Online Separator Optimization

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Typical Separator Tuning Approach: Model-based with manual tweaks

Process:

- Create a detailed computer model of the fragment separator
- Optimize model to find ideal setting (challenging, esp. in higher orders)
- Adjust beamline to match this setting (frustrated by inconsistencies)
- Manually tweak elements until the system operates as desired
- Or, iterate the model, or model-based perturbative tuning

Downsides of this approach:

- Requires months of intensive work
  - Model development, improvement, application: man hours, facility time, and computing resources
  - Tune development in system: man hours and beam time
- Results in sub-optimal tune (model discrepancies)

Online optics optimization goals

- Develop an automated, on-line optimization approach
  - Largely model independent → little effort to make ion optical models
  - Less time spent tuning → more time available for physics
  - Improve optical tunes → more physics per unit time
  - Make it feasible to develop more specialized tunes → different physics possible or more physics per unit time
- Has been done elsewhere before, but not with high-resolution separators.
- Develop to prepare tunes for recent & new large-acceptance, high-resolution systems
- Drawbacks:
  - Optimization must run on the system itself (no cluster/parallel)
  - Limited number of trial solutions possible (reliability is key)

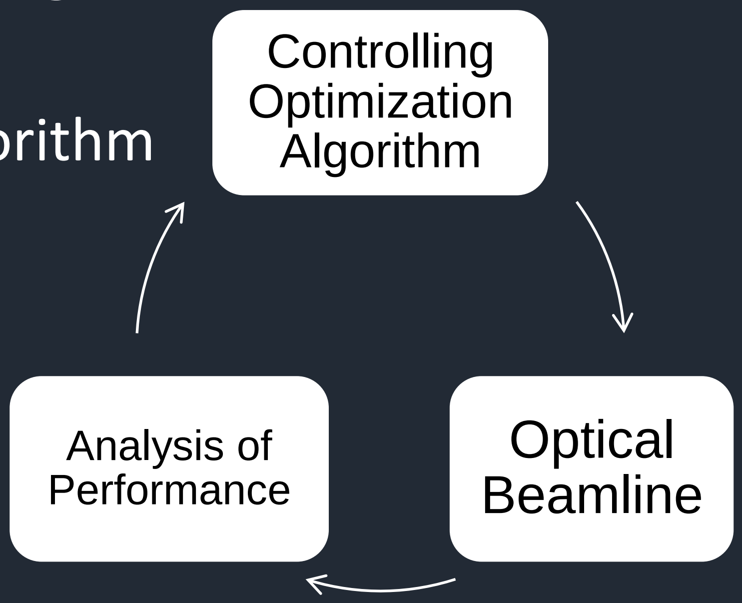
On-line Optimization Approach

Continuous feedback loop consisting of:

i. Controlling Optimization Algorithm

ii. Optical Beamline

iii. Analysis of Performance

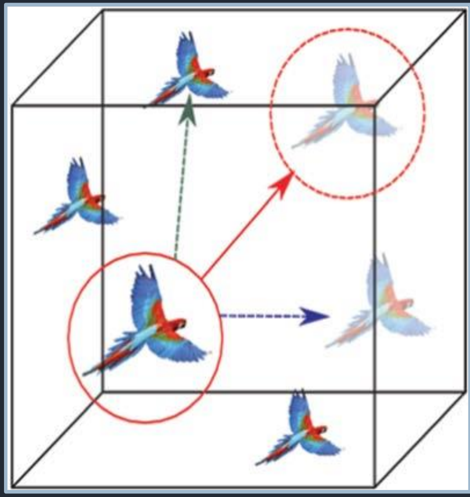


Particle Swarm Optimizer

- The optimizer used for higher order tunes of S^3 and ARIS
- Based on swarm intelligence of animals and insects
- Initialize swarm of “particles” in parameter space with random position and velocity distribution

  particle position vector = optical tune
  $\langle Q_1, Q_2, \ldots, Q_N, S_1, \ldots, S_N, O_1, \ldots, O_N \rangle$

- Particles ‘remember’ and accelerate toward the location of:
  - The particle’s own personal best
  - The swarm’s global best



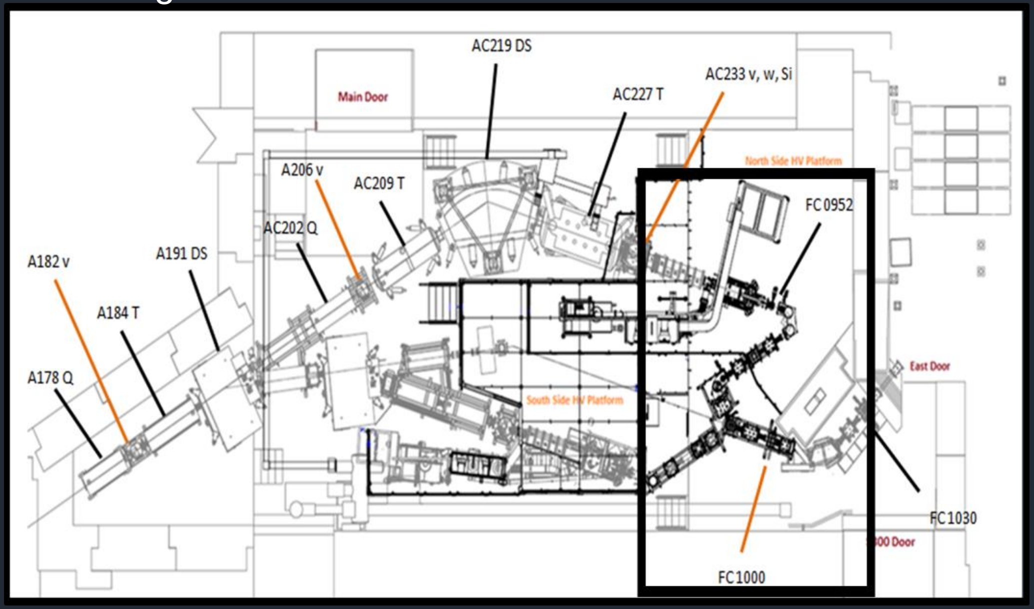
Kennedy, J.; Eberhart, R. (1995). "Particle Swarm Optimization". Proceedings of IEEE International Conference on Neural Networks IV. pp. 1942–1948.

