

Abstract: In experimental physics, computer algorithms are used to make decisions to perform measurements and different types of operations. To create a useful algorithm, the optimization parameters should be based on real time data. However, parameter optimization is a time consuming task, due to the large search space. In order to cut down the runtime of optimization we propose an algorithm inspired by the numerical method Nelder-Mead. This paper presents details of our method and selected experimental results from high-energy (CERN accelerators) to low-energy (Penning-trap systems) experiments as to demonstrate its efficiency. We also show simulations performed on standard test functions for optimization.

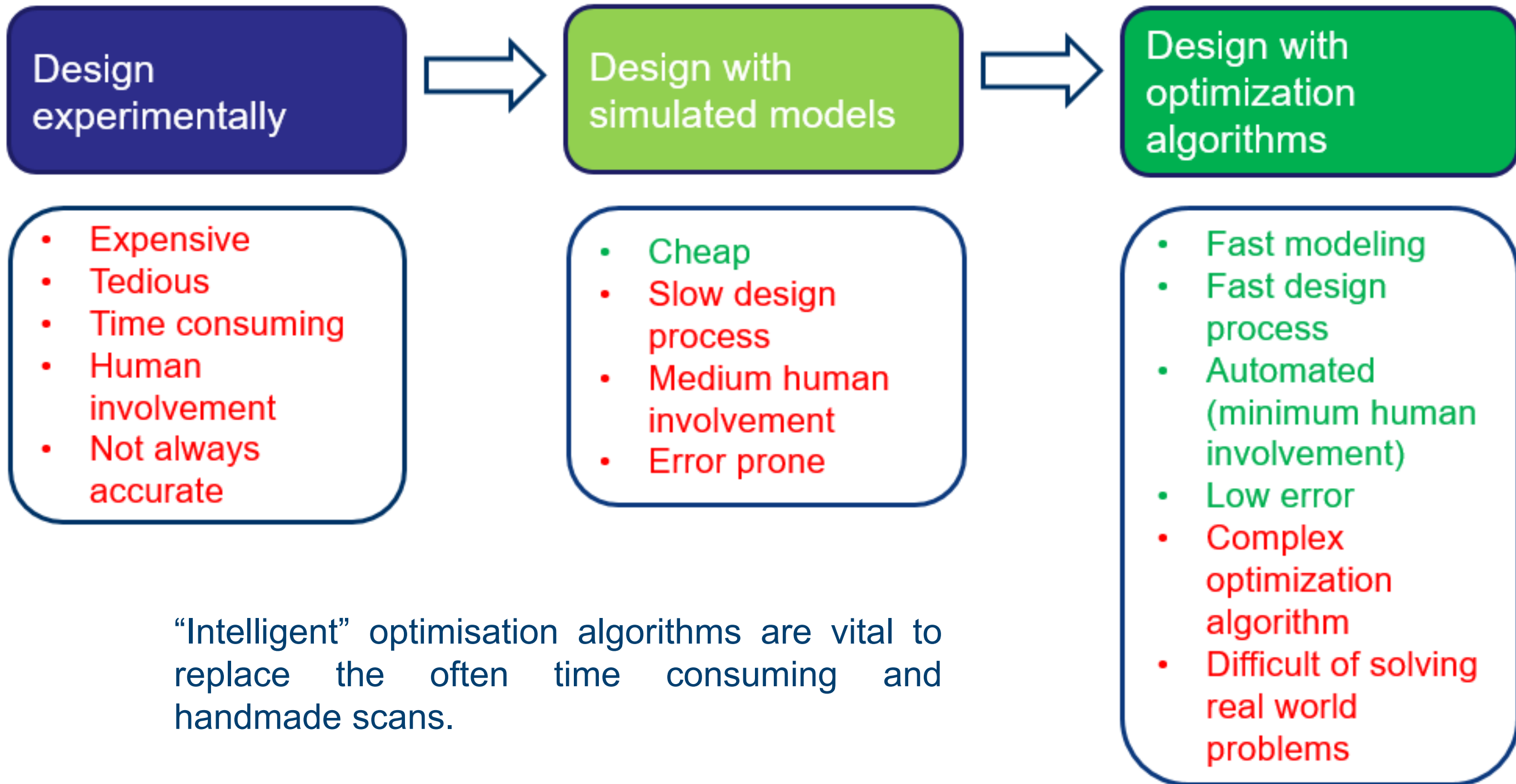
PHYSICS, SYSTEM OPTIMIZATION

Particle accelerators and detectors: essential components for any experiment in nuclear and sub nuclear physics.

