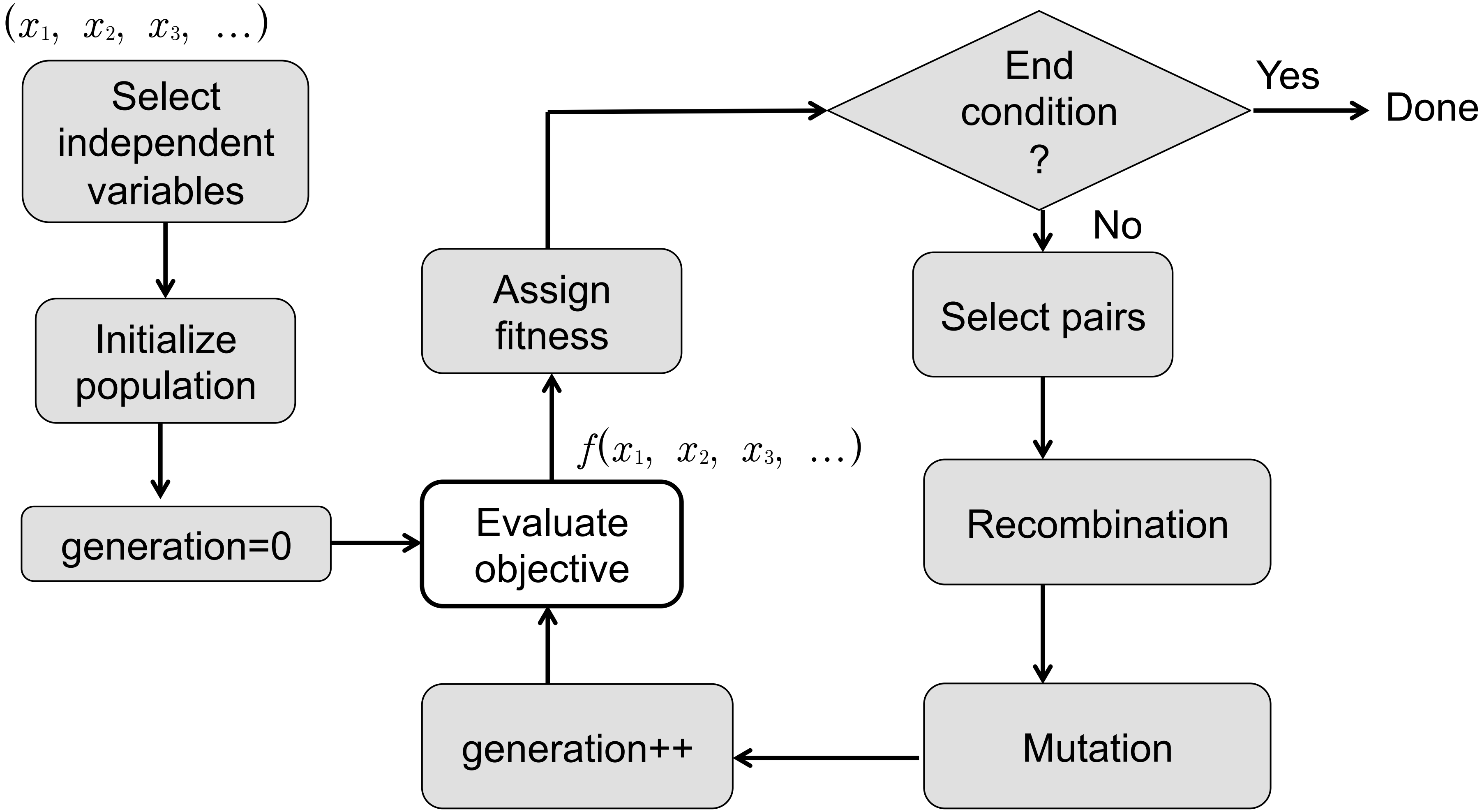
[7, 5, 2, 3, 1, 6, 1, 6, 7, 1, 0, 3] → [7, 5, 2, 3, 1, 6, 1, 5, 7, 1, 0, 3]

[7, 2, 2, 2, 3, 3, 2, 3, 5, 2, 0, 8] → [7, 2, 2, 2, 3, 3, 2, 3, 5, 2, 1, 8]

Crossover:



Typical Structure of GA Optimization

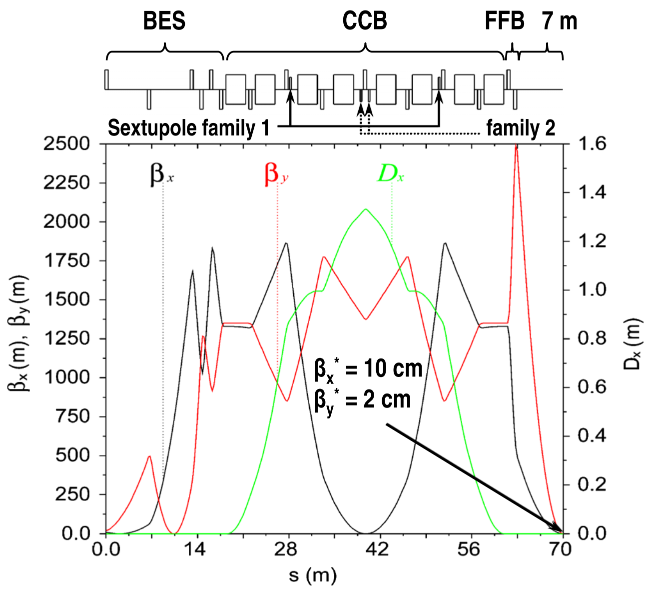


GA application:
Dynamic aperture (DA) maximization

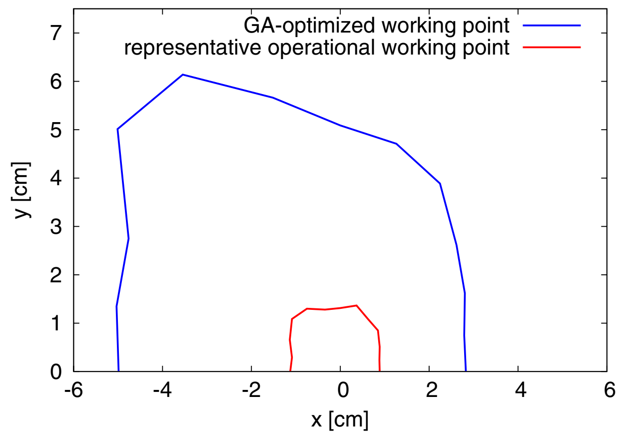
Single-objective, 2D, nonlinear optimization problem: $DA(Q_x, Q_y)$ Q_x, Q_y: tunes

Interaction section in a proposed e-A collider.
Dynamic aperture caused by sextupoles for chromaticity correction.

GA combined with the ELEGANT tracking code for the function evaluator

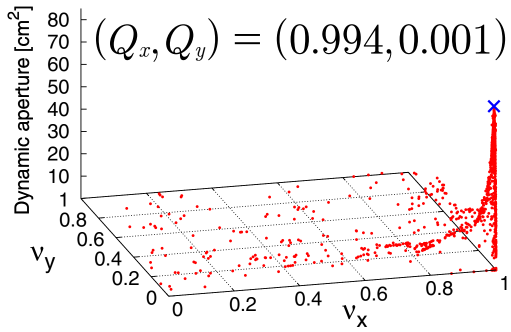


Dynamic aperture from ELEGANT



Optimized tunes:

$$(Q_x, Q_y) = (0.994, 0.001)$$



20 generations of 64 individuals

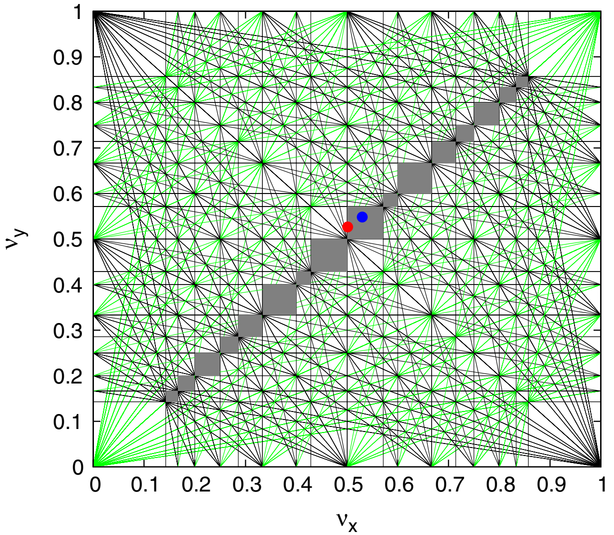
A. Hofler et al., Phys. Rev. ST-AB 16, 010101 (2013)

