

# Multi-objective genetic optimization



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**Pulsar Physics**

Photograph: André Karwath

## Overview: We want it all...

Proven  
design

Top  
performance

Affordable

# Overview: We want it all...



Top  
performance

Affordable

# Overview: We want it all...



**Affordable**

# Overview: We want it all...



# Multi-objective optimization: Examples



**Minimize weight *and* maximize strength**



**Maximize performance *and* minimize fuel consumption**



**Maximize profit *and* minimize risk**

...

# Multiple objectives: Beamline design

## WE WANT IT ALL

- **Typical objectives**
  - High charge / current
  - Low emittance
  - Small spot size
  - Short pulse duration
- **Variables**
  - RF-phase / amplitude
  - Solenoid position / strength
  - Electrode geometry
  - Emission process (size, charge)

## WE WANT IT NOW

- Time = money



Brian May, I want it all, I want it now

## Transform to single objective: Bad idea

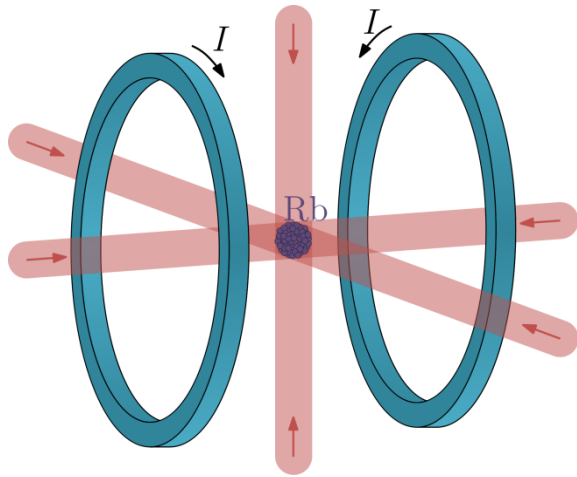
- Select a weight factor  $\alpha_i$  for each objective function  $f_i$ 
  - Minimize:

$$F(a,b,c,d) = \alpha_1 f_1(a,b,c,d) + \alpha_2 f_2(a,b,c,d) + \dots$$

- Problems:
  - Requires tradeoffs to be made a-priori  
How much extra weight is equivalent to 10% stronger ?
  - Doesn't give tradeoff information  
How much stronger can we make it for 10% heavier ?



# Ultracold Electron/Ion Source



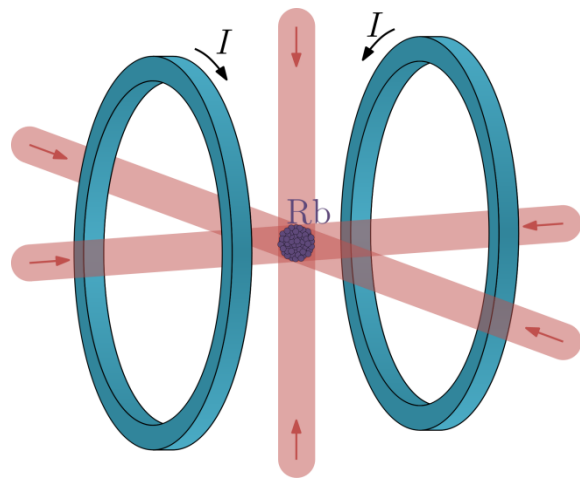
## Trap & Cool Magneto-optical trap

Density  $\approx 10^{16} / \text{m}^3$

RMS size  $\approx 1 \text{ mm}$

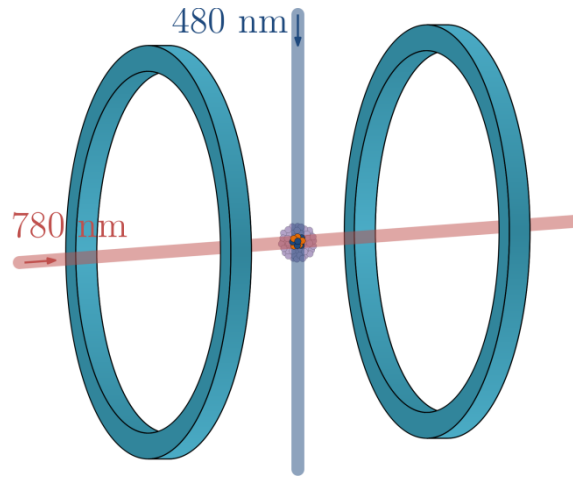
$T = 100 \mu\text{K}$

# Ultracold Electron/Ion Source



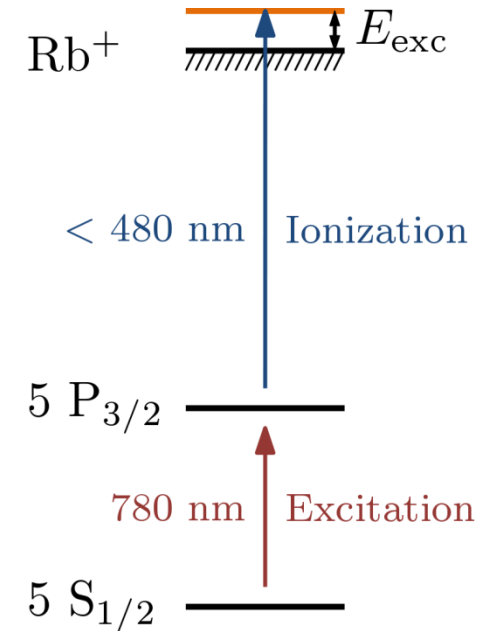
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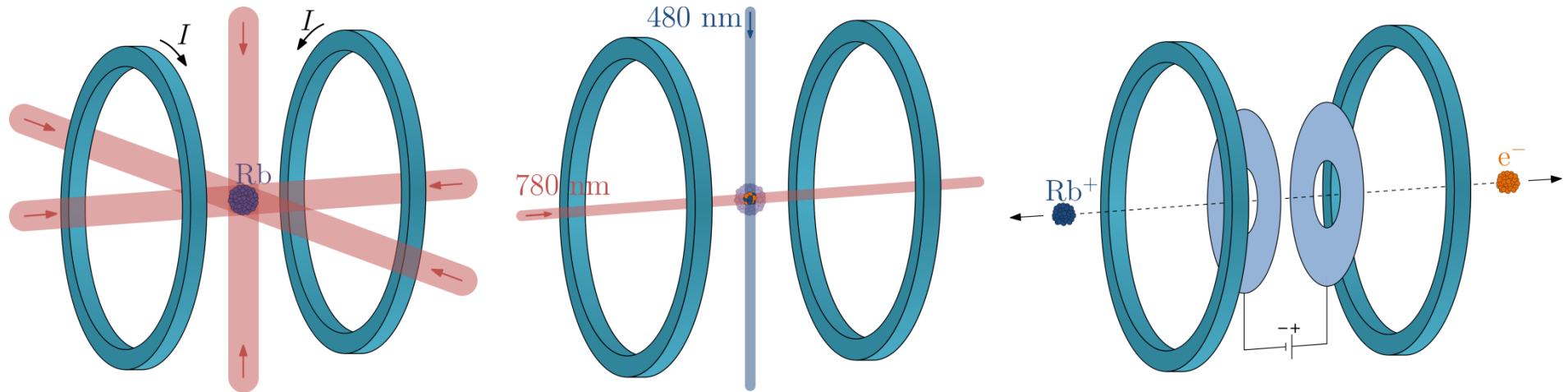
## Ionize Ultracold plasma

Ionization radius  $\approx 50 \mu\text{m}$



Killian et al.,  
PRL **83**, 4776 (1999)

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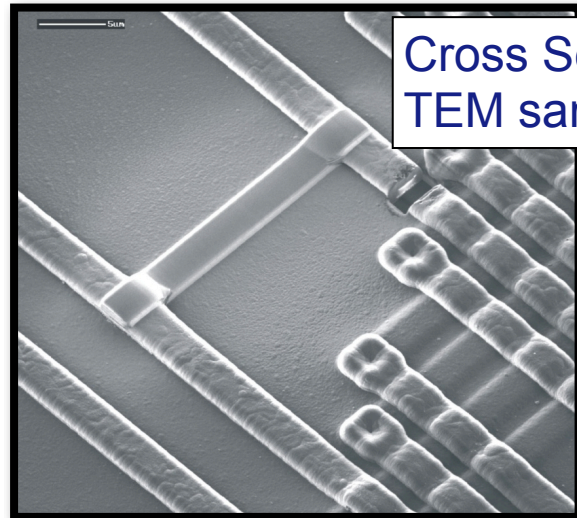
## Accelerate Ultracold source

Bunch energy  $E = 15 \text{ keV}$

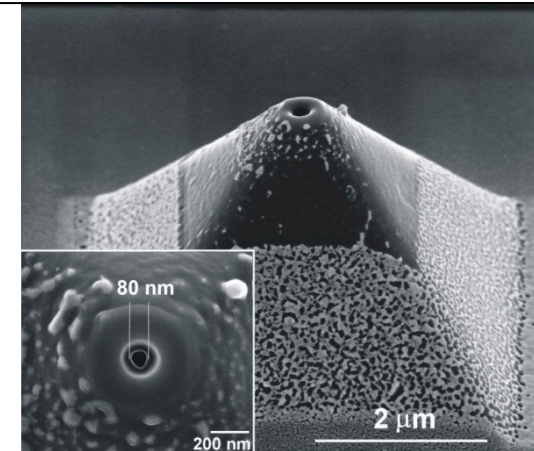
Killian et al.,  
PRL **83**, 4776 (1999)

Luiten et al.,  
PRL **95**, 164801 (2005)  
McCulloch et al.,  
Nat. Phys. **7**, 785 (2011)

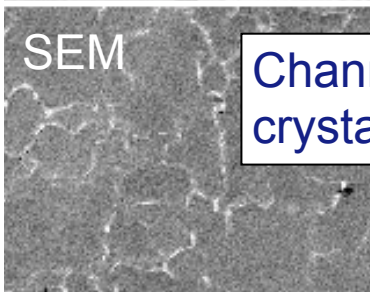
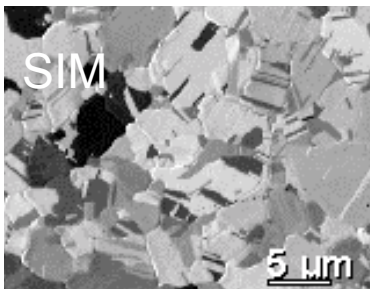
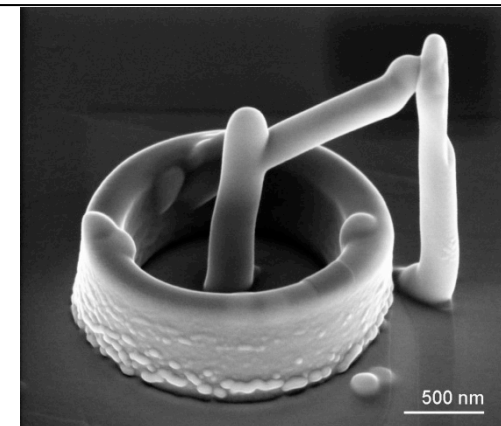
# Application: Focused ion beams (FIB)



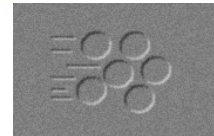
Machining, sputtering/milling



Beam-induced deposition



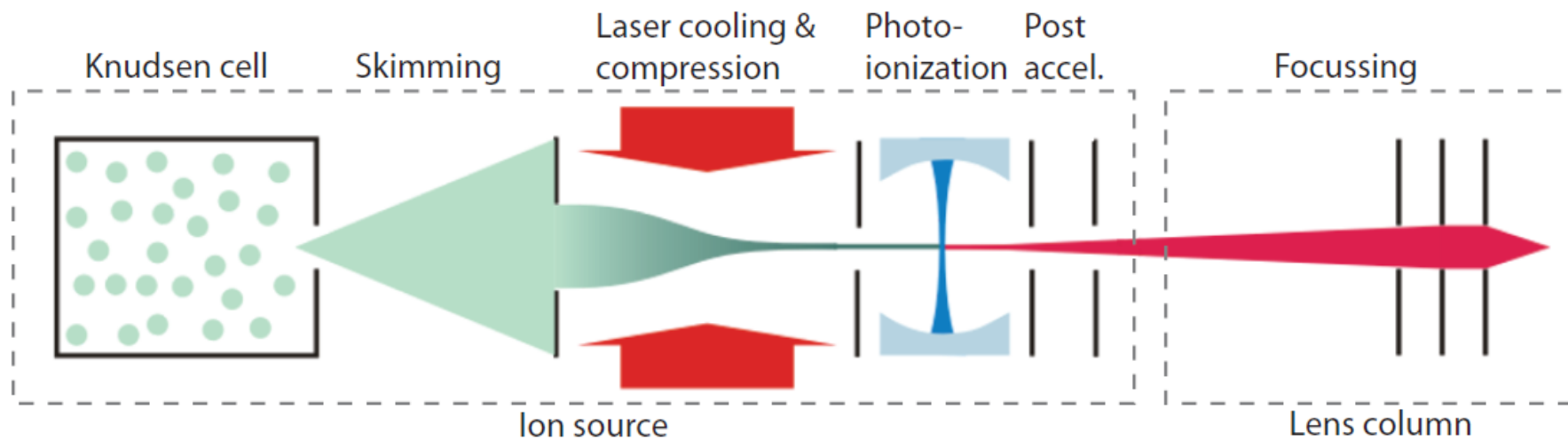
(Logo) engraving



<http://www.s3.infm.it/fib.html>

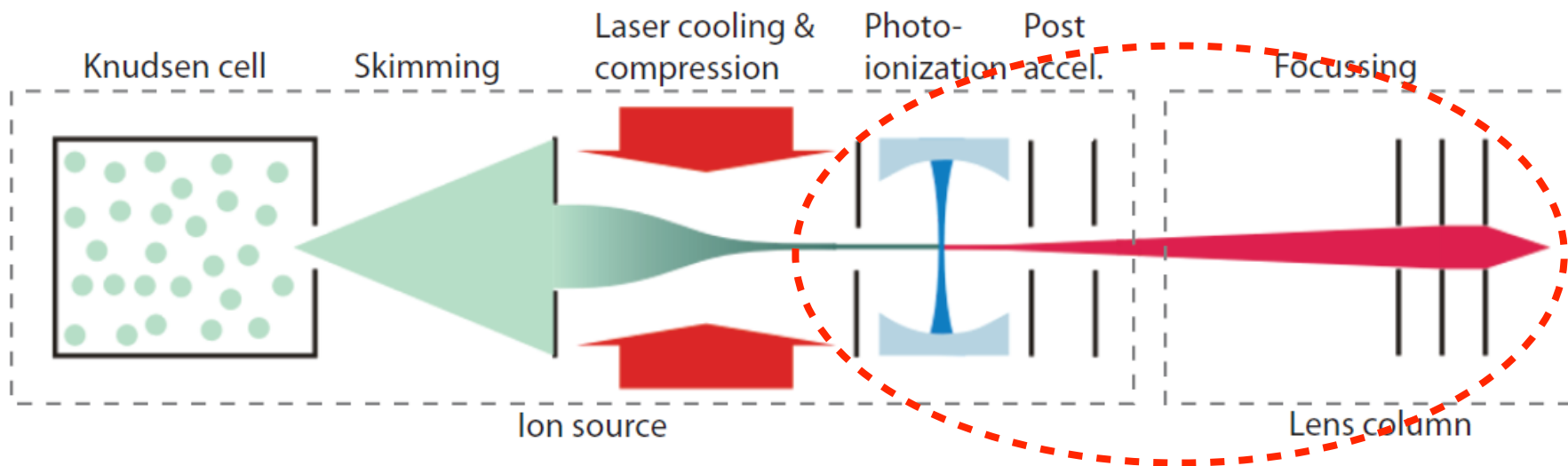
# Application: Focused ion beam

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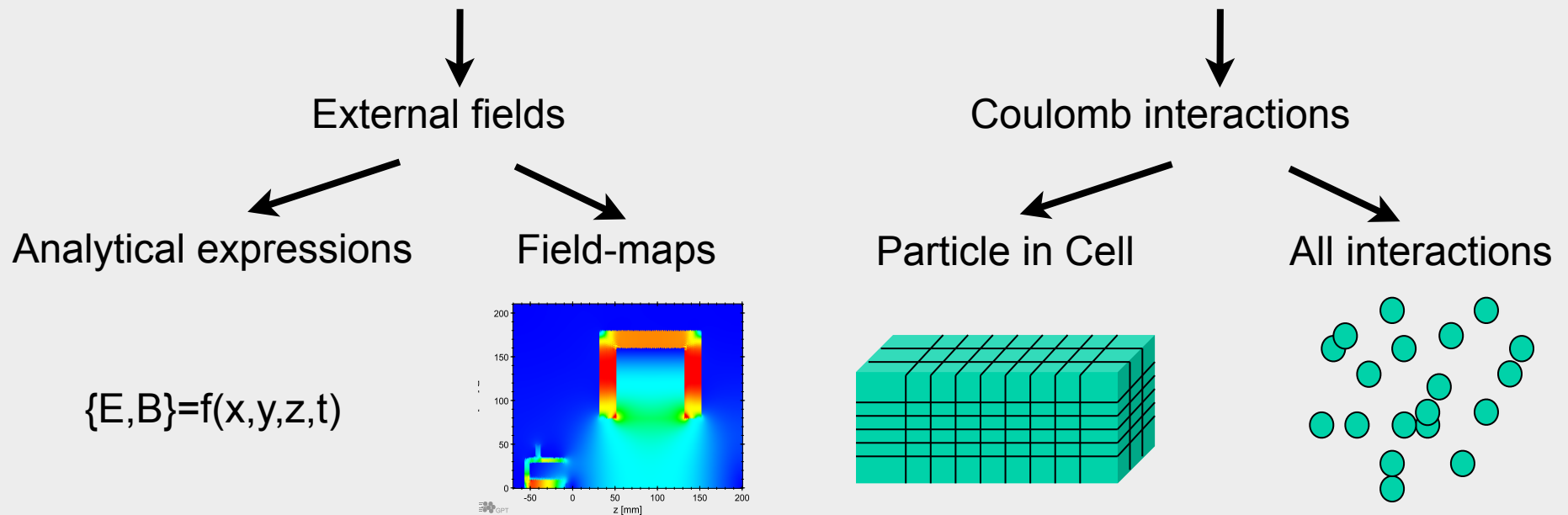




# 'Typical' simulation code: GPT

Tracks sample particles in **time-domain**

- Relativistic equations of motion
- Fully 3D, including all non-linear effects
- GPT solves with 5<sup>th</sup> order embedded Runge Kutta, adaptive stepsize
- GPT 3.2 beta includes a multi-objective genetic optimizer
- Challenge:  $\mathbf{E}(\mathbf{r},t)$ ,  $\mathbf{B}(\mathbf{r},t)$ , flexibility without compromising accuracy





# Coulomb interactions

## Macroscopic (mean field):

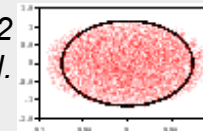
- **Space-charge**
- Average repulsion force
- Bunch expands
- Deformations in phase-space
- Governed by Poisson's equation

## Microscopic:

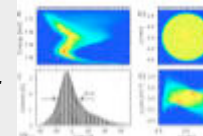
- **Disorder induced heating**
- Neighbouring particles 'see' each other
- Potential energy  $\rightarrow$  momentum spread
- Stochastic effect
- Governed by point-to-point interactions

GPT simulations

*PRL* 93, 094802  
O.J. Luiten et. al.



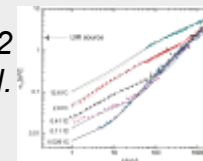
*JAP* 102, 093501  
T. van Oudheusden et. al.



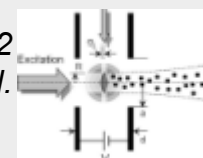
*PRST-AB* 9, 044203  
S.B. van der Geer et. al.



*PRL* 102, 034802  
M. P. Reijnders et. al.

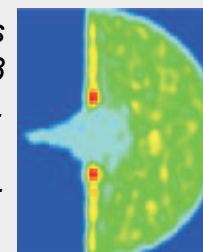


*JAP* 102, 094312  
S.B. van der Geer et. al.