Best particle beams needs many adjustments and CONTROLS plays a key role. All parameters should be controlled and adapted to the requested experiments.

Optimization is the discipline that deals with formulating useful models in applications, using efficient methods to identify the best possible solution. In mathematics, optimizing means finding the values which maximize or minimize a function.

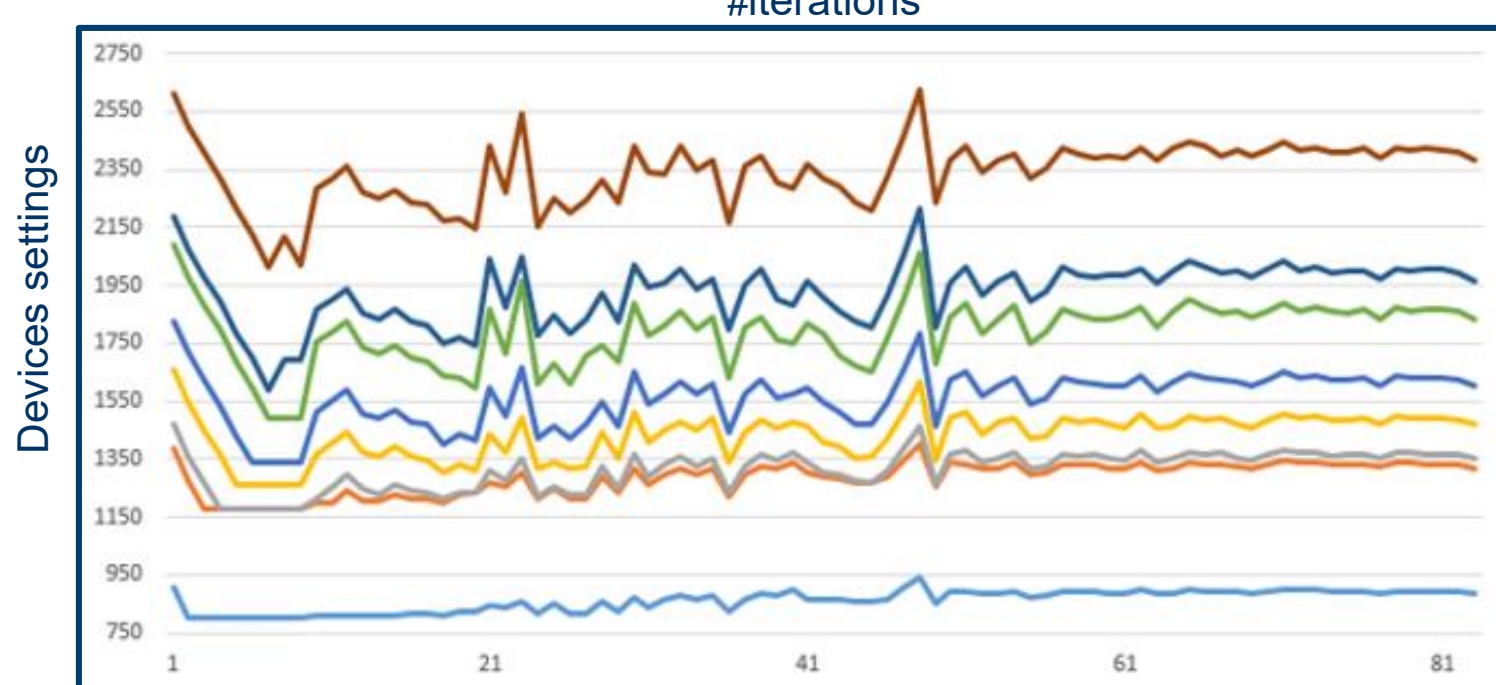