GA example: Optimum tunes with beam-beam

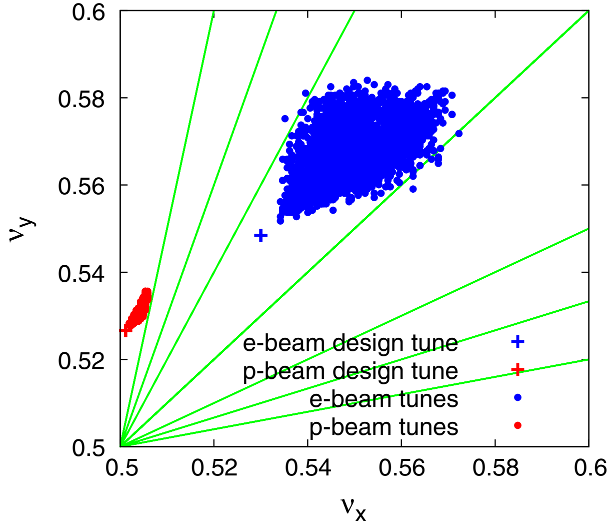
Single-objective, 2D, nonlinear optimization problem: $L(Q_x^A, Q_y^A, Q_x^e, Q_y^e)$ Luminosity:

$$L = nf\frac{N_e N_A}{\pi\hat{\beta}^*\varepsilon}$$

Resonance diagram with optimum tunes for e and A beams.



Obtained optimum machine tunes with incoherent tune distribution



GA combined with the BEAMBEAM3D tracking code as the function evaluator

A. Hofler et al., Phys. Rev. ST-AB 16, 010101 (2013)

Multi-objective genetic algorithms (MOGA)

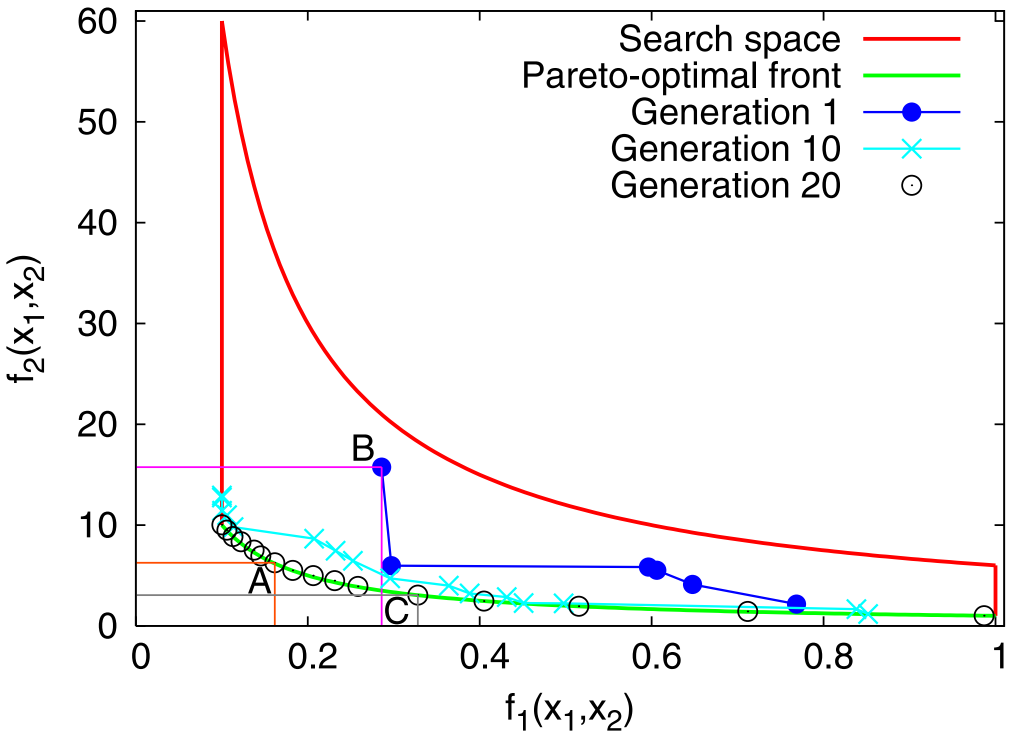
Two objectives:

$$f_1(x_1,x_2) = x_1$$

$$f_2(x_1,x_2) = \frac{1+x_2}{x_1}$$

2D parameter space:

$$0.1 \leq x_1 \leq 1 \qquad 0 \leq x_2 \leq 5$$



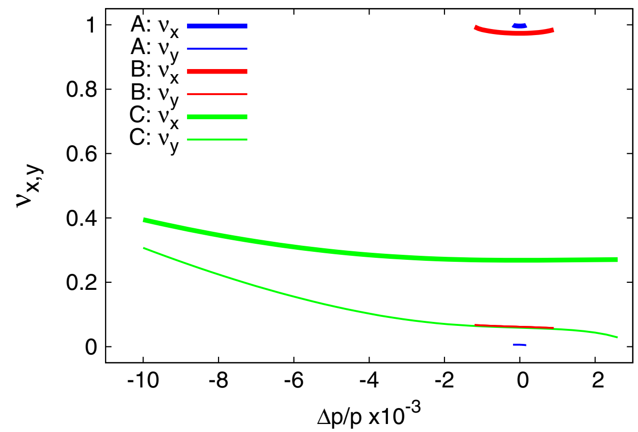
A. Hofler et al., Innovative applications of genetic algorithms in accelerator physics, Phys. Rev. ST-AB 16, 010101 (2013)