*Nature Photonics*  
Vol 2, May 2008  
M. Centurion et. al.

And many others...





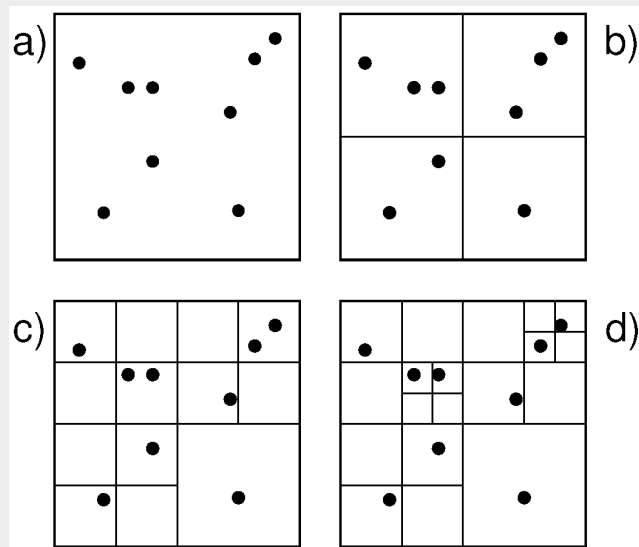


# Barnes-Hut

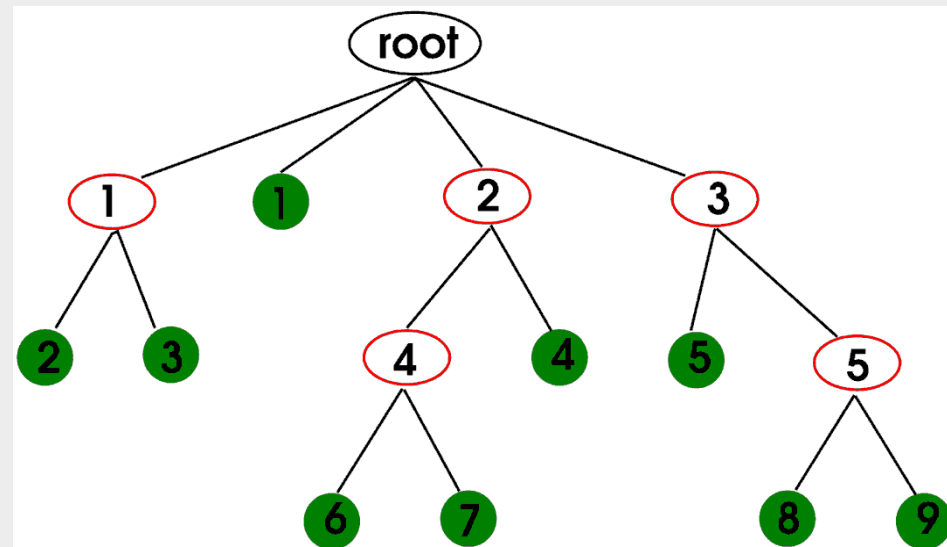
Hierarchical tree algorithm:

- Includes *all* Coulomb interactions
- $O(N \log N)$  in CPU time
- User-selectable accuracy

Division of space

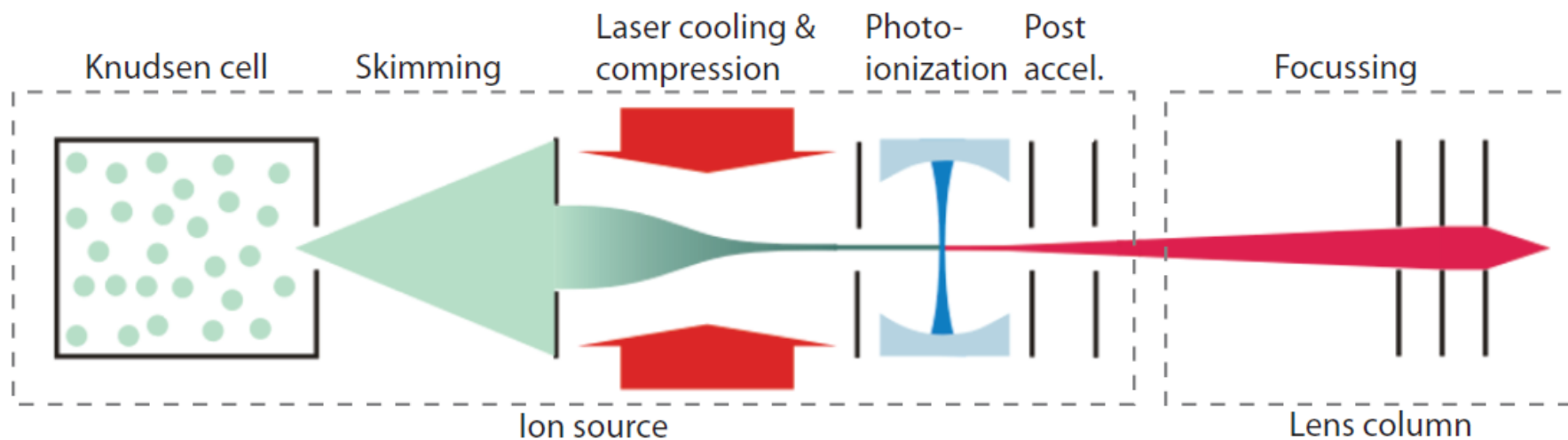


Tree data structure



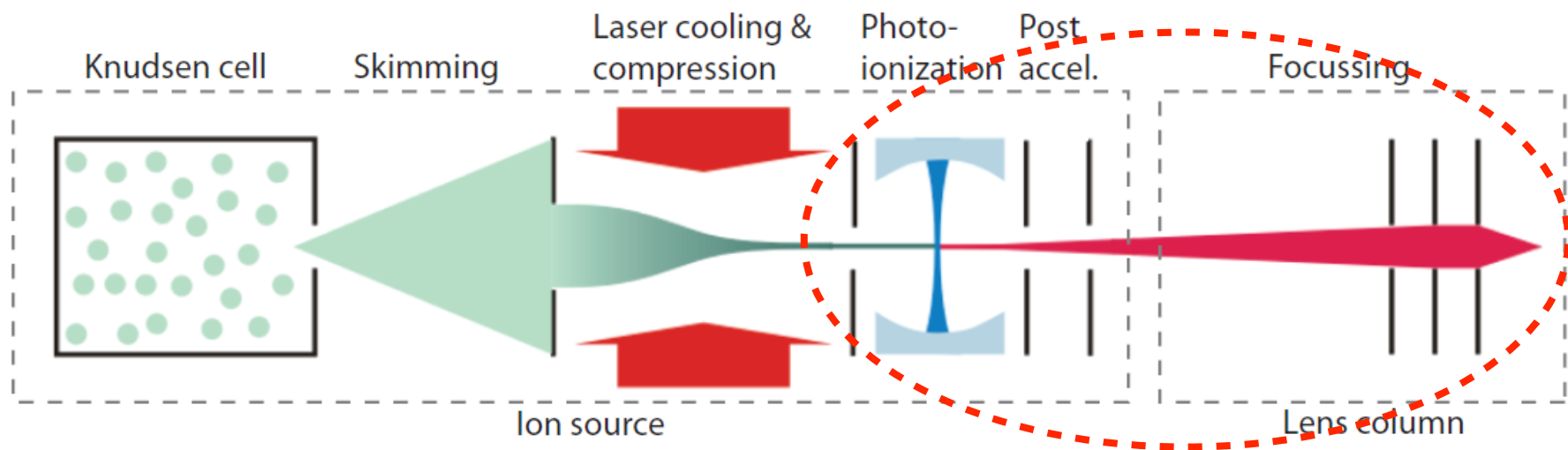
# Application: Focused ion beam

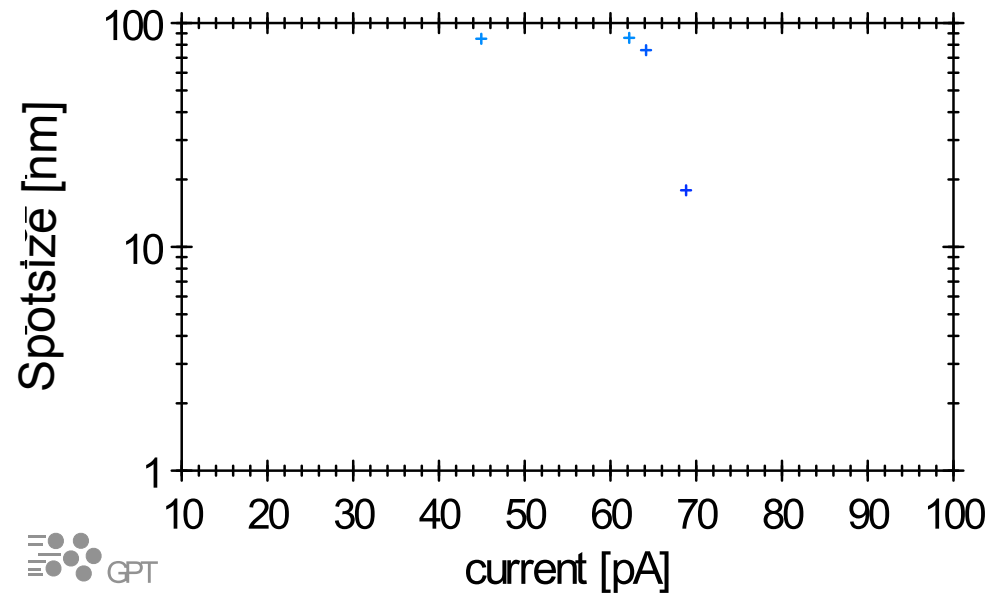
- **Aim: Lots of current at nm spotsizes**
- Design disaster: Beams heats up during acceleration
- **Multi-objective global optimization**



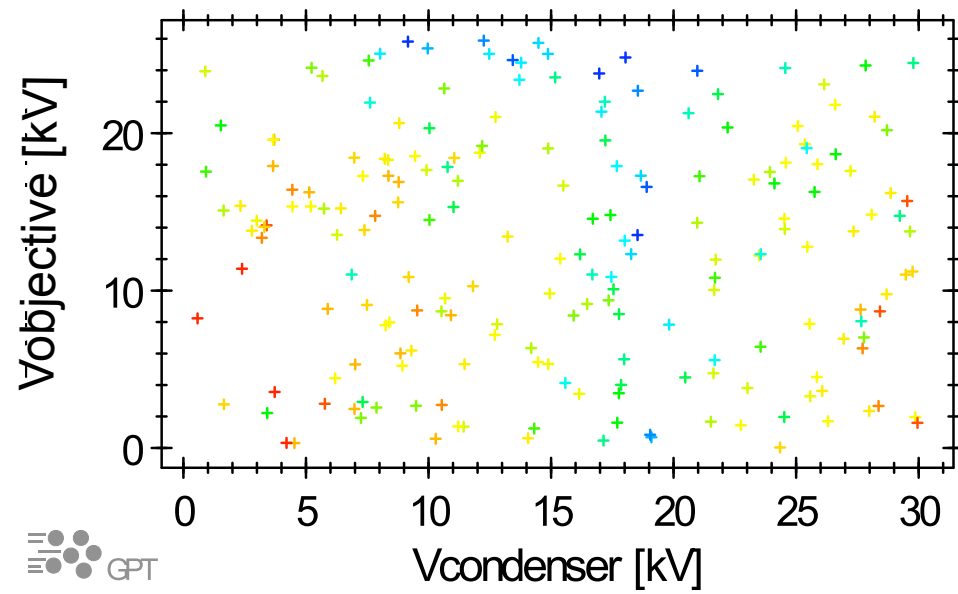
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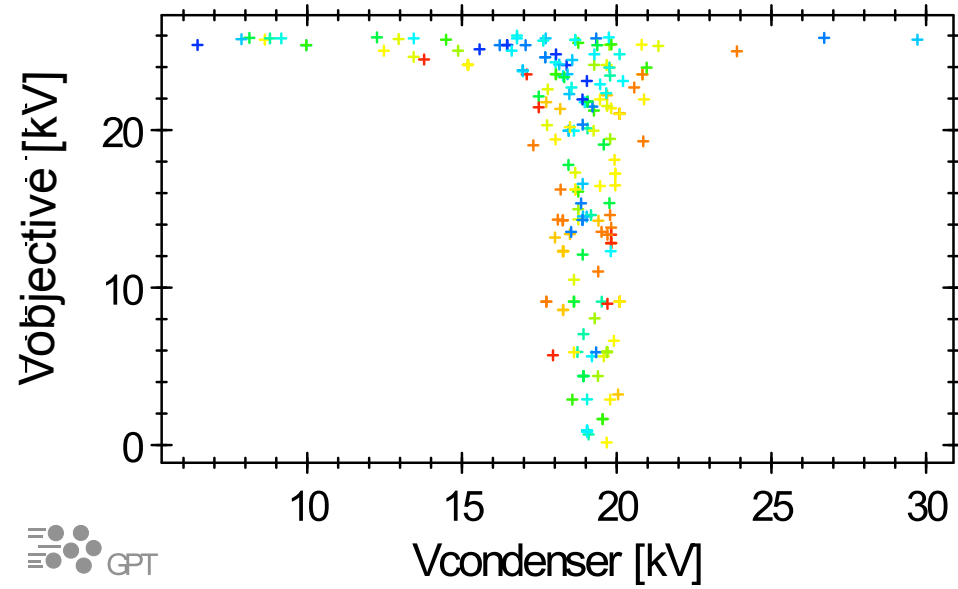
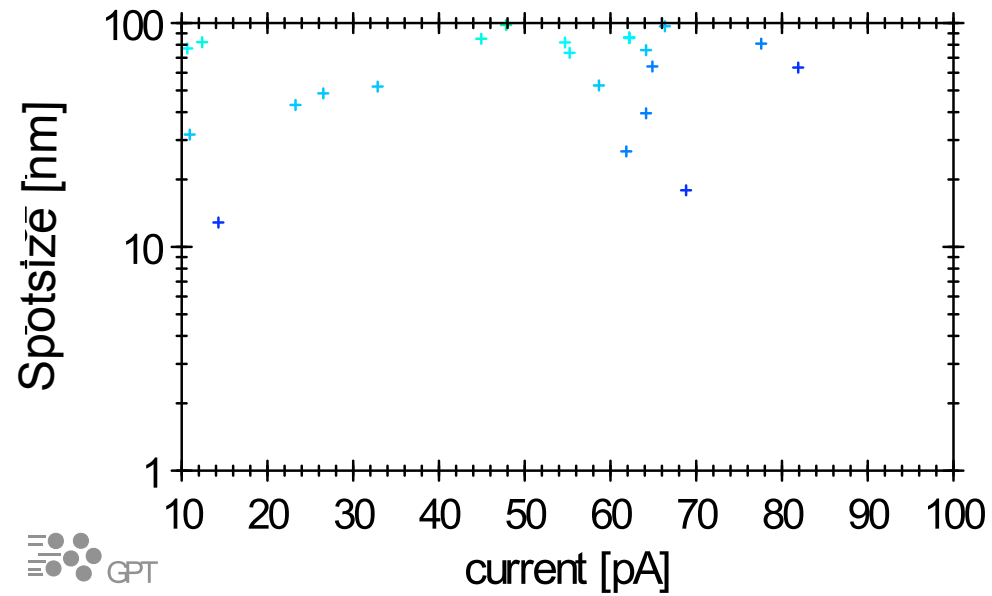
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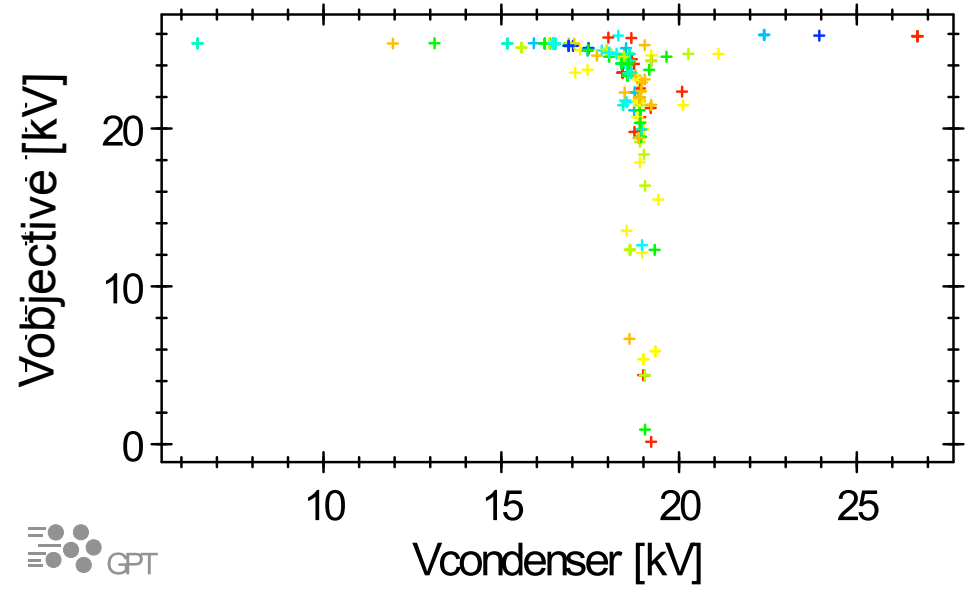
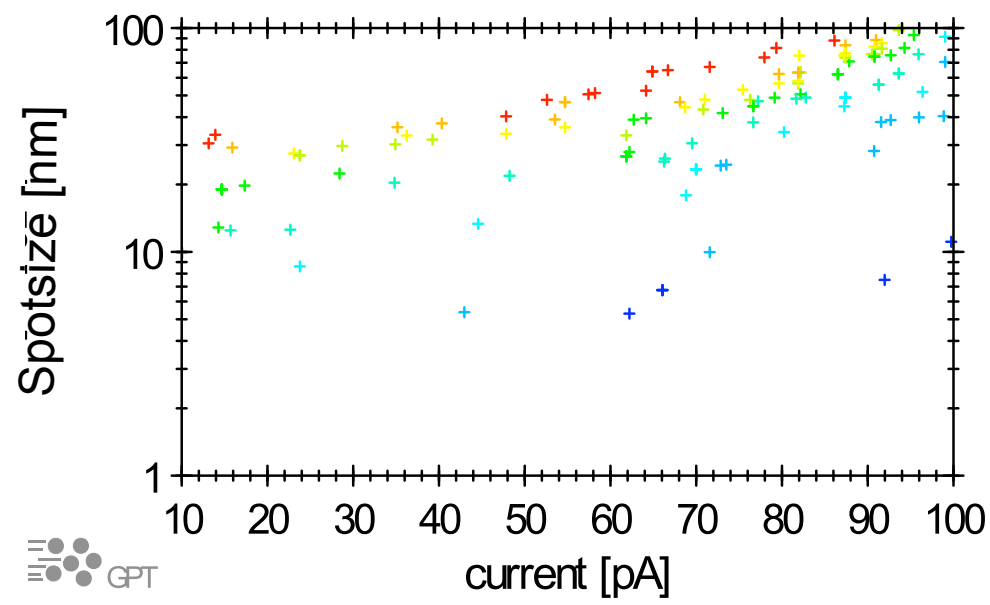