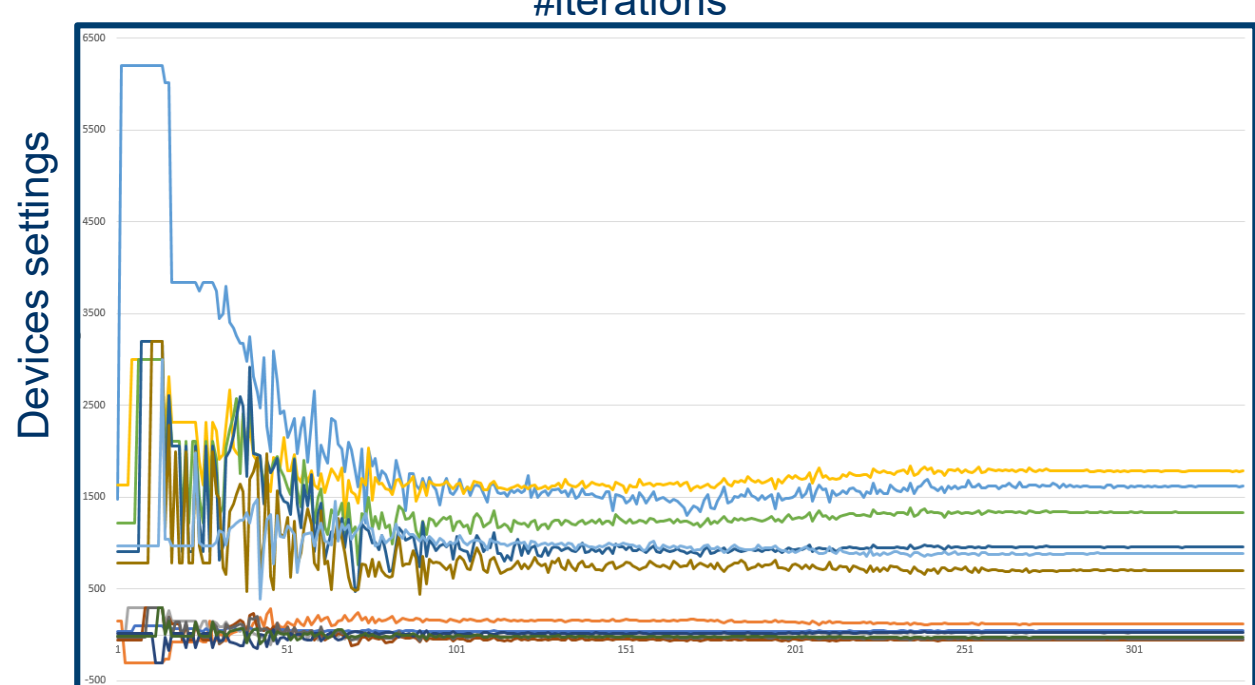
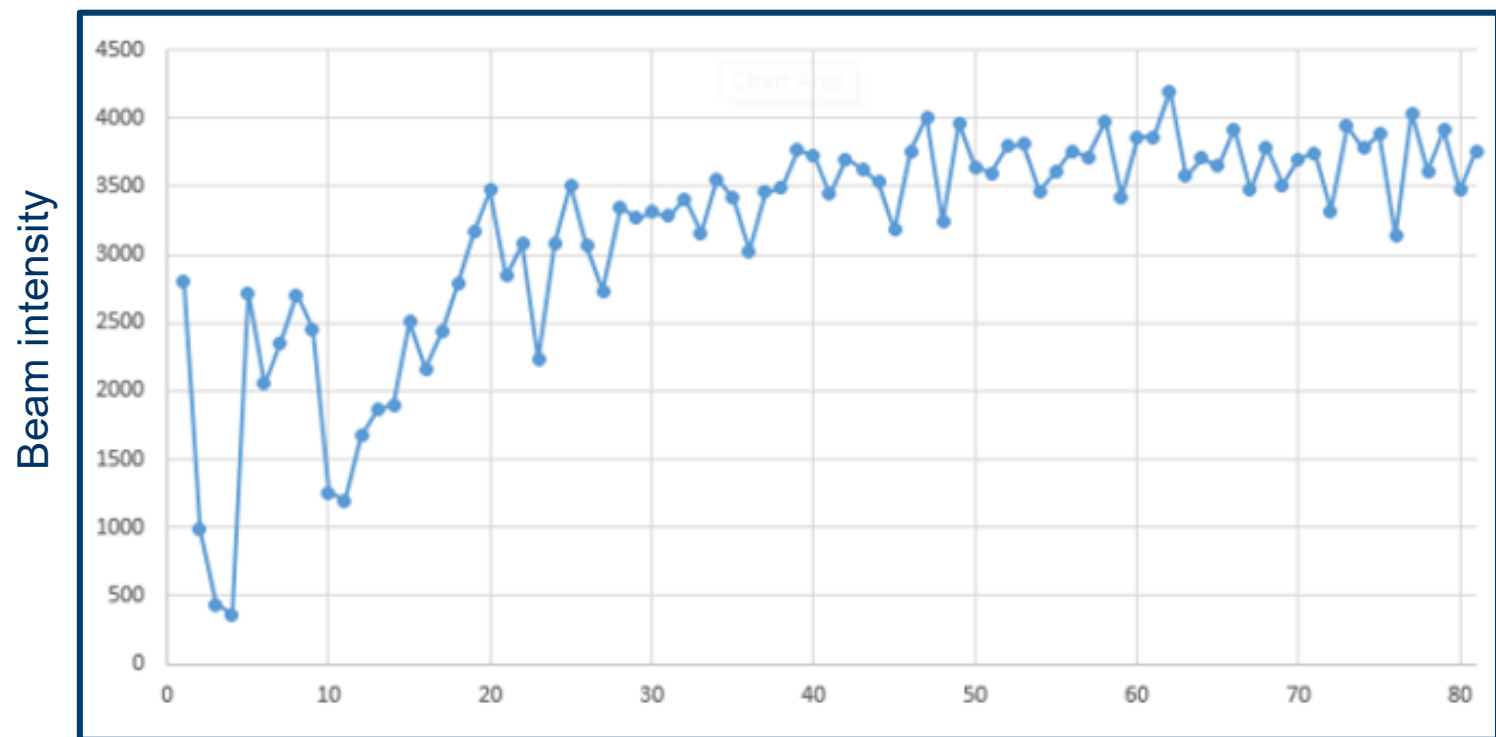
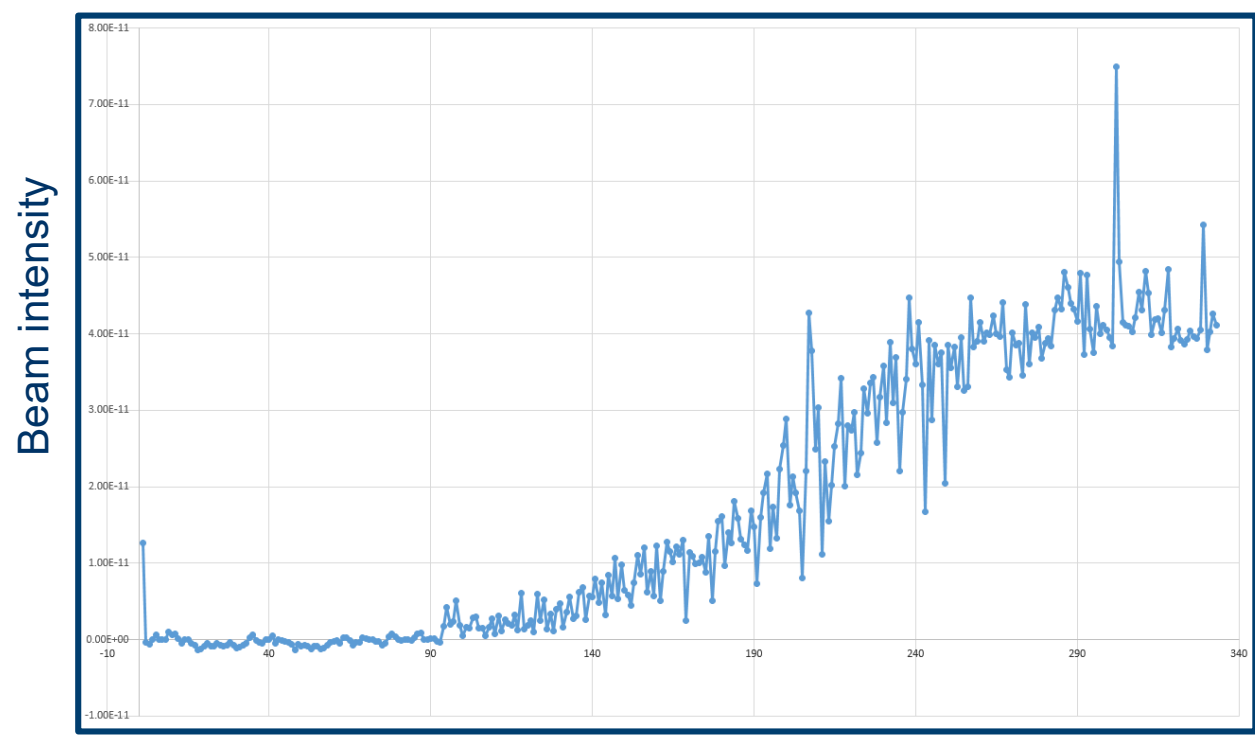
Different approaches of finding optimal designs for a system are summarised here:



USE CASES

ISOLDE [2]: Facility is dedicated to the production of a large variety of radioactive ion beams

The GANDALPH experiment [3] (Fig. 9) aims at measuring the reaction between singly charged negative ions and a laser beam



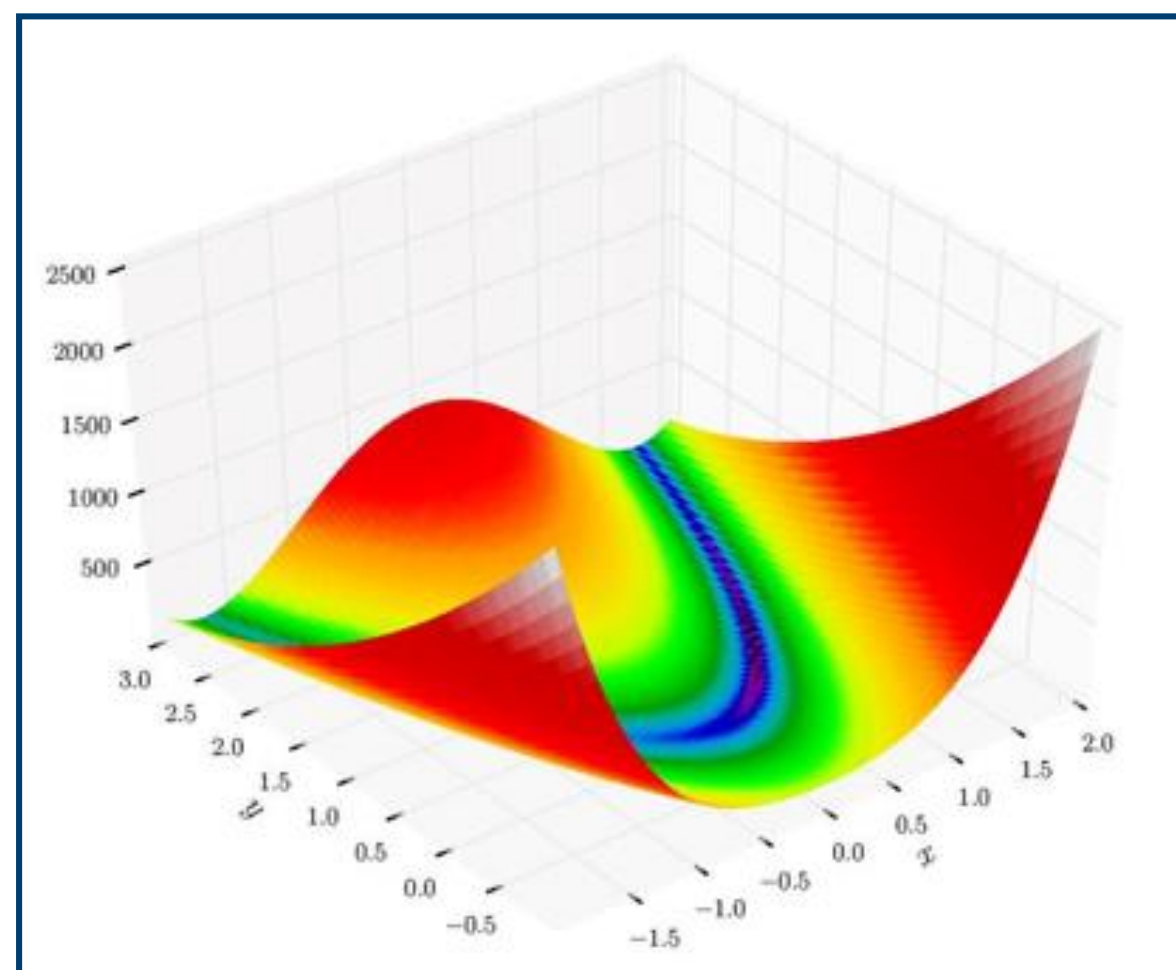
13 parameters +325% 330 iterations @3Hz

8 parameters +140% 80 iterations @1Hz

SIMULATIONS

Rosenbrock function [4]: $f(\vec{x}) = \sum_{k=1}^{n-1} 100 \cdot (x_{k+1} - x_k^2)^2 + (x_k - 1)^2$