Multiobjective Optimization: DA and Chromaticity

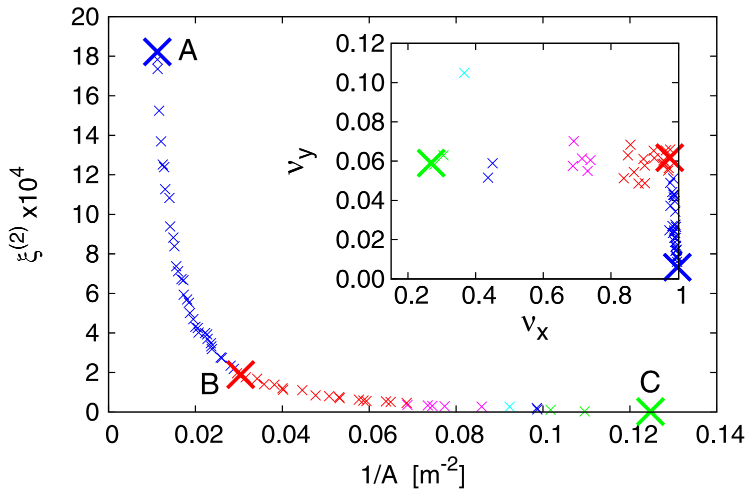
Two-objective, 2D, nonlinear optimization problem: $DA\left(Q_x, Q_y\right) \quad \xi^{(2)}\left(Q_x, Q_y\right)$

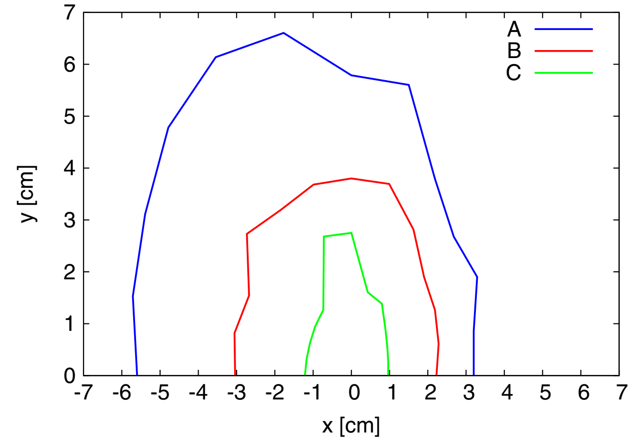
2nd-order chromaticity -> momentum acceptance

Goal: Find a working point that gives a balance between a large momentum acceptance and large DA



Pareto front after 24 generations of 64 individuals





A. Hofler et al., Phys. Rev. ST-AB 16, 010101 (2013)

Other example applications of GA

Magnet design optimization
S. Ramberger, S. Russenschuck, *Genetic algorithms for the optimal design of superconducting accelerator magnets* EPAC 98

Magnet sorting in a storage ring.
Chen, J., Wang, L., Li, W.-M., & Gao, W.-W. ,*Optimization of magnet sorting in a storage ring using genetic algorithms*, Chinese Physics C (2013)

Linac settings for high intensity
Pang, X., & Rybarcyk, L. J., *Multi-objective particle swarm and genetic algorithm for the optimization of the LANSCE linac operation.*NIMA 741 (2013)

Minimization of the energy consumption of an accelerator facility
Ripp, C., Boine-Frankenheim, O., Hanson, J., Stadlmann, J., Spiller, P., Lindenberg, J., Zimmer, H. *Electric energy consumption of an accelerator facility*. IYCE (pp. 1–3) IEEE 2013

Real machine based optimization in a storage ring
Tian, K., Safranek, J., & Yan*, Machine based optimization using genetic algorithms in a storage ring*, Phys. Rev. ST AB, 17 (2013)

Conclusions

During the last years evolutionary, and more specifically, genetic algorithms became very popular in the numerical optimization of accelerators.

Existing simulations codes are used as function evaluators.

Performance of the accelerator codes is crucial for the optimization.

To be completed ….