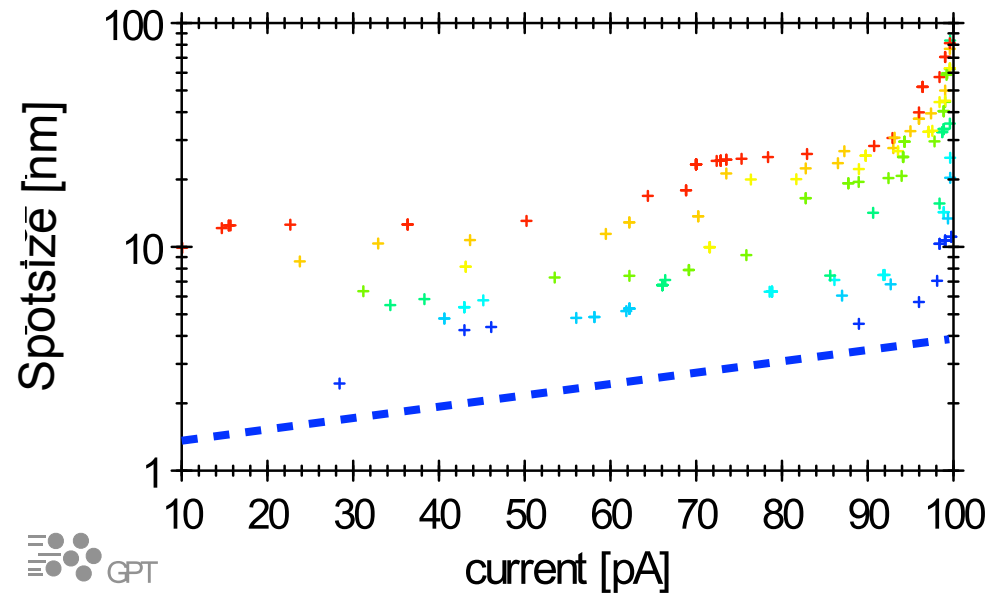
**Initial population:**  
Very large spotsizes  
Off scale



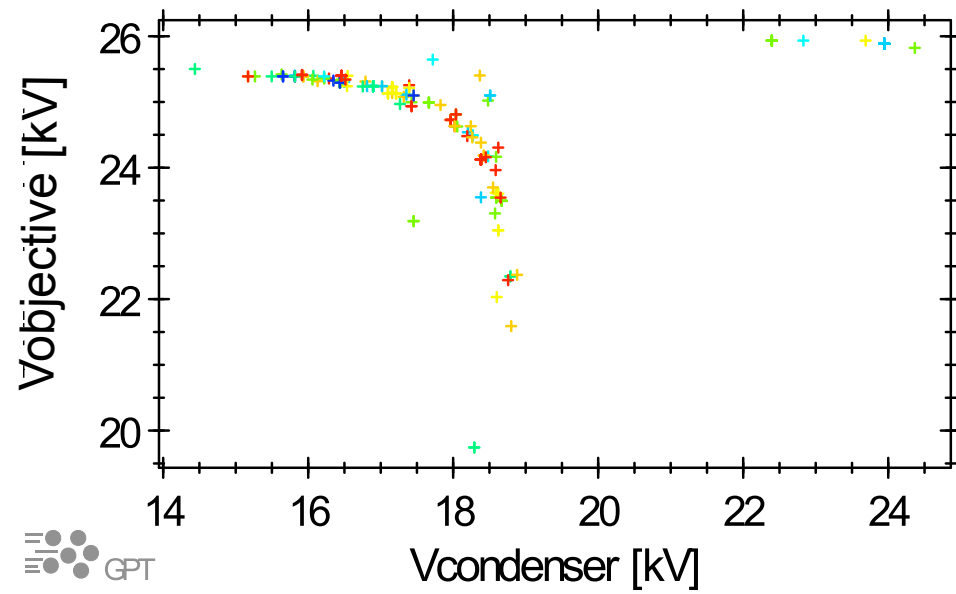


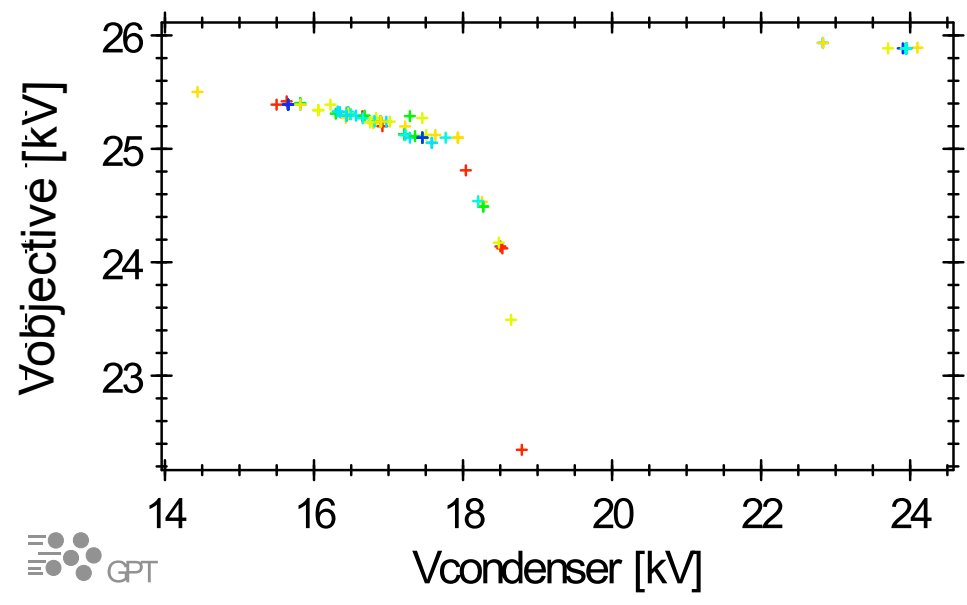
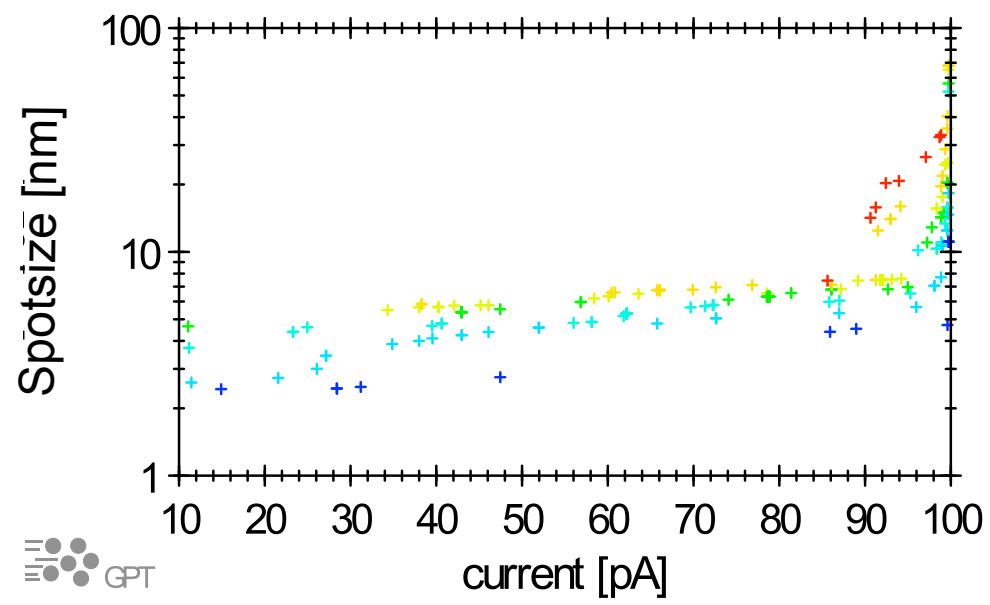
**Initial steps:**  
Volume in variable space  
significantly reduced



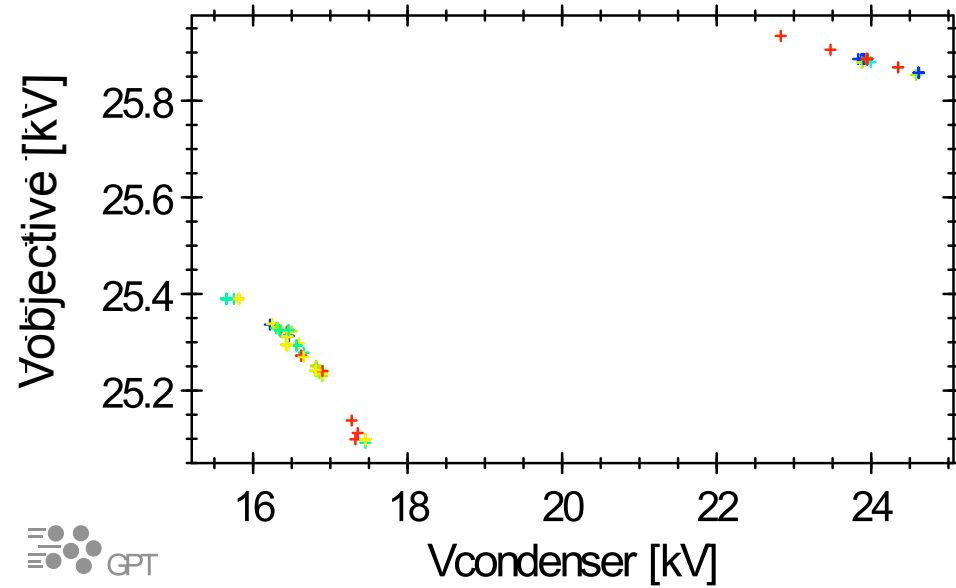
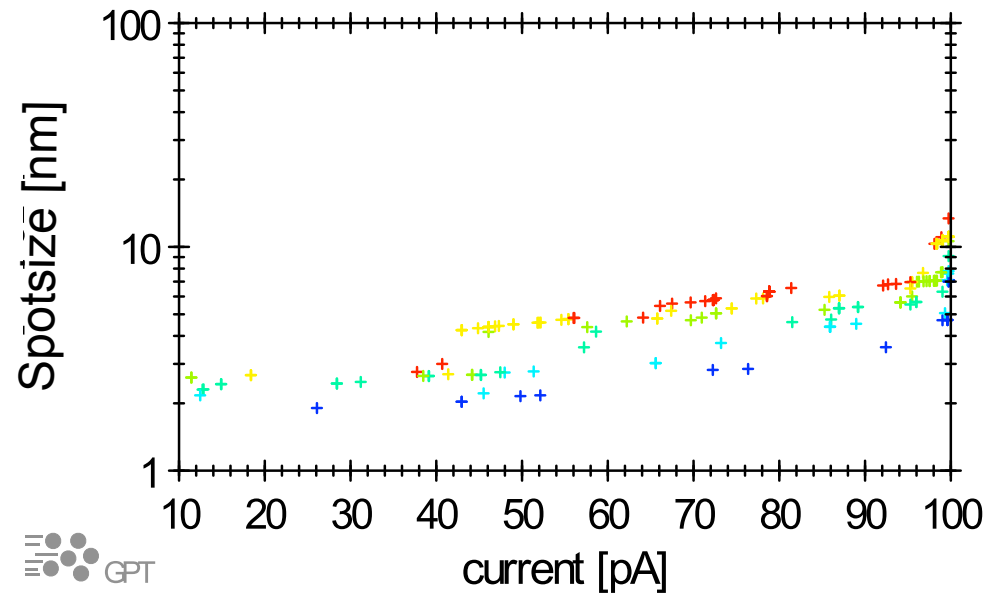


**Pareto front:**  
Impossible to improve one objective without degrading at least one other objective







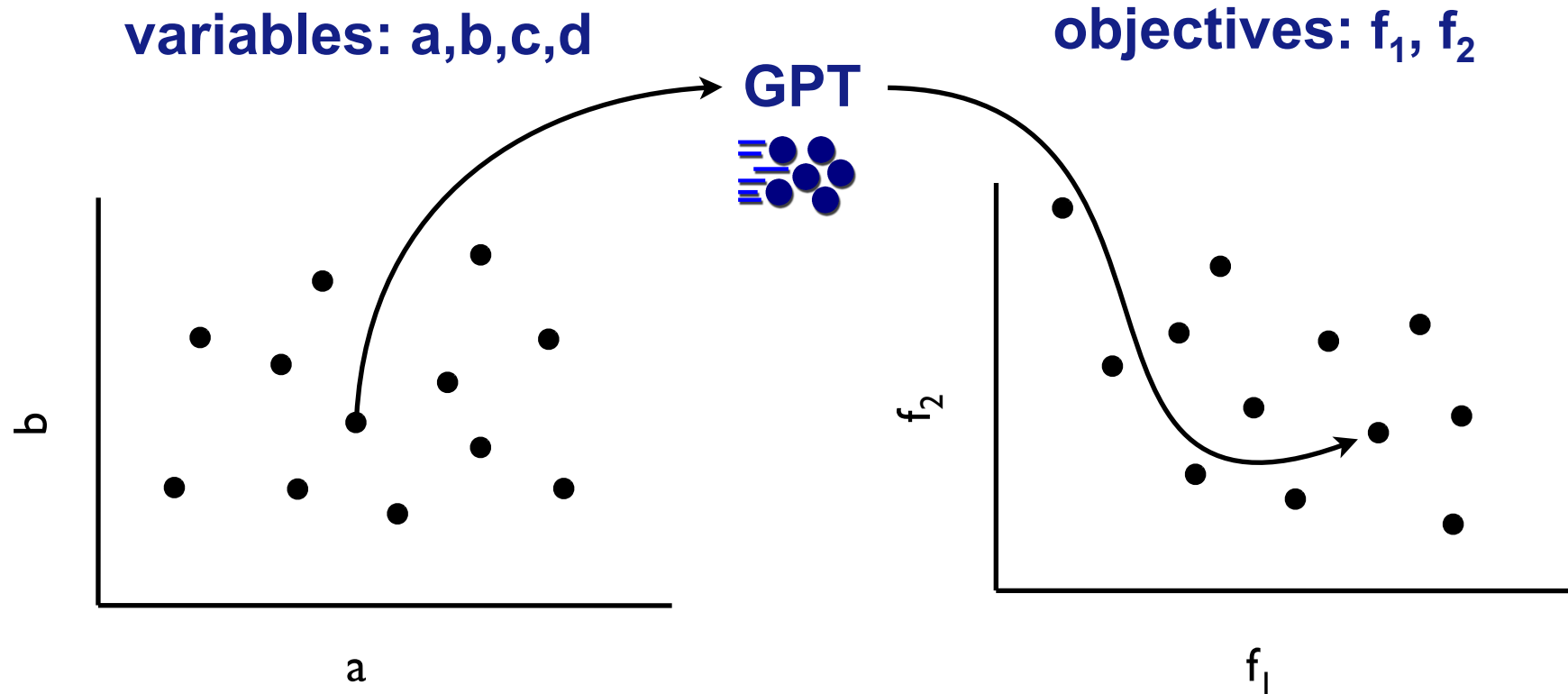


**Break-up in variable space:**  
 Different scenario's:  
 With and without crossover

4 slides are intentionally removed

# Variables and objectives

- Objectives  $f_n$  are a function of all variables
  - $f_1(a,b,c,d)$ ,  $f_2(a,b,c,d)$ , ...



# The problem: Too many knobs to turn



# The solution: Multi-objective optimization



# Multi-objective optimization

- **Work iteratively with a population of samples**
- **At each iteration:**
  - **Add new samples using ‘best’ samples in population**
  - **Remove “worst” samples**
- **Aim:**
  - **Nicely sampled pareto front**

PHYSICAL REVIEW SPECIAL TOPICS - ACCELERATORS AND BEAMS 14, 072001 (2011)

**Comparison of dc and superconducting rf photoemission guns for high brightness high average current beam production**

Ivan V. Bazarov, Allen Kim, Manu N. Lakshmanan, and Jared M. Maxson  
*Cornell Laboratory for Accelerator-based Sciences and Education, Cornell University, Ithaca, New York 14853, USA*

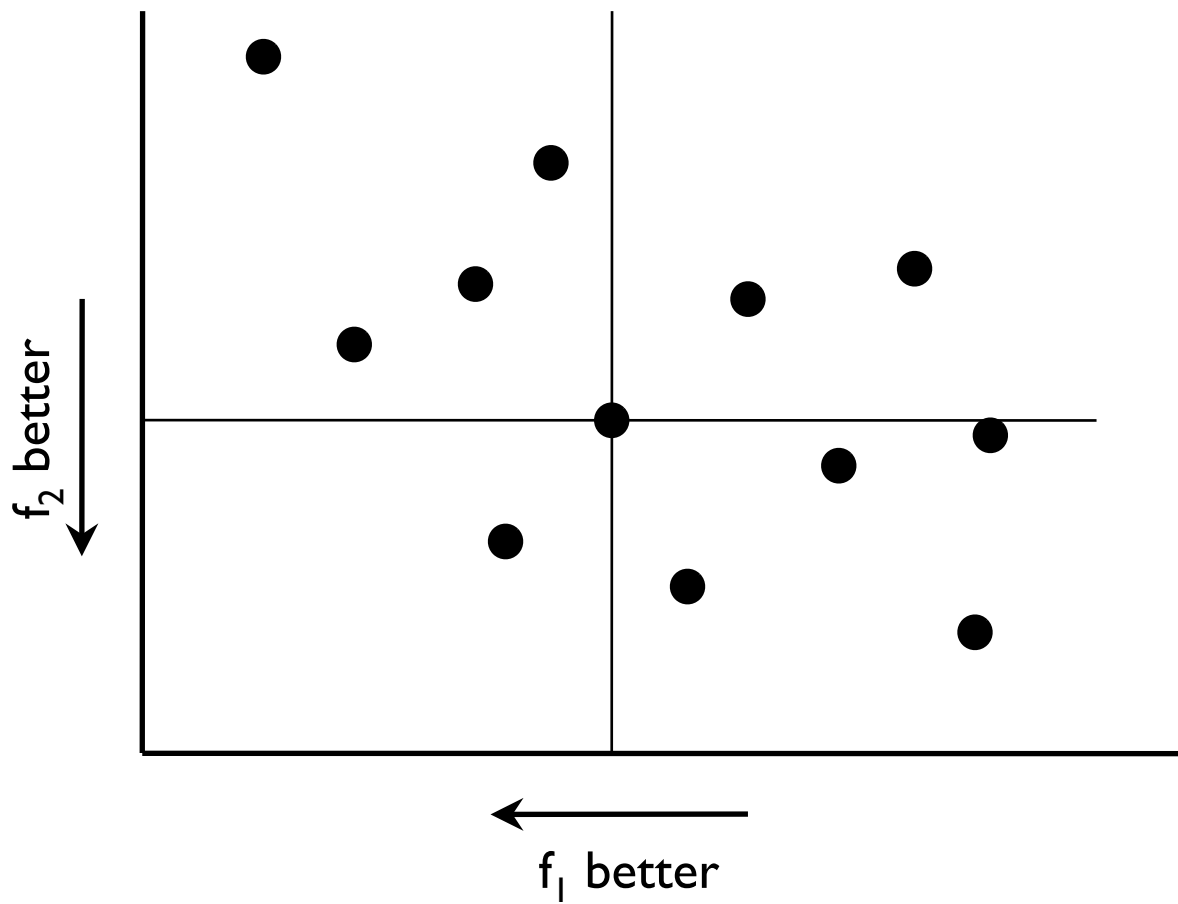
TUAA12

Proceedings of ICAP2012, Rostock-Warnemünde, Germany

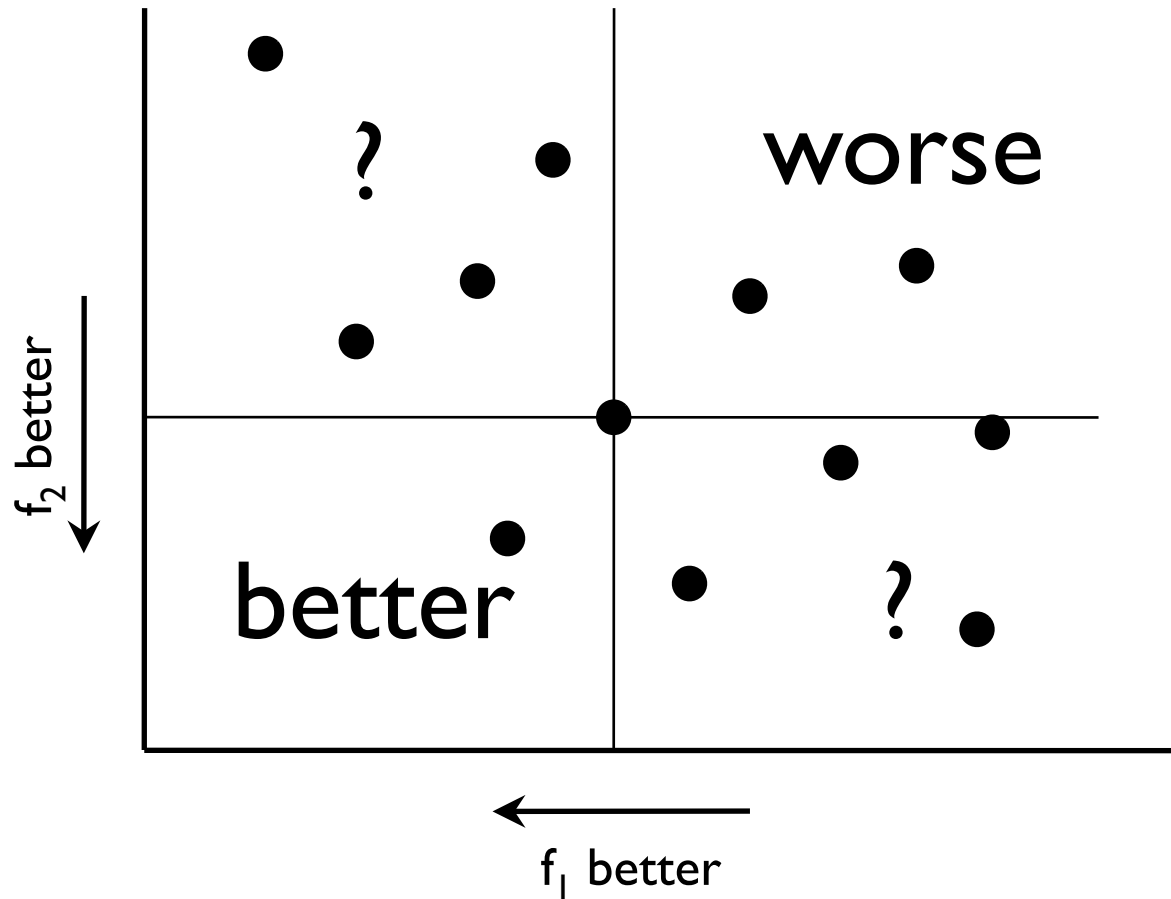
**A MASSIVELY PARALLEL GENERAL PURPOSE MULTI-OBJECTIVE OPTIMIZATION FRAMEWORK, APPLIED TO BEAM DYNAMIC STUDIES**