Global minimum $f(\vec{x}) = 0$ in a narrow parabolic valley $\vec{x} = (1, 1, \dots, 1)$



Rosenbrock 2D function [5]

Algorithm tested with a different number of variables and the same value range $[-10, 10]$ for each parameter. Random initial settings within the range.

| Variables | Evaluation for convergence |
|-----------|----------------------------|
| 2 | $\cong 80$ |
| 4 | $\cong 400$ |
| 8 | $\cong 1000$ |

Algorithm tested adding Gaussian noise with different σ . The results still showed good response, even though it did not converge to the minimum.

| Variables | σ | Convergence values |
|-----------|----------|-----------------------------------|
| 4 | 0.001 | $\cong [0, 0.1] \forall$ variable |
| 4 | 0.01 | $\cong [0, 2.4] \forall$ variable |
| 8 | 0.001 | $\cong [0, 1] \forall$ variable |
| 8 | 0.01 | $\cong [0, 0.5] \forall$ variable |

CONCLUSIONS

The algorithm has been fully tested and showed important improvements in the operations of different experiments. The collaboration with Max Planck Institute for Nuclear Physics in Heidelberg and different CERN groups will significantly improve the functionality of this tool. We foresee to add noise reduction filtering, based on real time averaging and to improve the automatic loop restarting to be able to explore different regions of interest.

AKNOWLEDGMENTS

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BEAM OPTIMIZATION ALGORITHM

Beam optimization algorithm has been developed modifying the Nelder-Mead technique [1].

Simplex: polytope in n-dimensional space with n+1 (e.g. a triangle in \mathbb{R}^2 , a tetrahedron in \mathbb{R}^3 , etc.).

In our implementation of the algorithm we have replaced the simplex points by the set of values of the n beam parameters to be optimized and the function by the beam observables.

Beam parameters (variables) are subject to constraints: $\vec{x}_{min} \leq \vec{x}_k \leq \vec{x}_{max} \quad \forall k \in [1, n]$

Steps (for maximization):

- Initial simplex \mathbf{S} (n+1 vertices $\vec{x}_0, \vec{x}_1, \dots, \vec{x}_n$): initial point $\vec{x}_0 \in \mathbb{R}^n + \vec{x}_k$ set to possible combinations of \vec{x}_{min} and $\vec{x}_{max} \quad \forall k \in [0, n]$
- Ordering: find indexes of the best (h), the second best (s) and the worst vertex (l) in \mathbf{S} , respectively h,l,s:
 - $f_h = \max_k(f_k)$
 - $f_s = \max_{k \neq h}(f_k)$
 - $f_l = \min_{k \neq h}(f_k) \quad \forall k \in [0, n]$
- Centroid calculation opposite to \vec{x}_h : $\vec{x}_c = \frac{\sum_{k \neq h} \vec{x}_k}{n}$
- New simplex calculation calculated using one of these four different operations:
 - Reflection: reflection point $\vec{x}_r = 2 \cdot \vec{x}_c - \vec{x}_h$
 - Expansion: expansion point $\vec{x}_e = 2 \cdot \vec{x}_r - \vec{x}_c$
 - Contraction: contraction point $\vec{x}_{cont} = \vec{x}_c \pm \frac{1}{2} \cdot (\vec{x}_c - \vec{x}_h)$
 - Shrinkage: new points set: $\vec{x}_k = \vec{x}_h + \frac{1}{2} \cdot (\vec{x}_k - \vec{x}_h) \quad \forall k \in [1, n]$