Y. Ineichen, A. Adelman\*, PSI, Villigen, Switzerland  
C. Bekas, A. Curioni, IBM Research – Zurich, Switzerland  
P. Arbenz, Department of Computer Science, ETH Zurich, Switzerland

# Domination



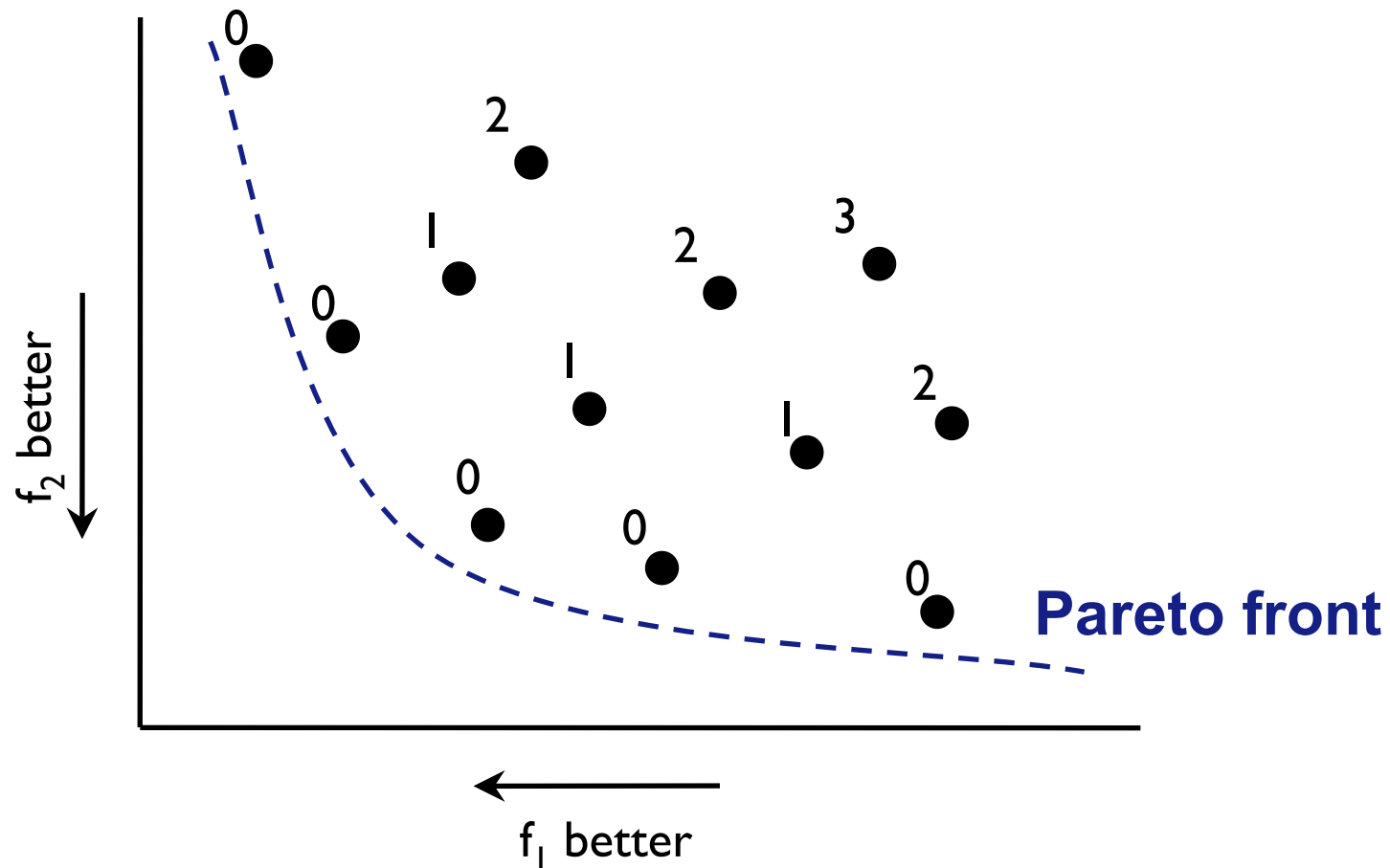
# Domination: Who dominates who





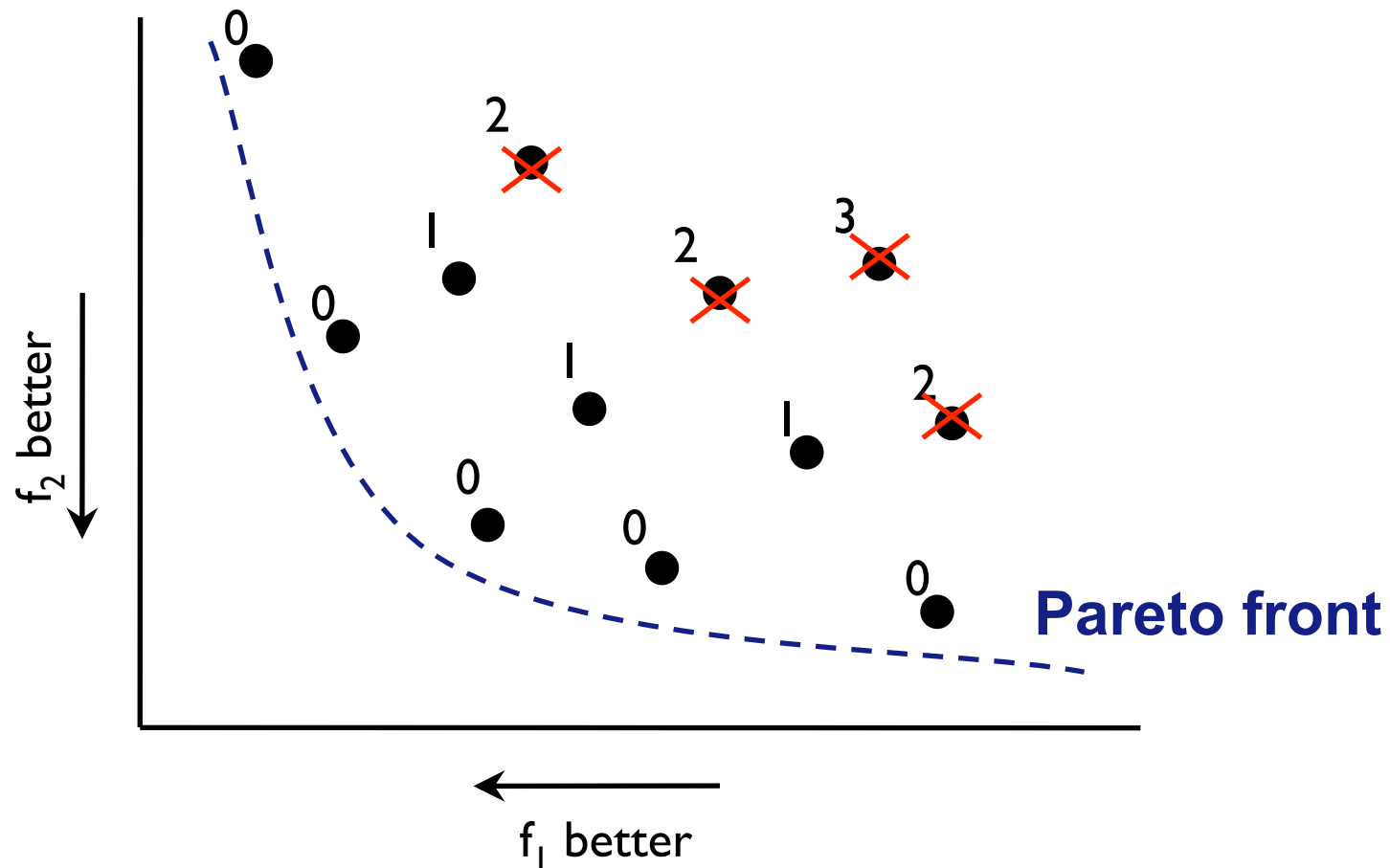
# Algorithm: Rank on domination and remove

- Ranking starts closest to (unknown) pareto front



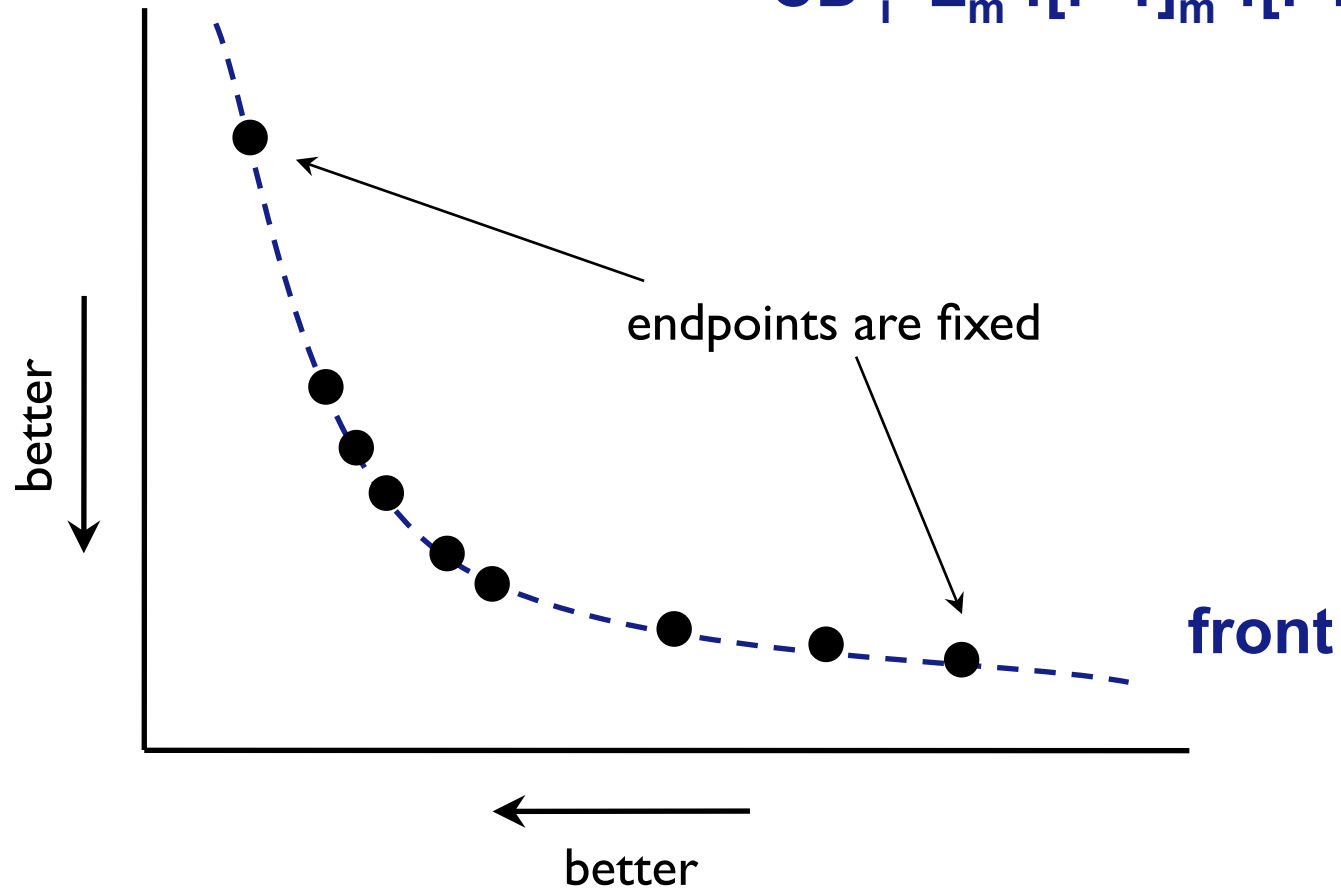
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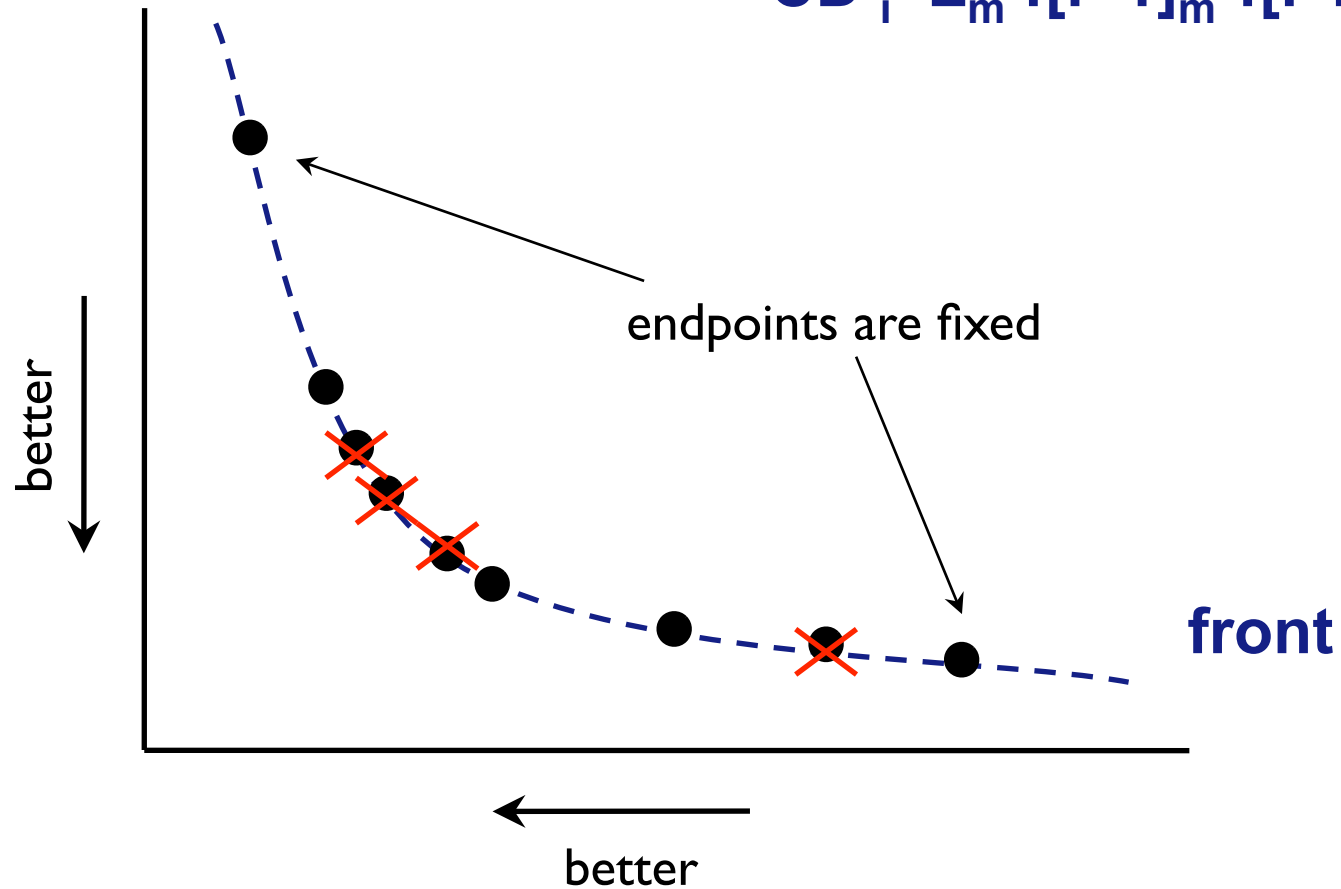
# Algorithm: Uniform front

- Crowding distance (CD)
- $CD_i = \sum_m f[i+1]_m - f[i-1]_m$



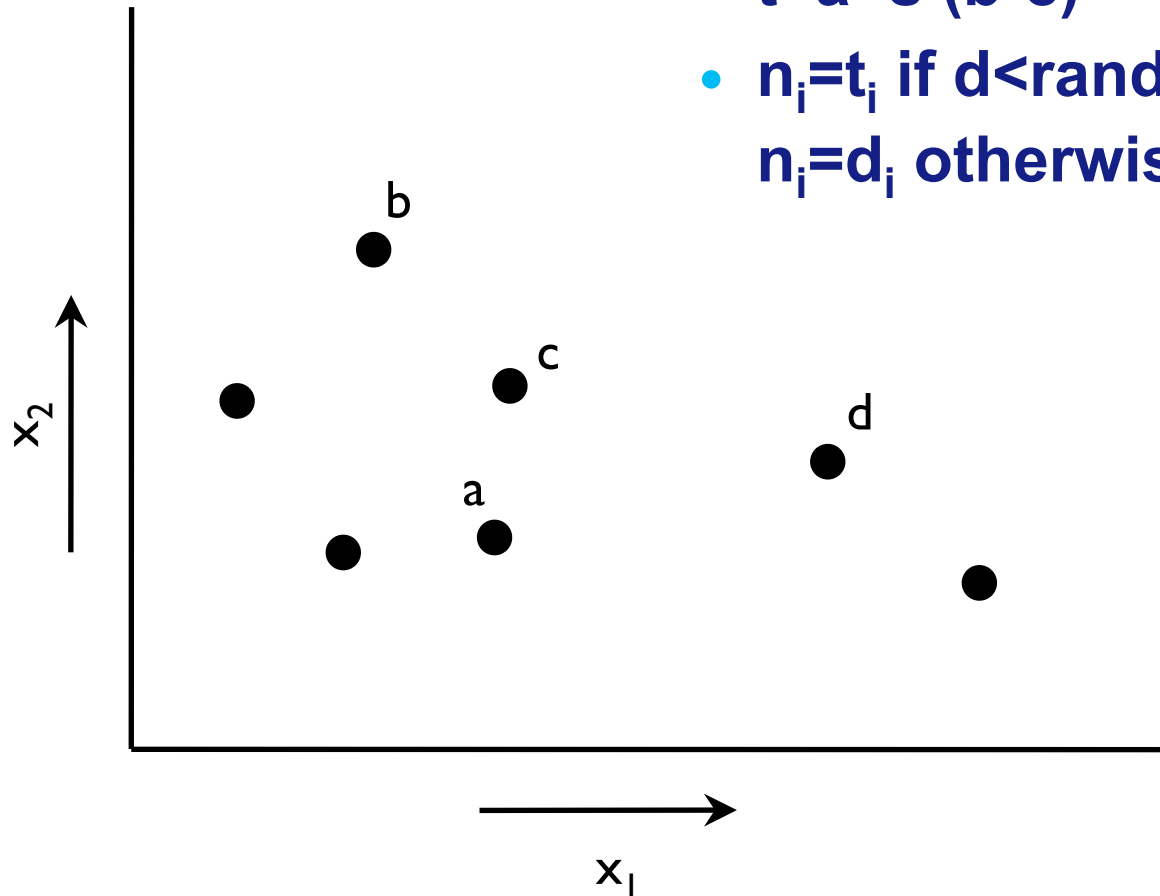
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# Algorithm: New points (just one method)

- Differential evolution
- Select 4 random points
- $t = a + s(b - c)$
- $n_i = t_i$  if  $d < \text{random}(0, 1)$   
 $n_i = d_i$  otherwise



# Algorithm: New points (just one method)

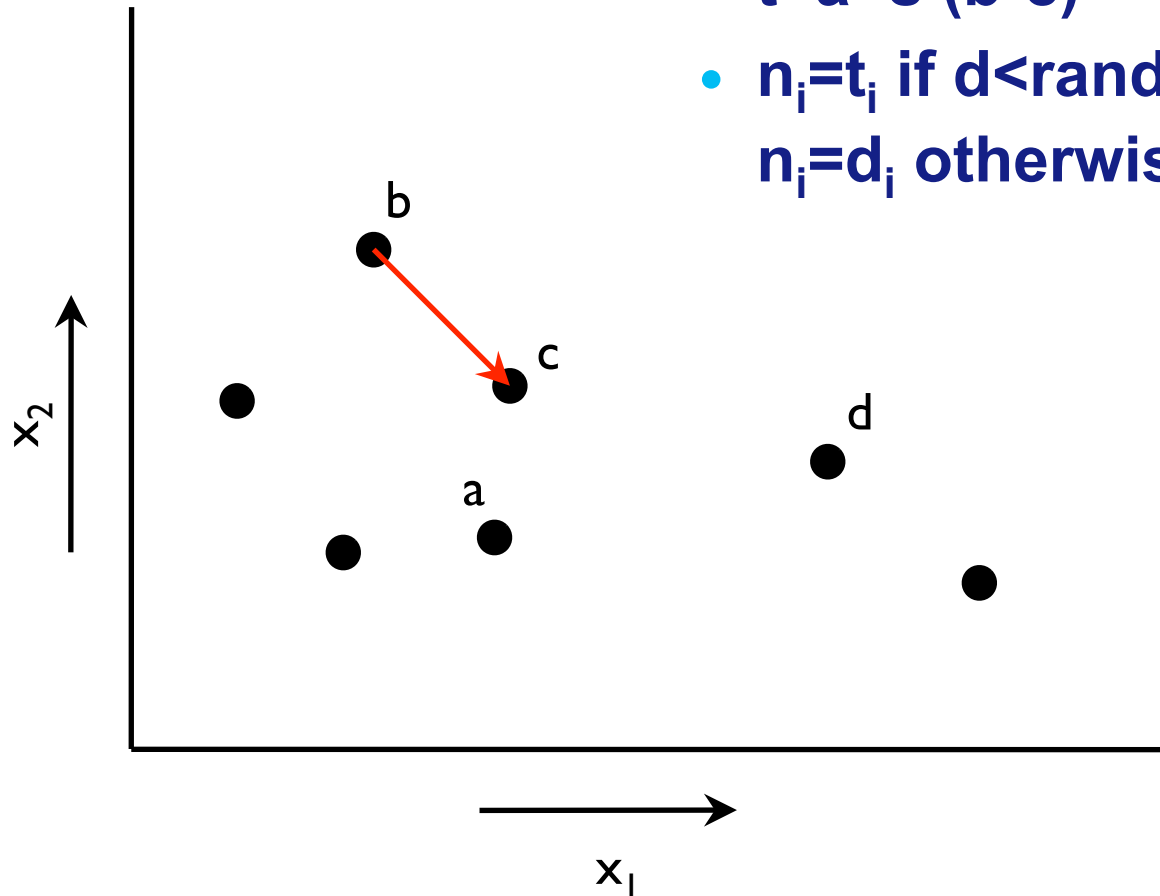
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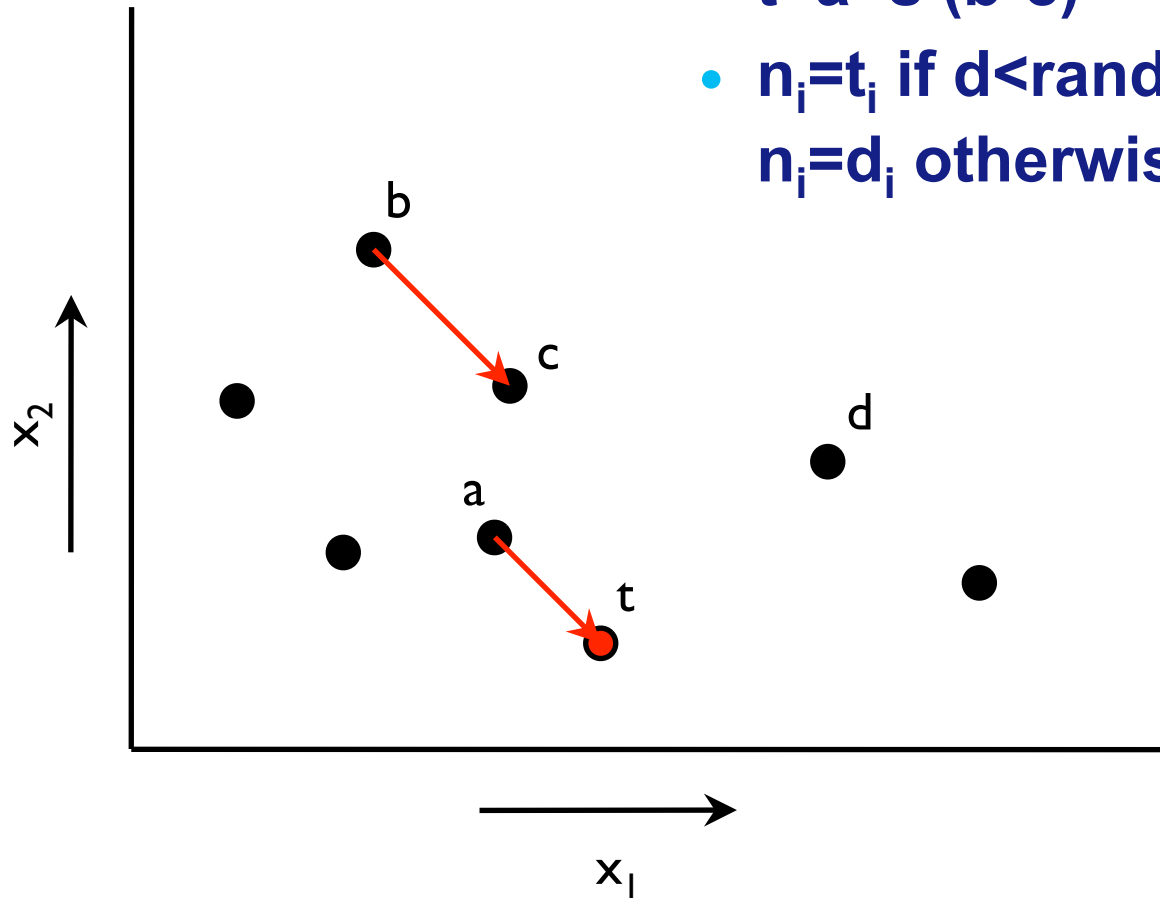
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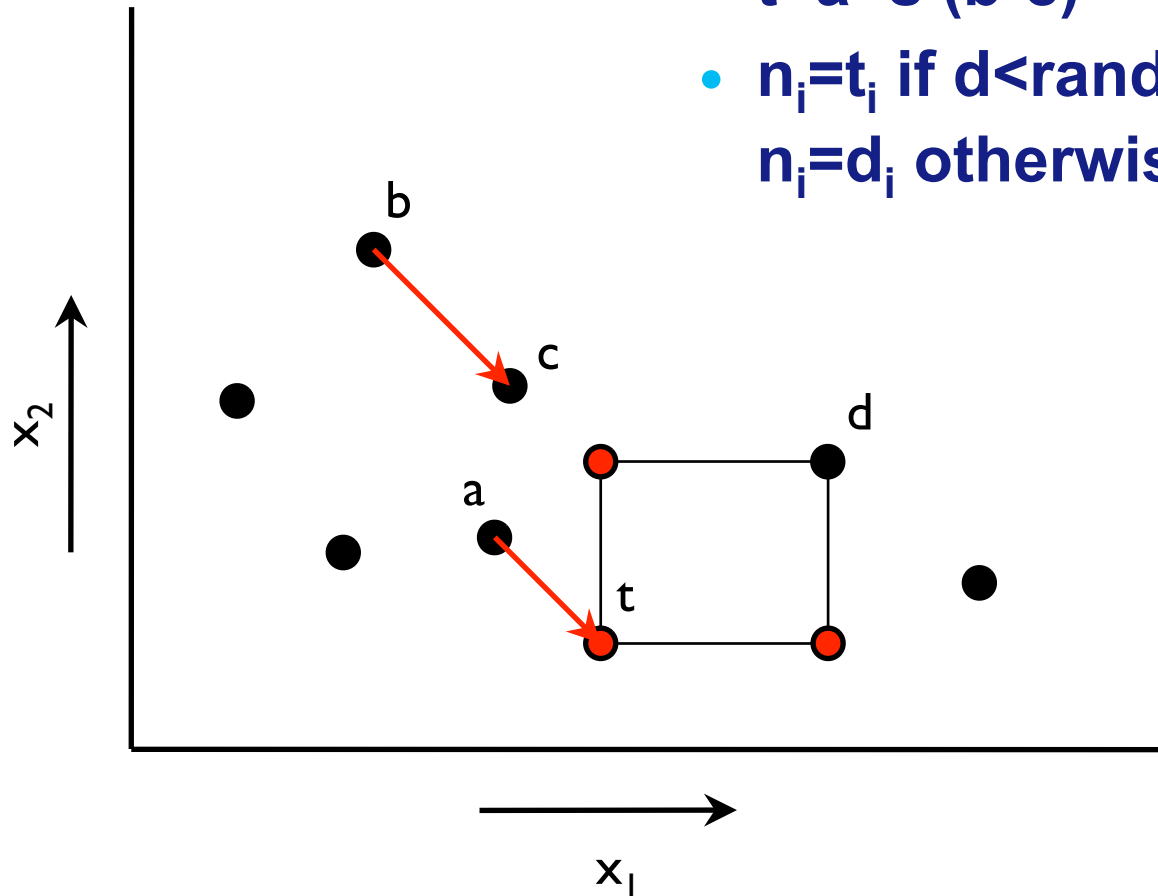
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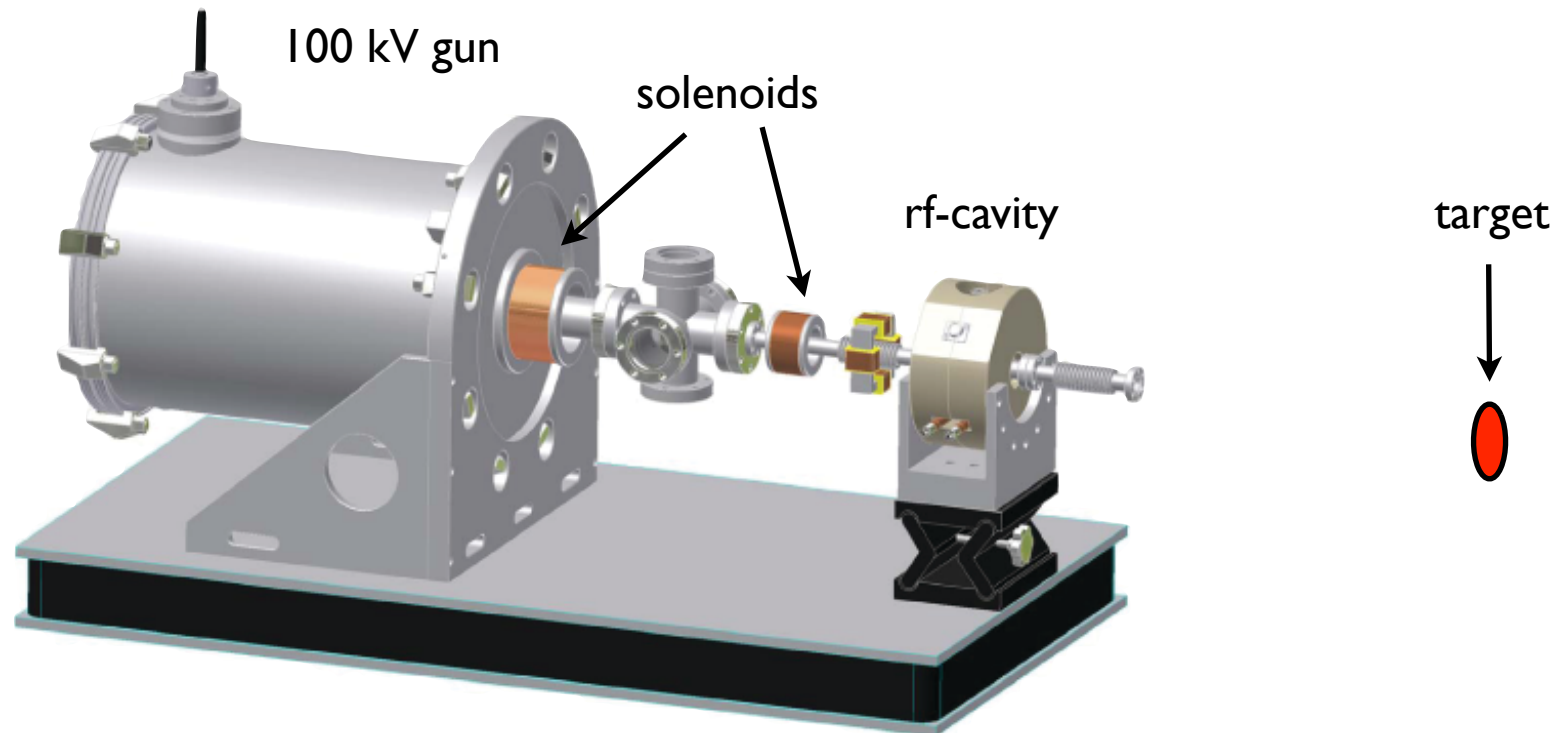


# Algorithm: Constraints

- **In practice we always have**
  - **Multiple objectives**
  - **AND constraints**
- **Examples:**
  - **We need to stay within budget**  
**(but there is no point calculating the optimal design for each and every price)**
  - **We want a ‘short’ pulse at the target**  
**(but there is no point going below 100 fs since our detector has more jitter than that anyway)**
- **Constraints can easily be added to the sorting**

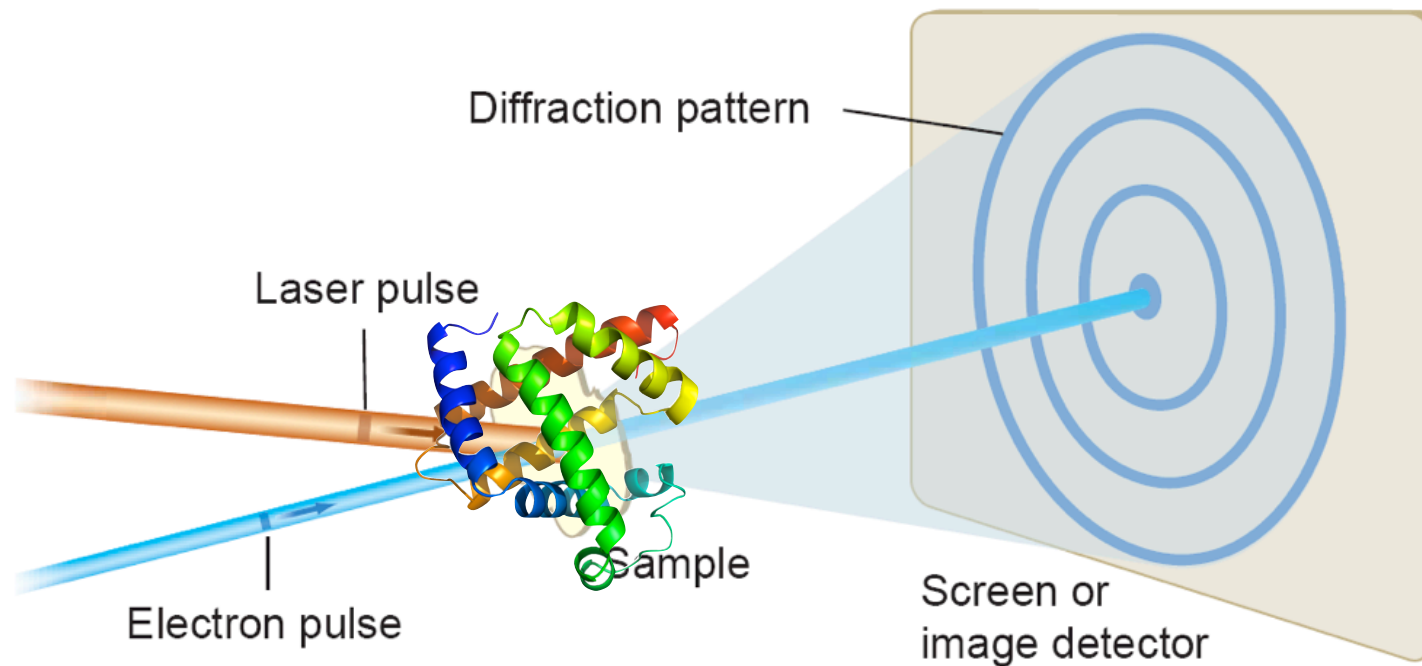
## Example: Ultrafast electron diffraction

- Variables: rf-amplitude, phase, solenoid1, solenoid2
- Conflicting objectives: Q, Lc, spot size, pulse length
- Performance dominated by non-linear effects



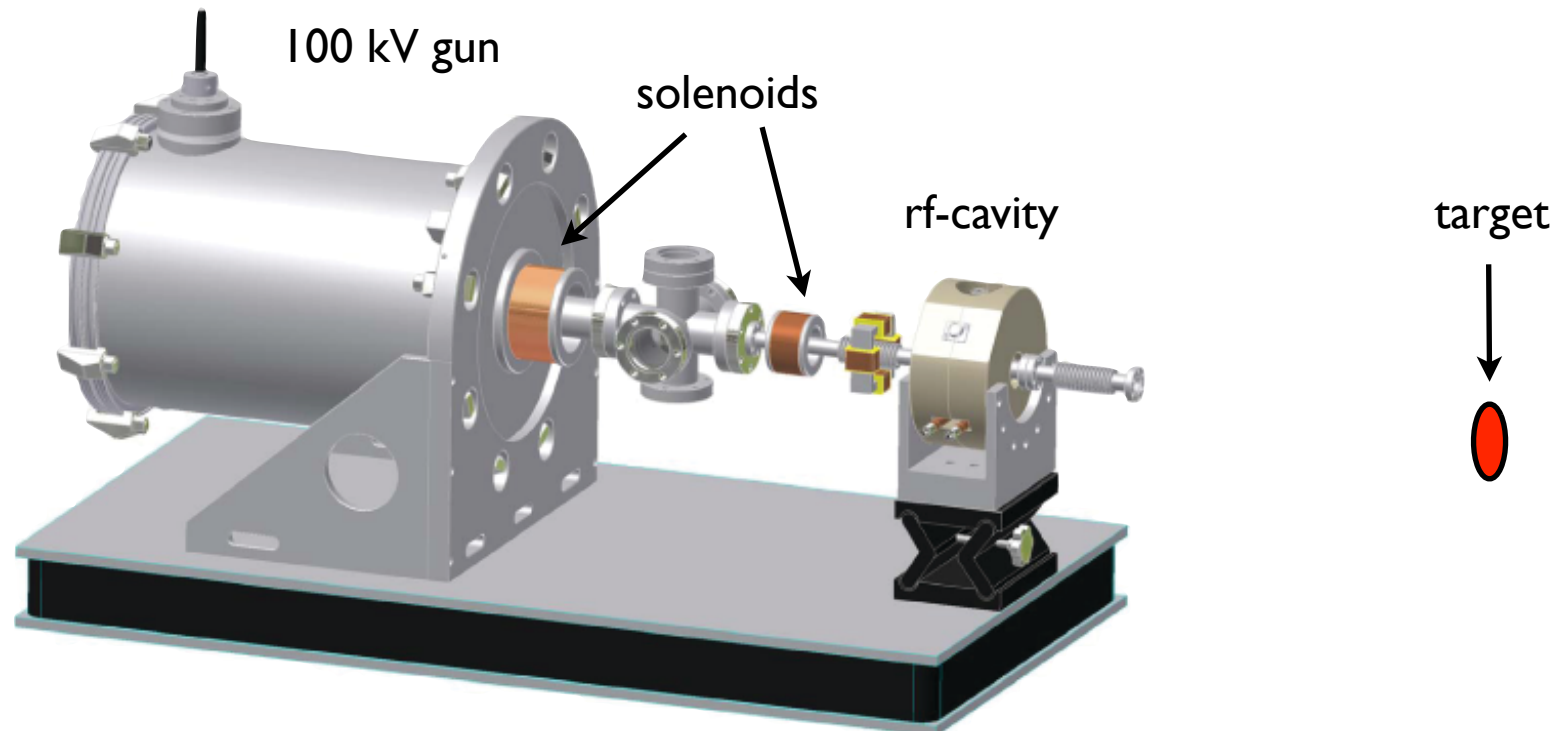
# Application: Ultrafast electron diffraction