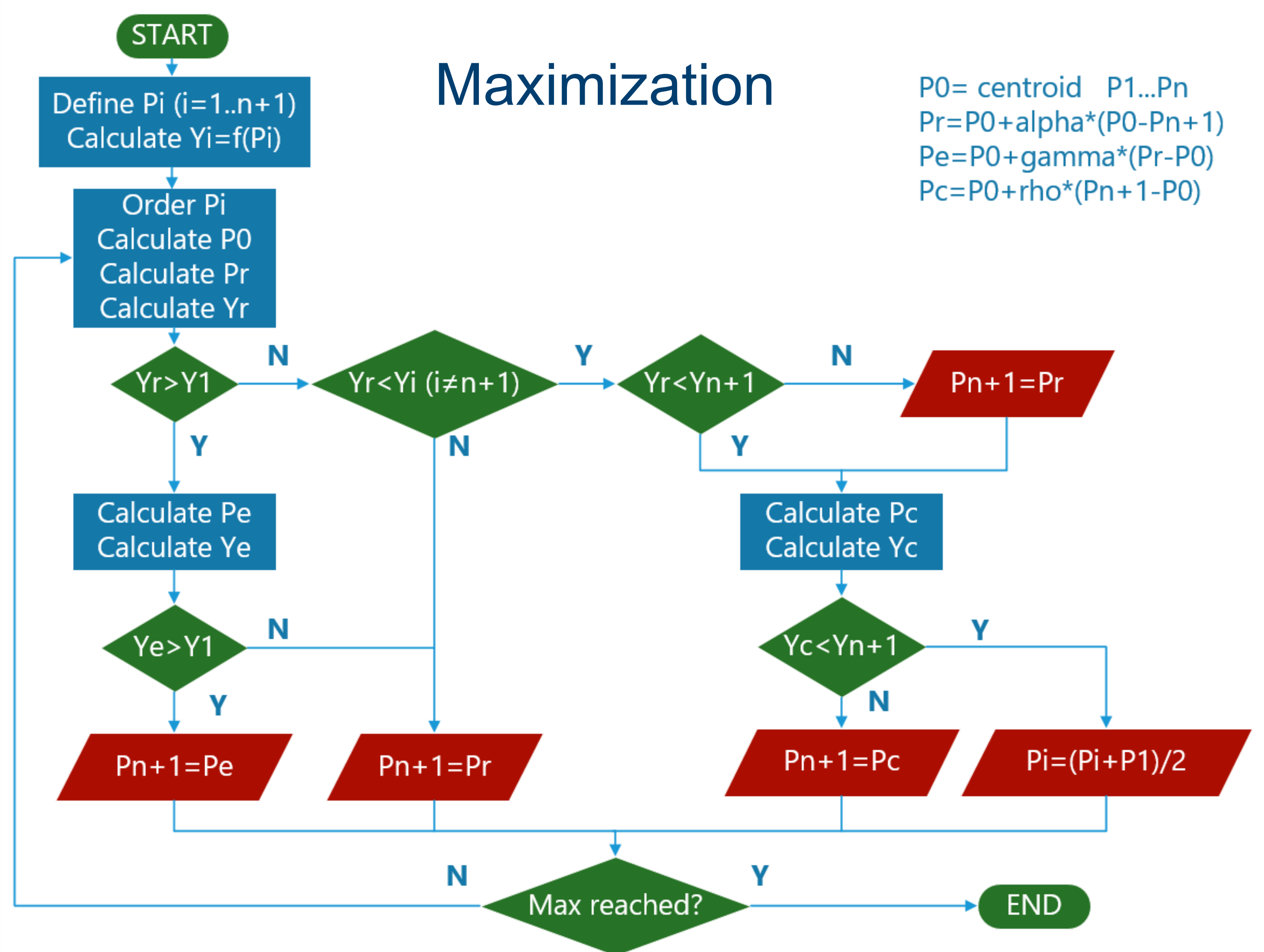
Variable settings "outside" the box constraints: function estimation is worse than the worst value found so far. In this way, we try to "move" the simplex away from that parameters space region.

Convergence options:

- $|f_k - f_m| \leq s_c \quad \forall k \in [n, n + it_c]$ max/min: f_m min iterations it_c
- $|f_k - f_{k-1}| \leq \frac{f_k \cdot s_r}{100} \quad \forall k \in [n, n + it_c]$ stability ratio s_r restart iterations it_r
- max convergence size s_c max iterations it_{max}

Automatic restart:

If $|f_{it_r} - f_m| > s_c$ and RESTART iterations $> \frac{it_{max}}{it_r}$ times \Rightarrow RESTART $\vec{x}_0 = \vec{x}_{it_r}$



REFERENCES

- [1] Margaret H. Wright, "Nelder, Mead, and the Other Simplex Method"; Documenta Mathematica · Extra Volume ISMP (2012) 271–276
- [2] <http://isolde.web.cern.ch/>
- [3] J. Phys. G: Nucl. Part. Phys. 44 (2017) 104003 (10pp)
- [4] <https://www.sfu.ca/~ssurjano/rosen.html>