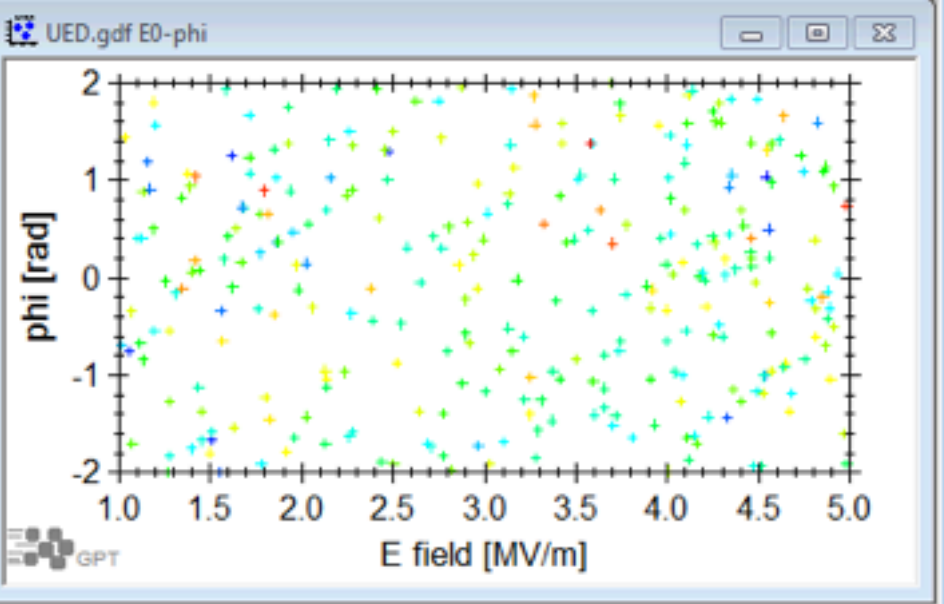
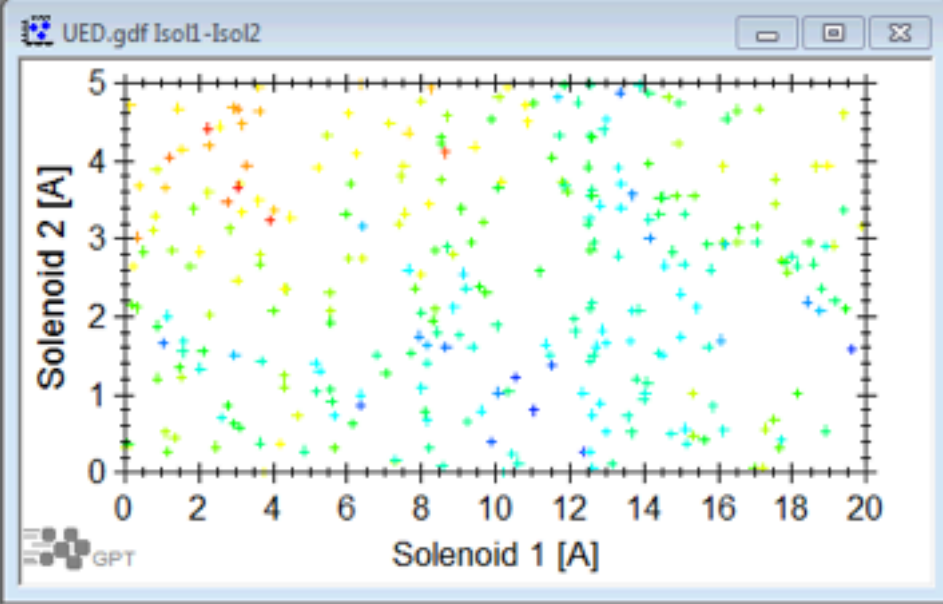
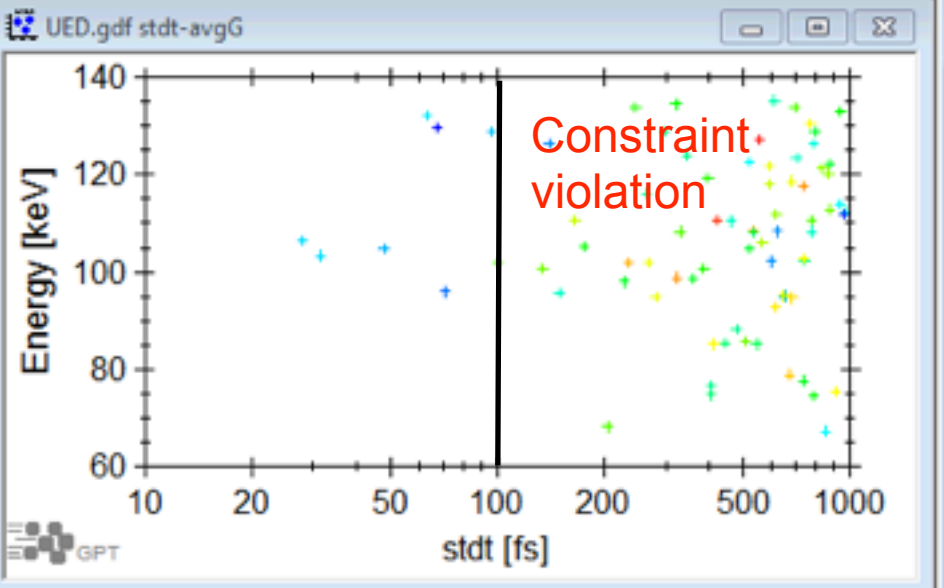
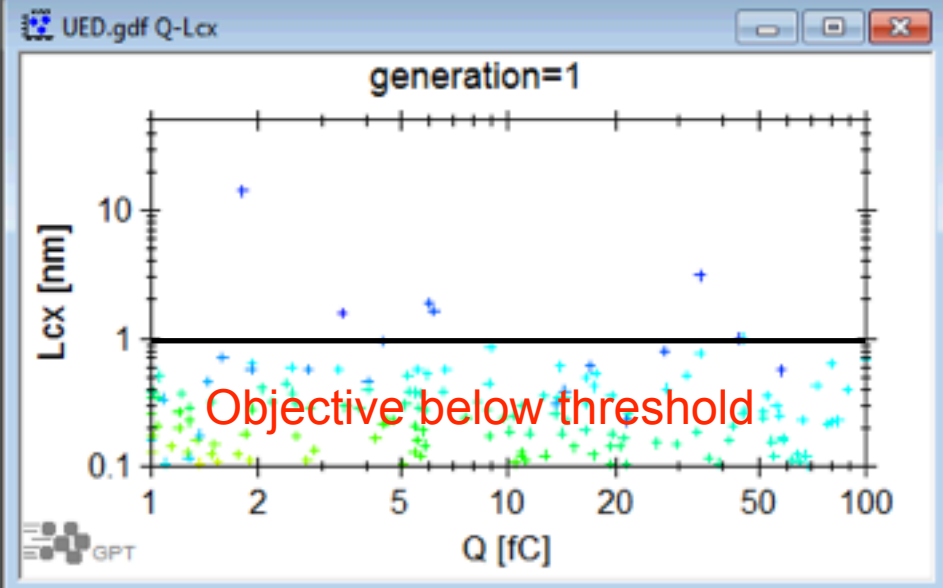
- **Structural dynamics**
- Resolve atomic **length** and **time scales**:  $\sim 1 \text{ \AA}$ ,  $\sim 100 \text{ fs}$

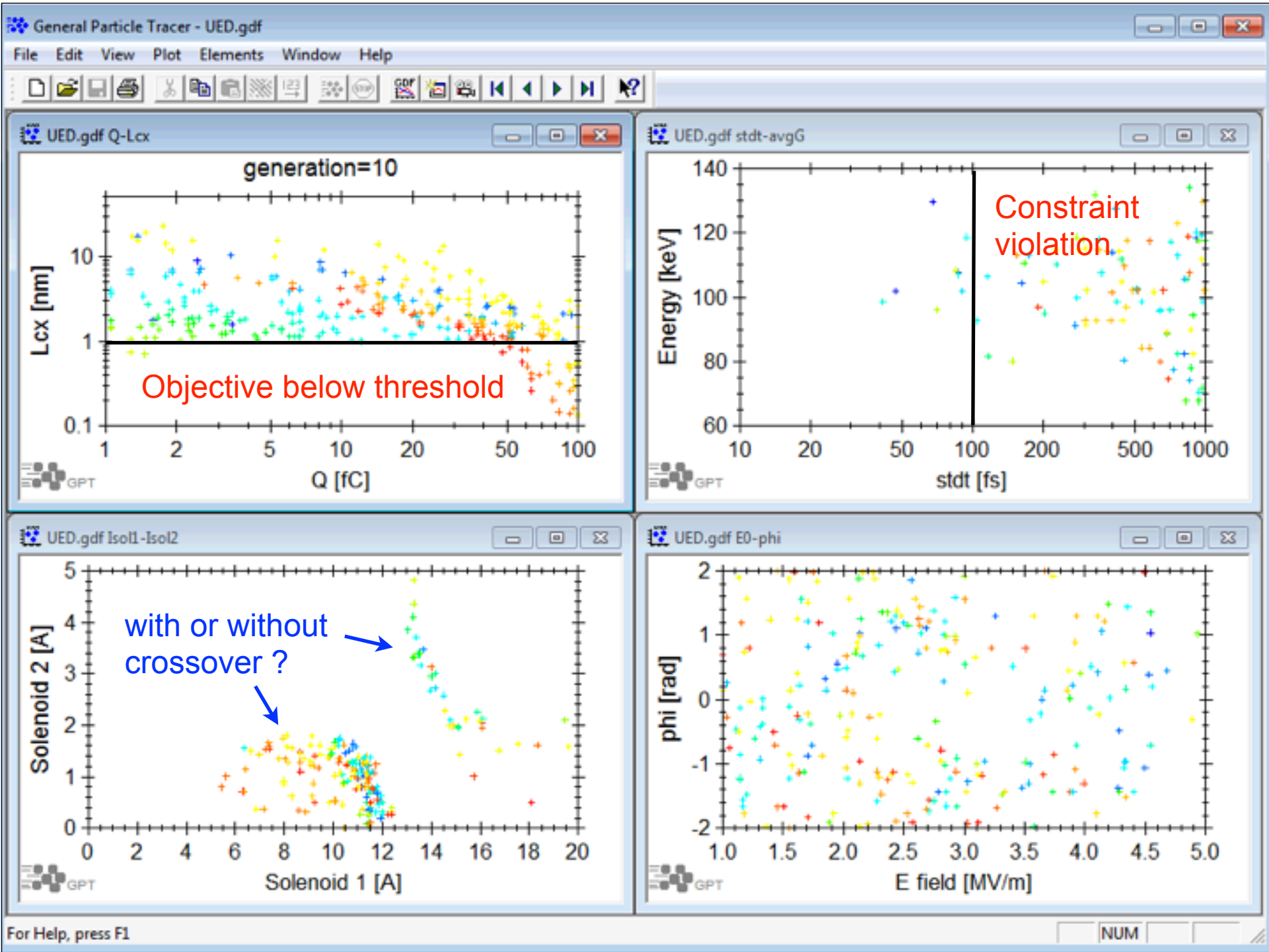


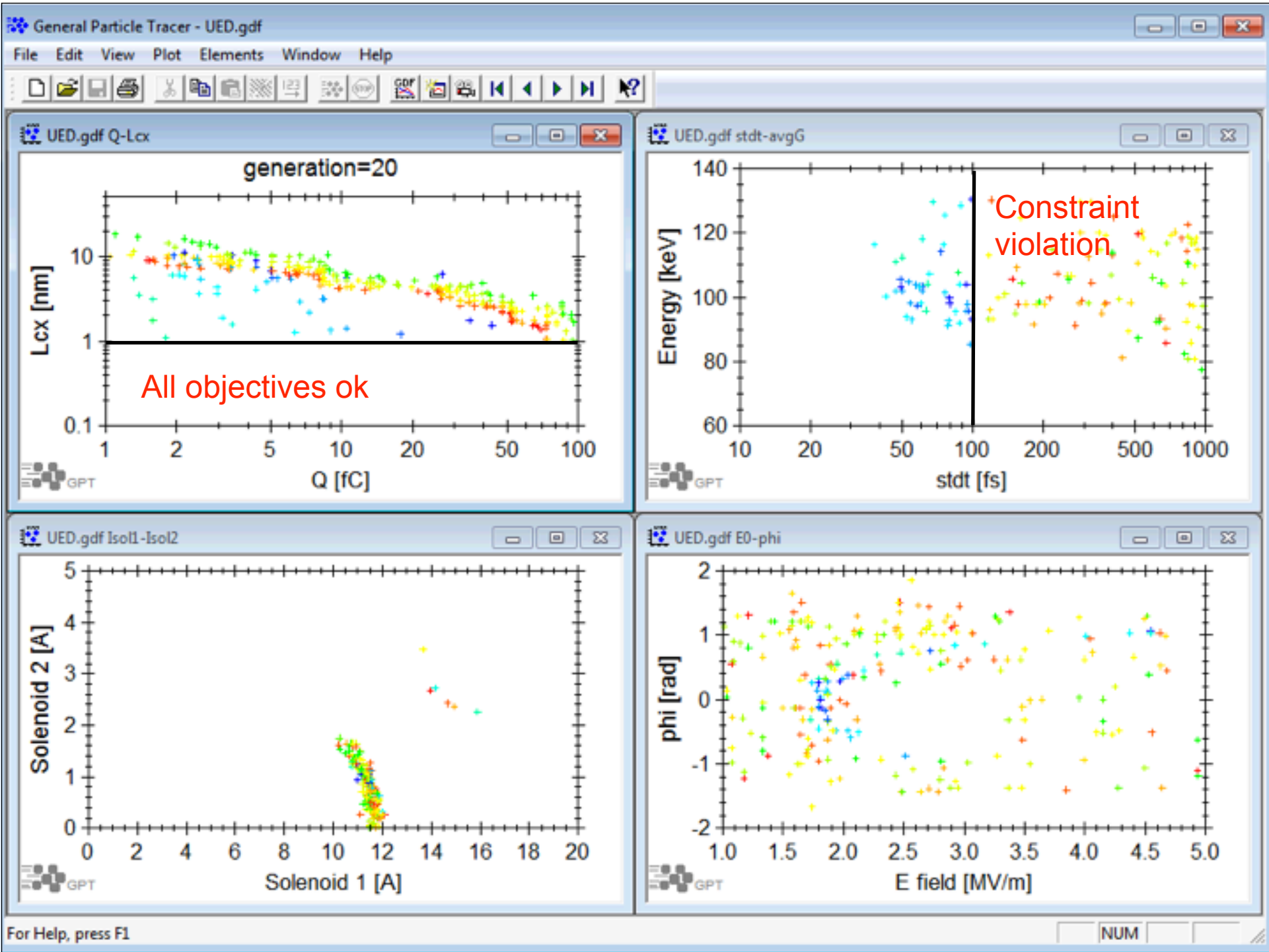
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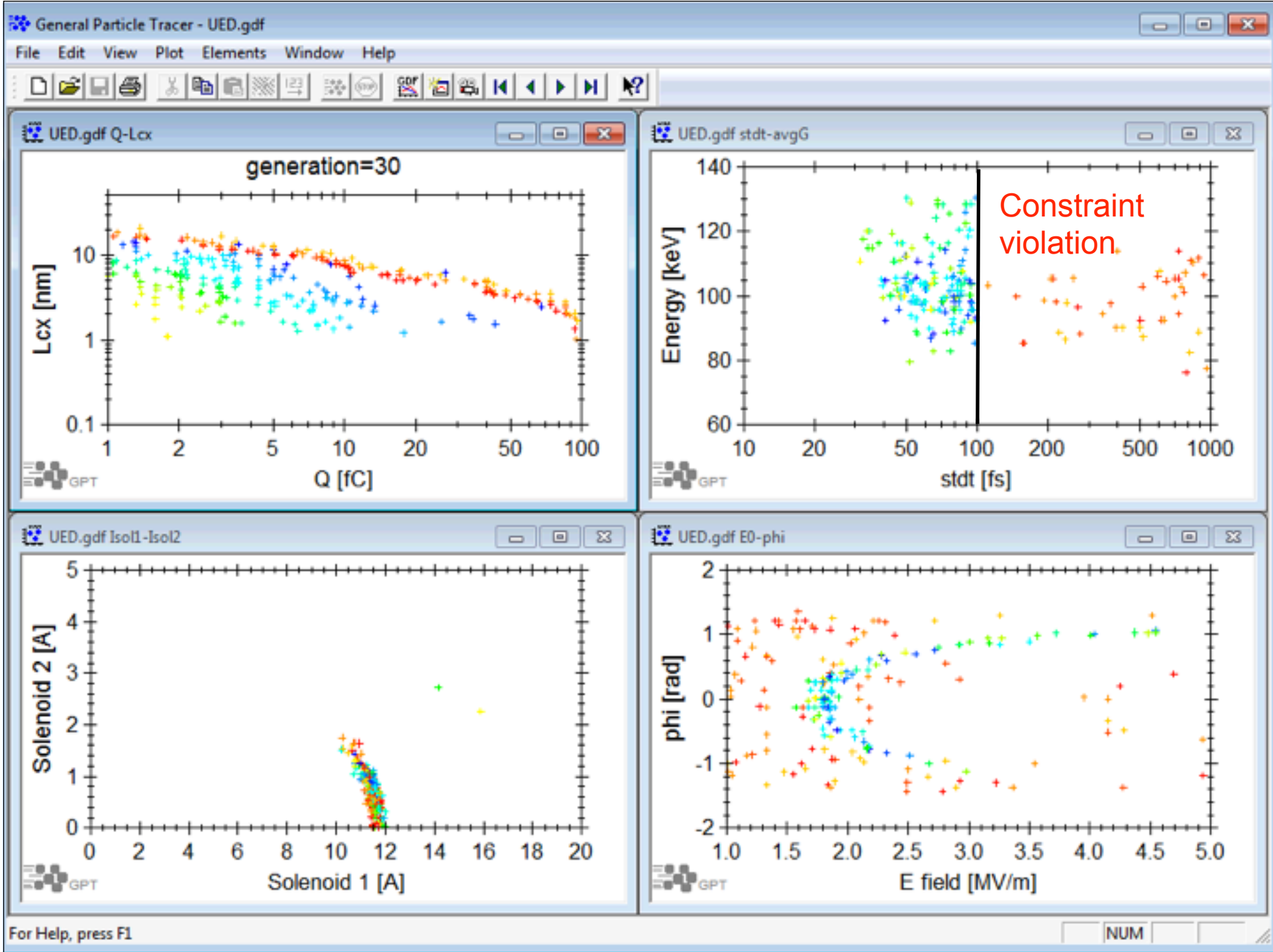
- Variables: rf-amplitude, phase, solenoid1, solenoid2
- Conflicting objectives:  $Q$ ,  $L_c > 1$  nm
- Constraints: pulse length  $\leq 100$  fs, spot size  $\leq 250$   $\mu\text{m}$



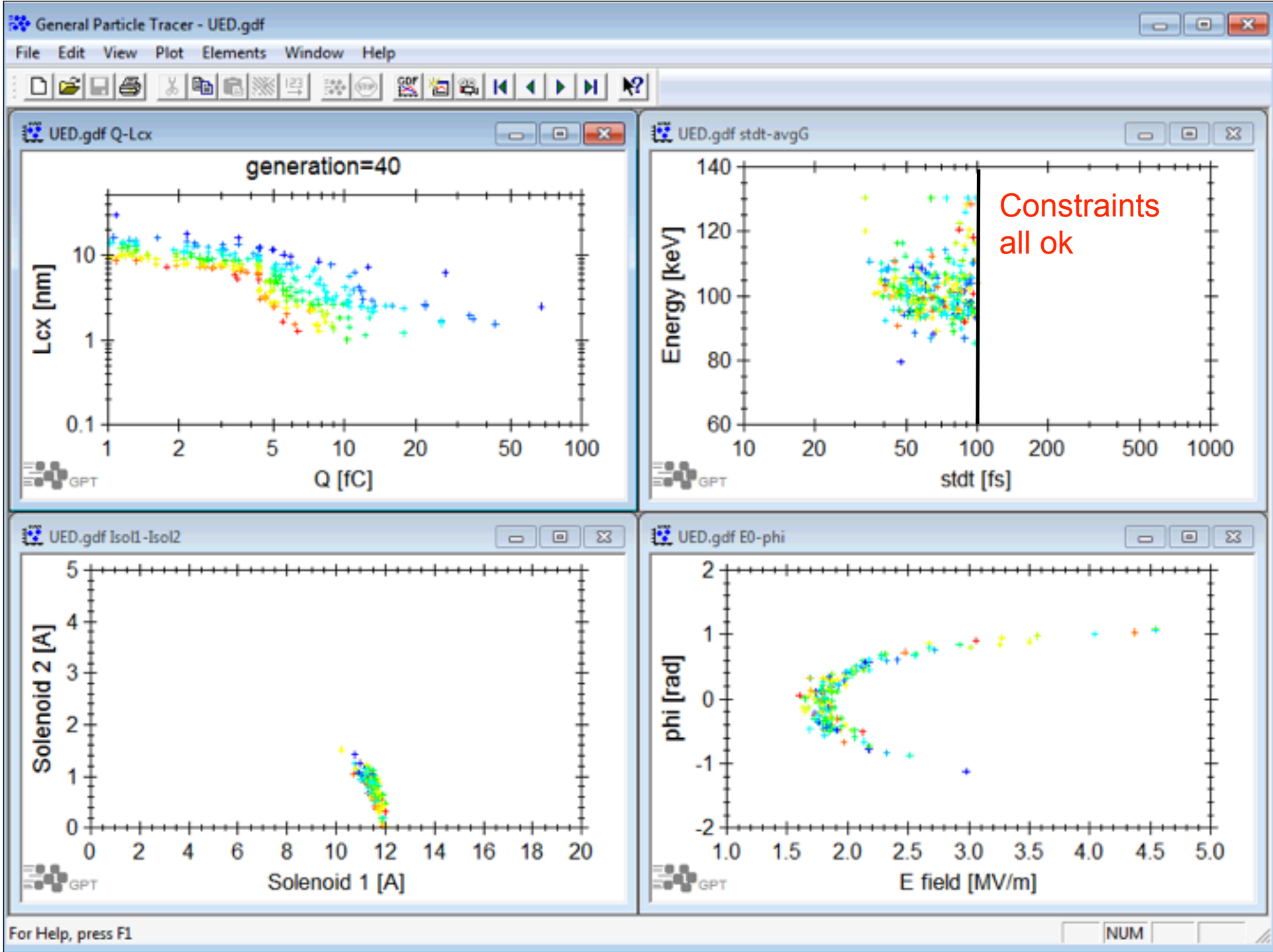


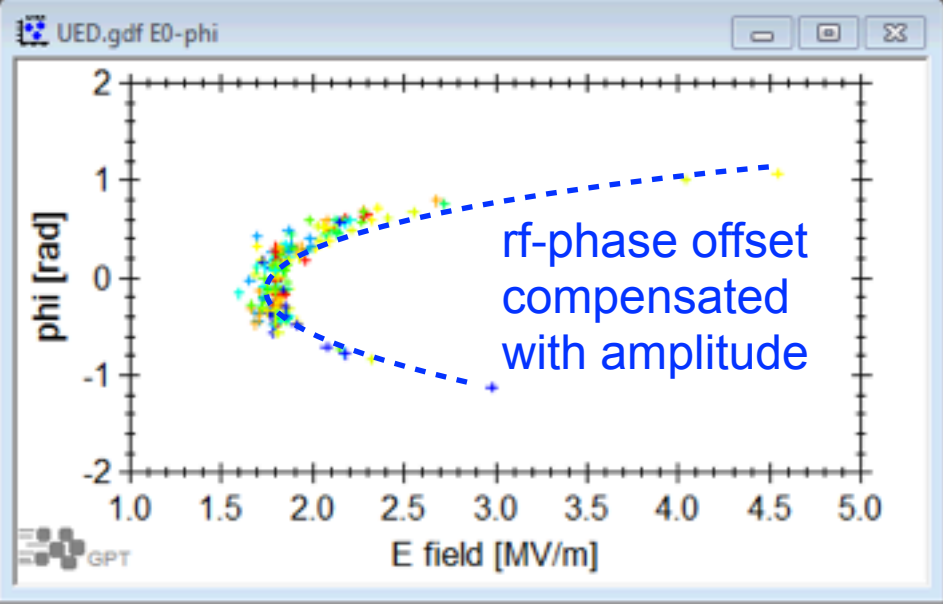
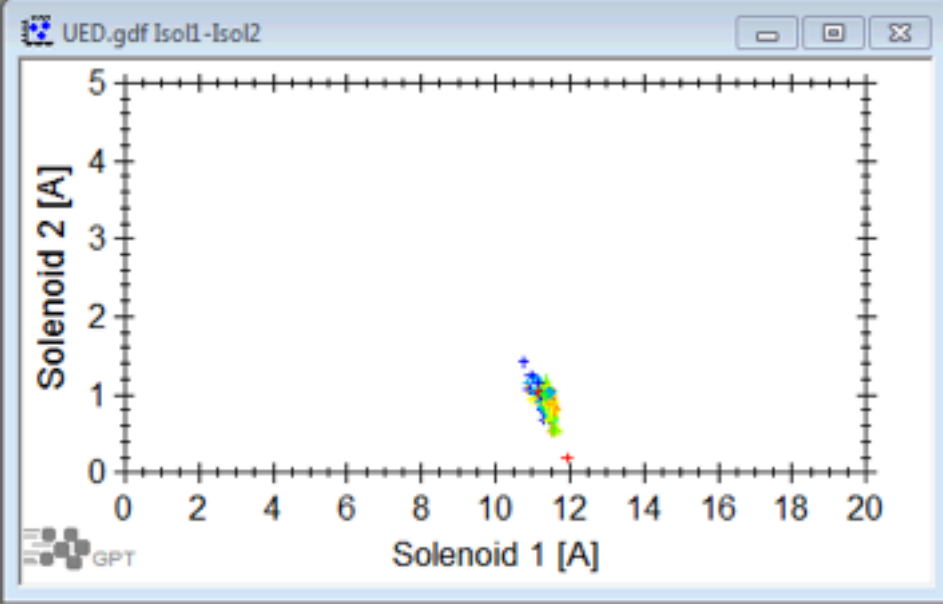
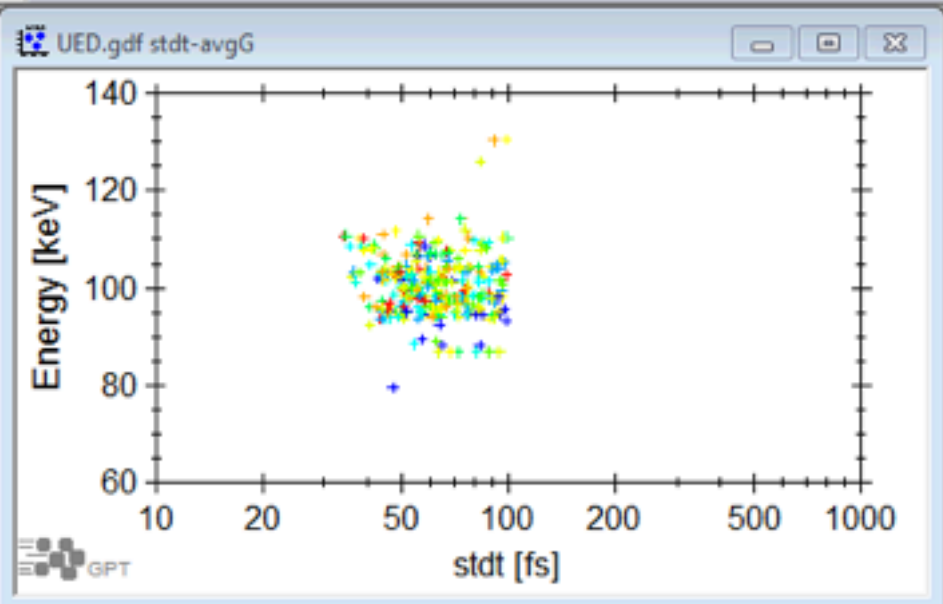
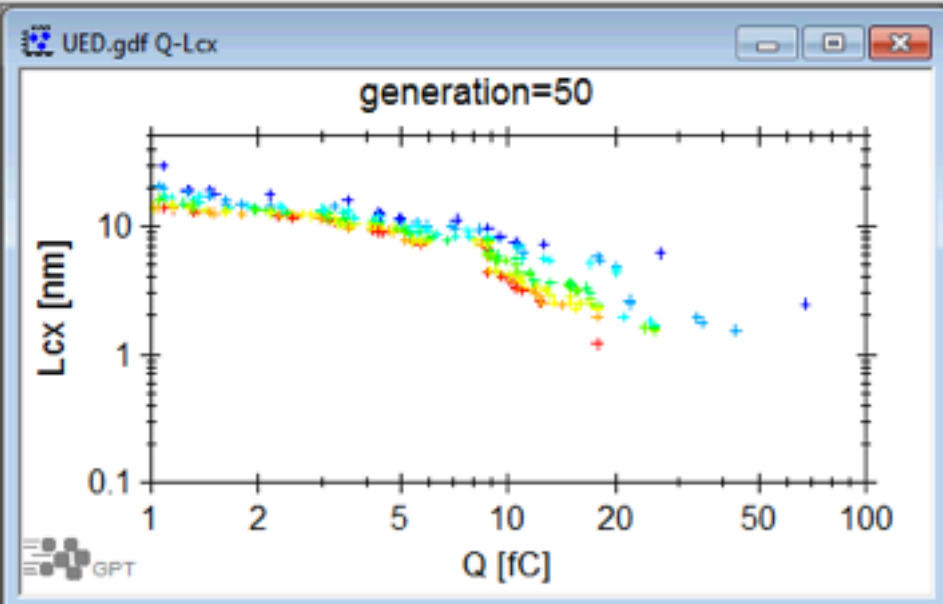


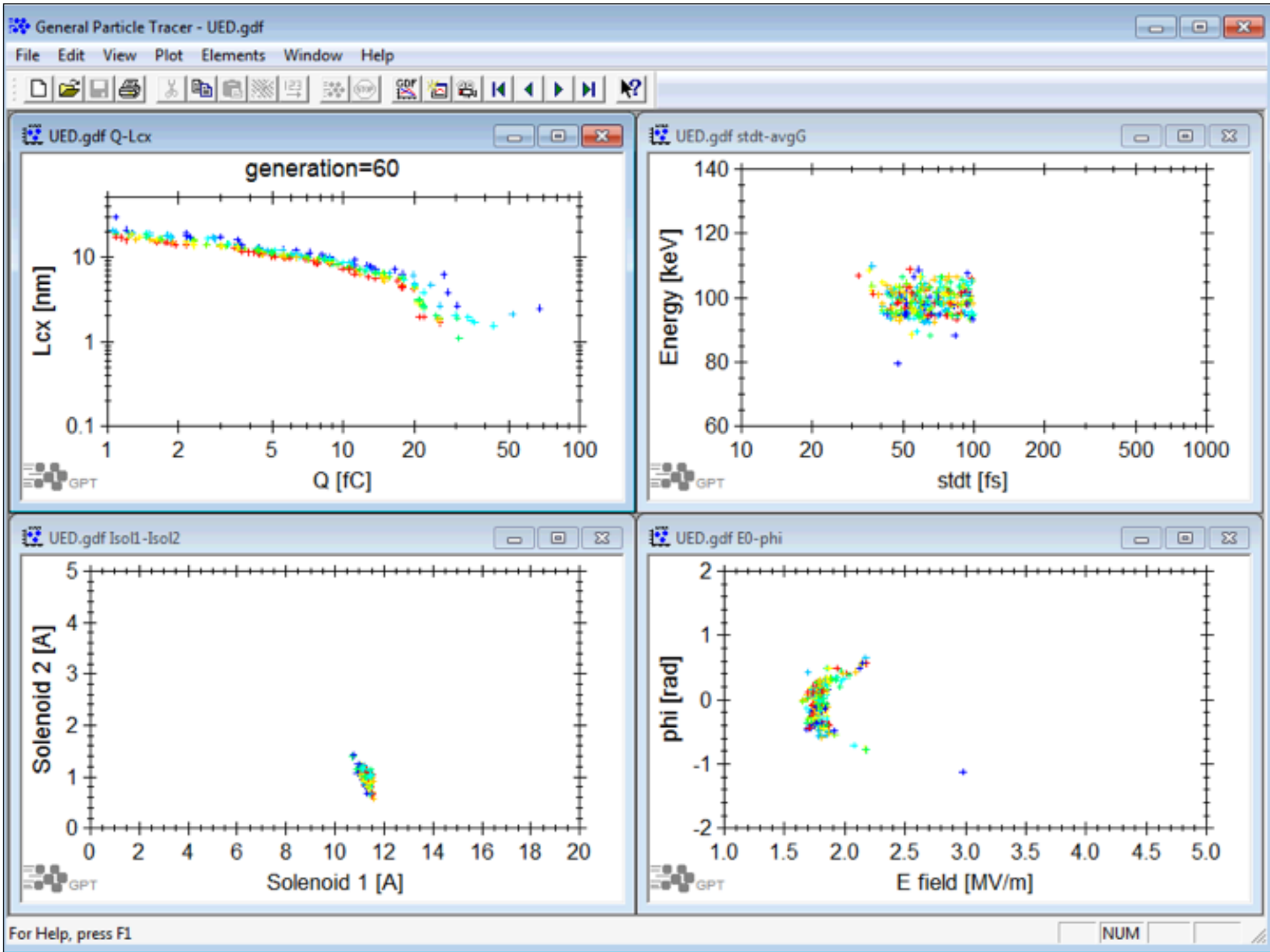


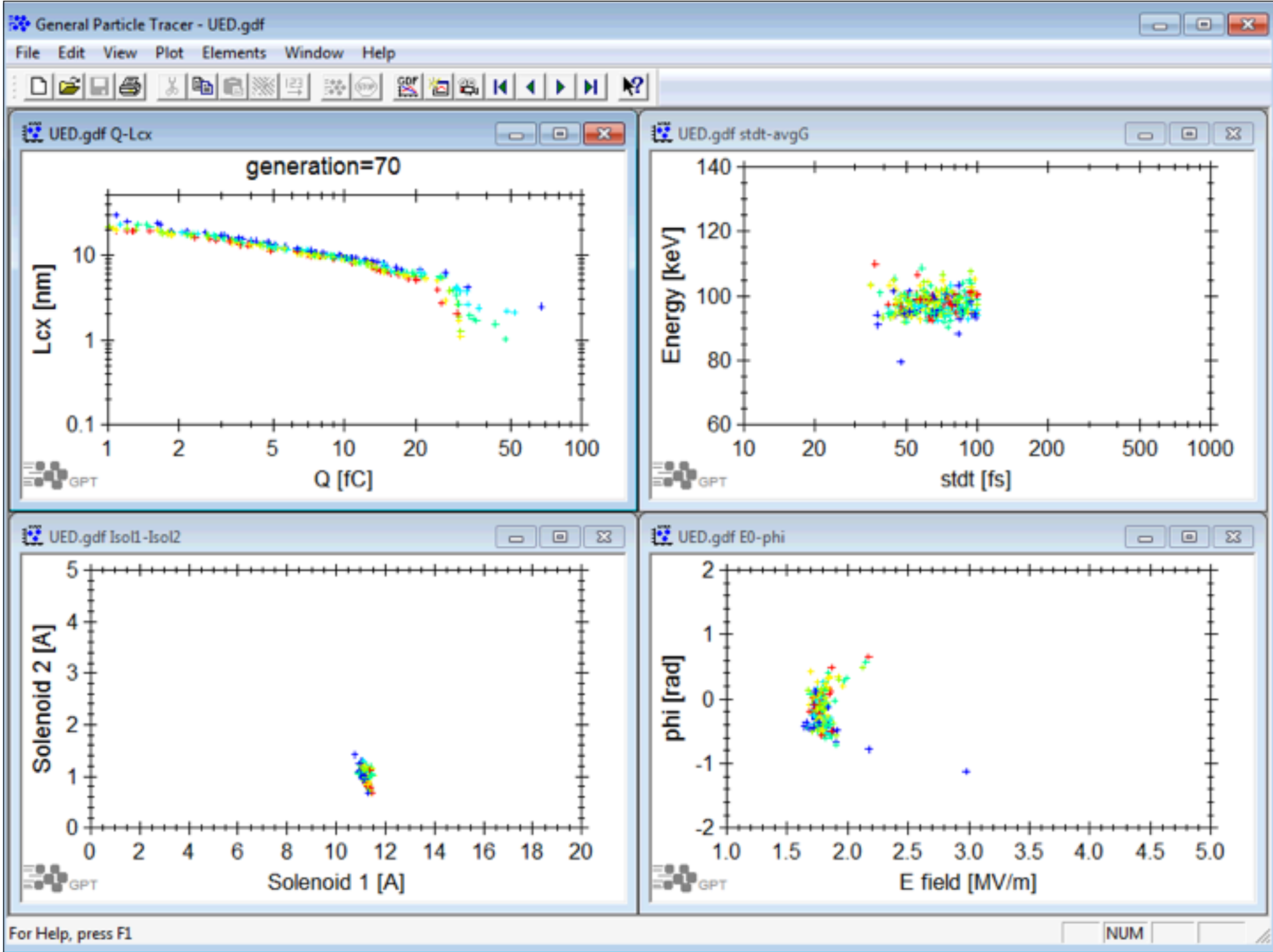






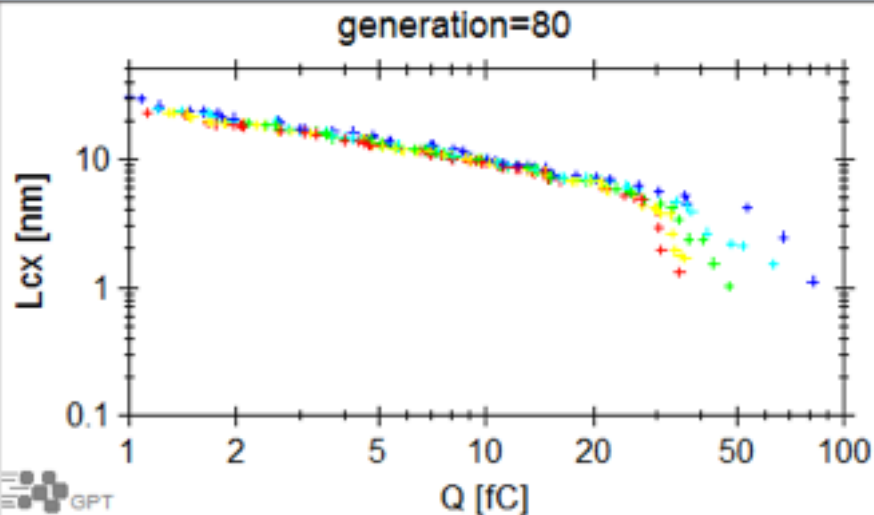




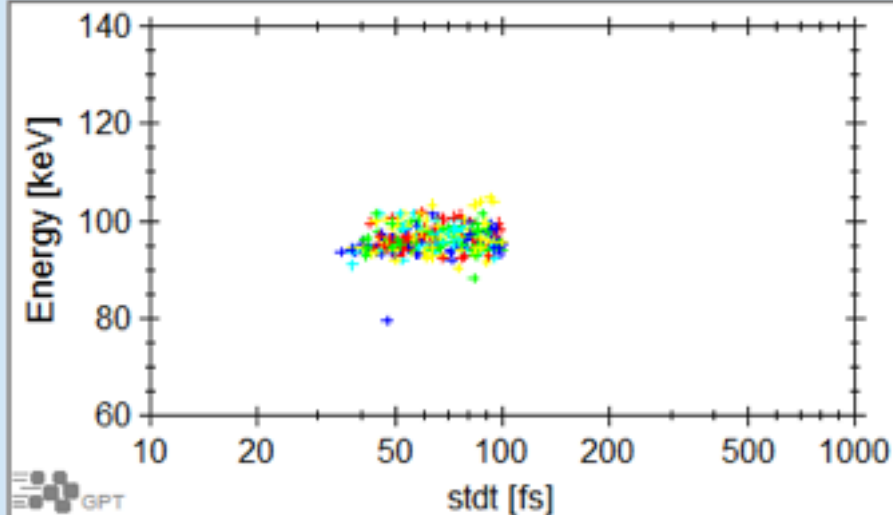




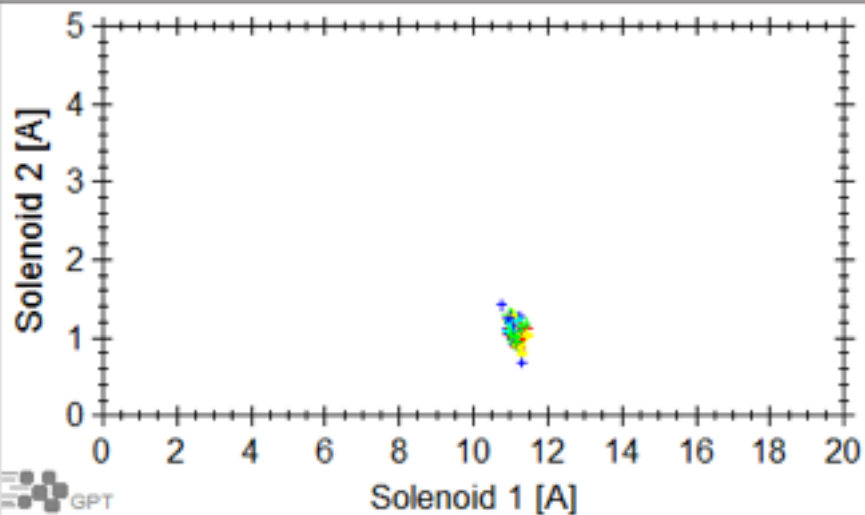
UED.gdf Q-Lcx



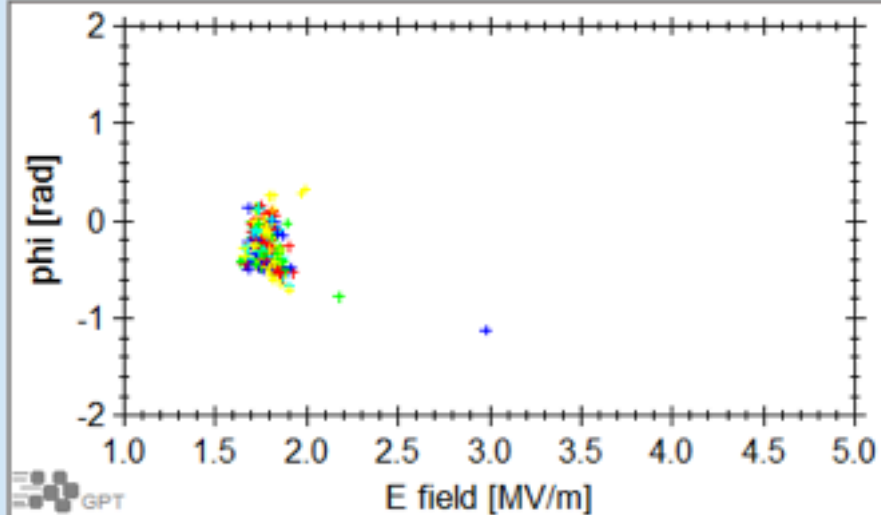
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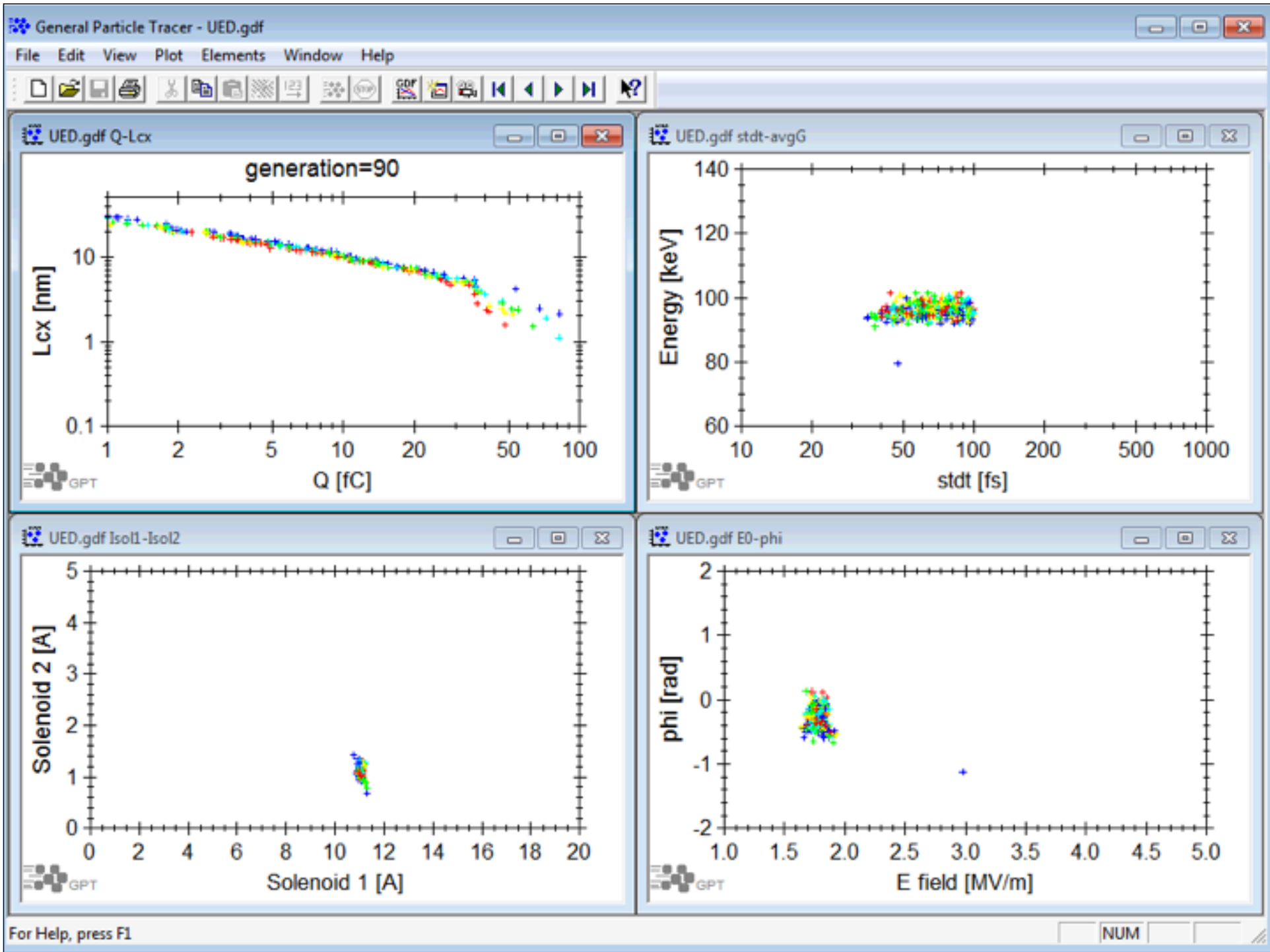


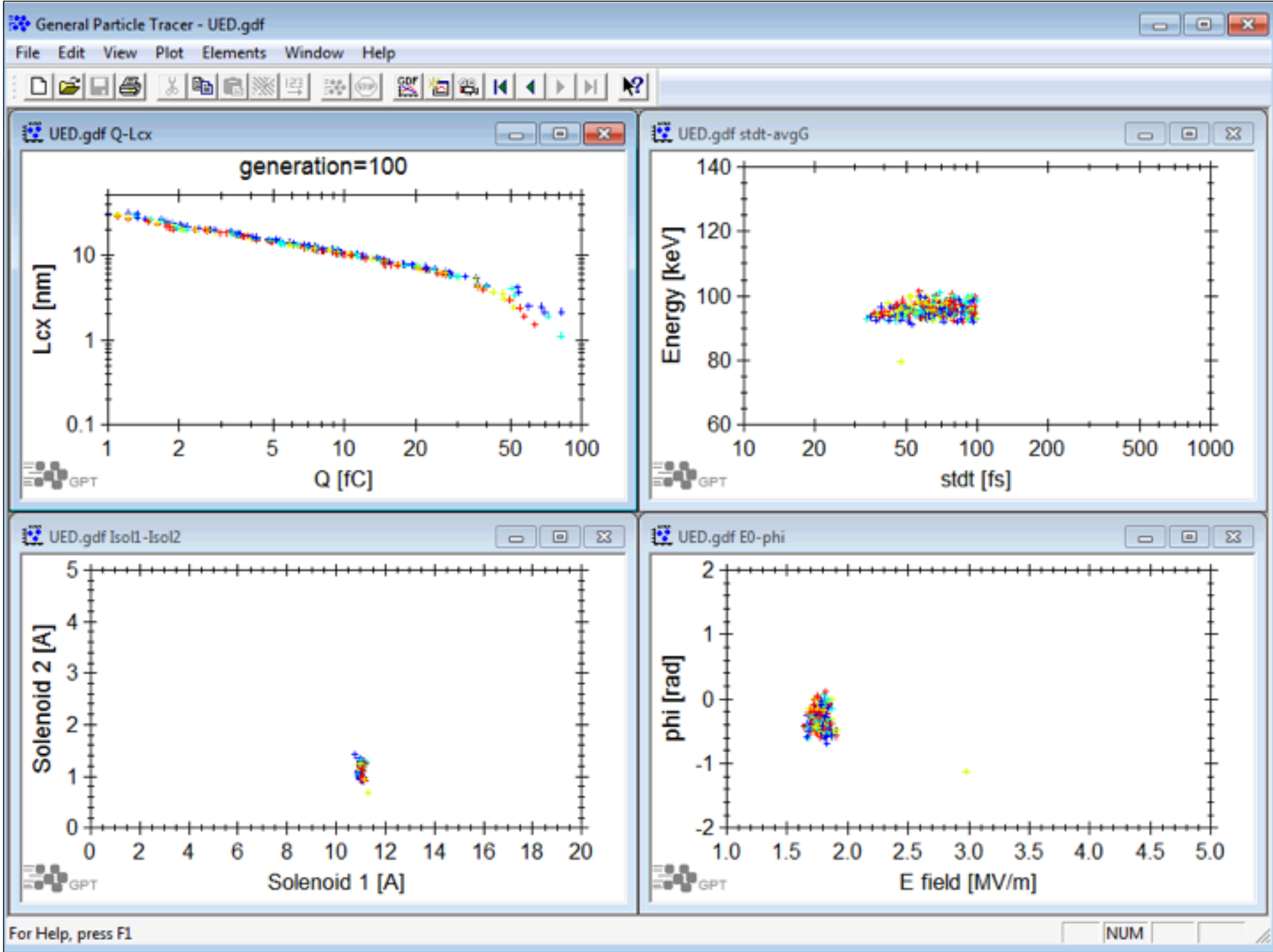
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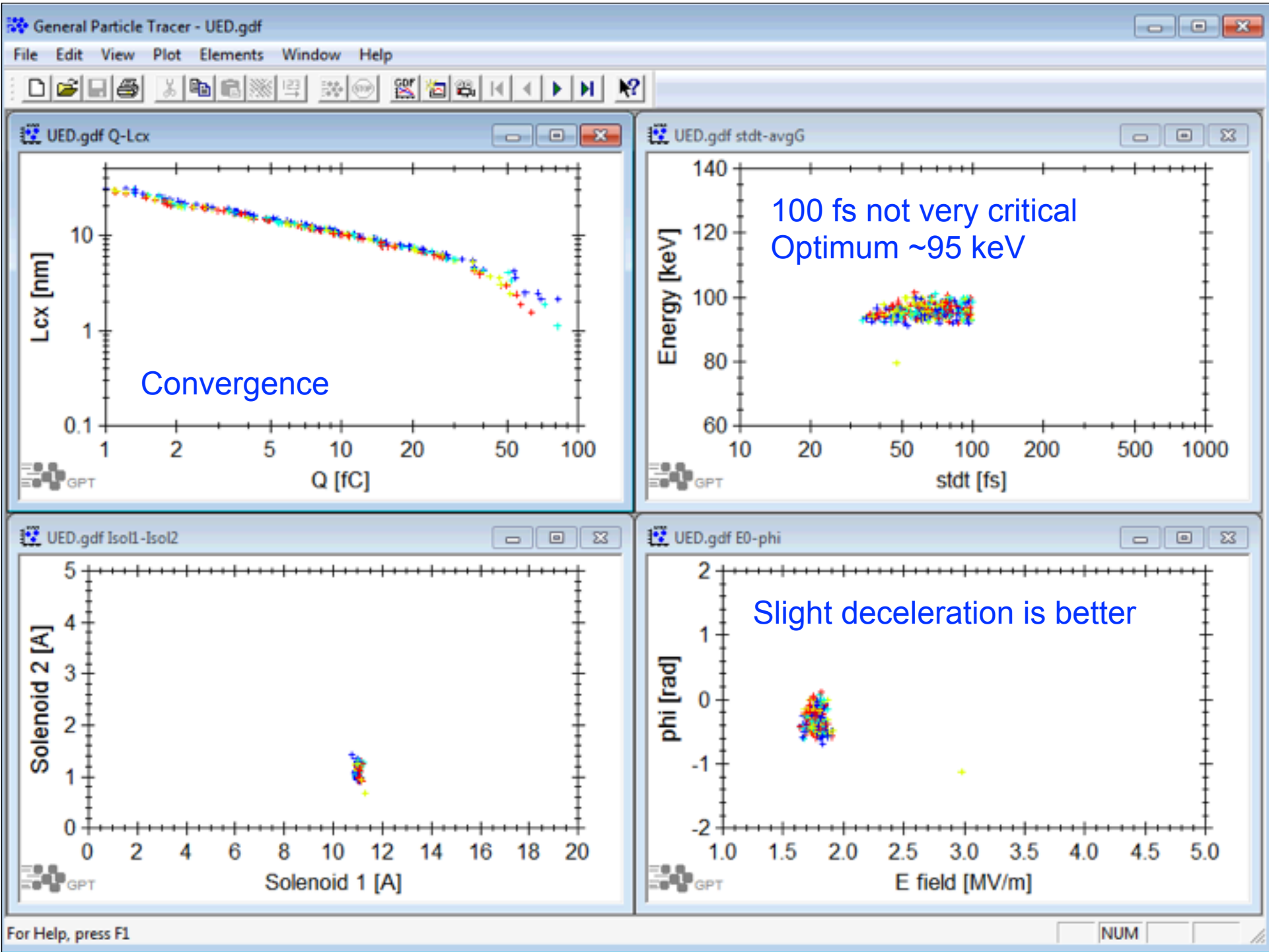


UED.gdf E0-phi





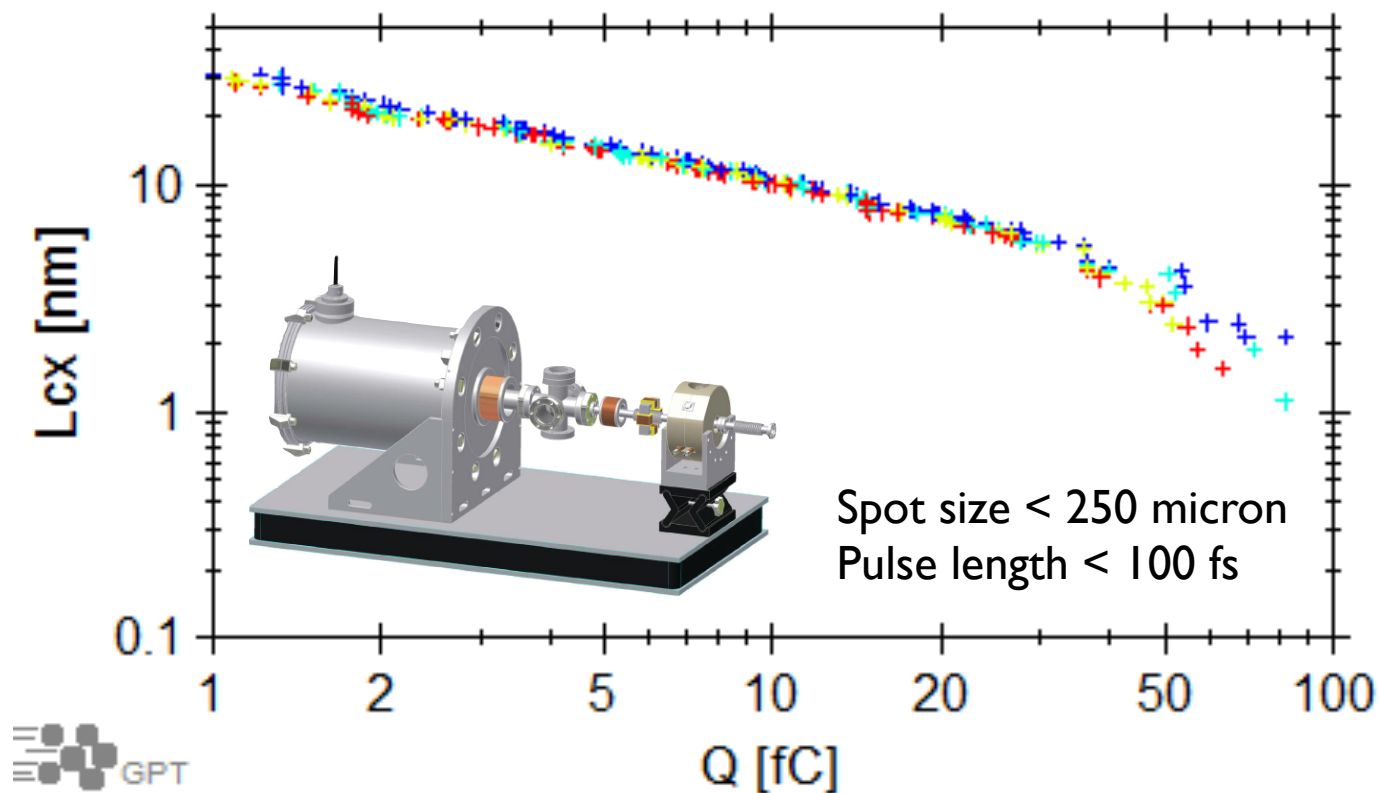






# Example: Ultrafast electron diffraction

- Variables: rf-amplitude, phase, solenoid1, solenoid2
- Conflicting objectives: Q, Lc



# Conclusion

**Every design process has multiple objectives**

**Multi-objective genetic optimization (MGO):**

- **Fully automates the design process**
- **Gives trade-offs, not 'best' solutions**
- **Relatively insensitive to local minima**
- **Can handle additional constraints**
- **Requires robust simulation tools  
(such as GPT)**

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**AND**

**MGO is a perfect match with a multi-core supercomputer**

# Multi-objective genetic optimization



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Photograph: André Karwath