Our Initial Test:
NSCL D-line, July 2015

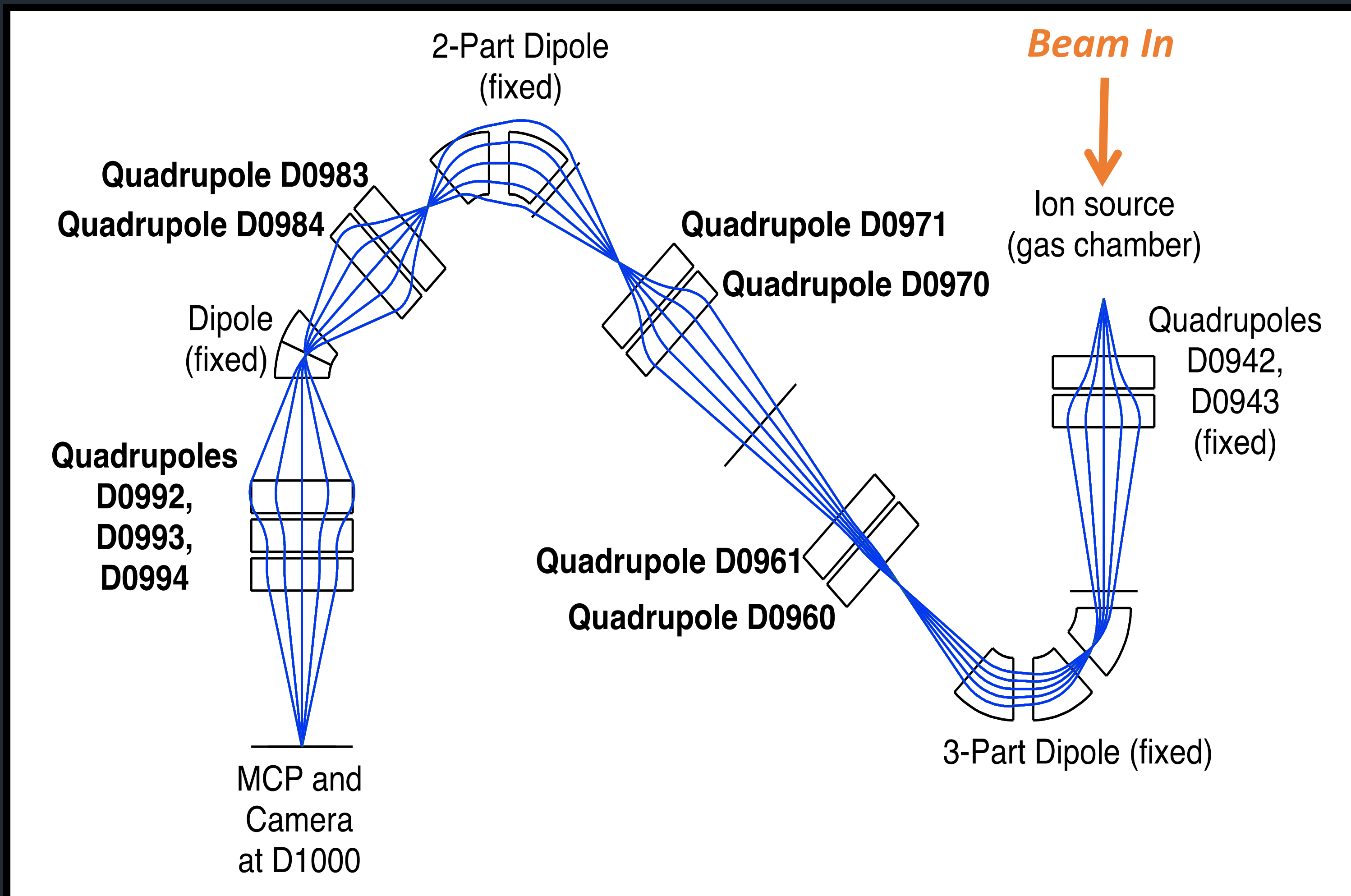
Ideal for a first test

- Relatively low cost of operation
- Relatively simple optical system
- Rapidly tunable electrostatic elements (full range <1 second)

Incoming beam line from transfer hall with the D-Line boxed



D-Line Optical System



Beam envelope

COSY Infinity Version 9.1: K. Makino, M. Berz, Nuclear Instruments and Methods A558 (2005) 346-350.

Portillo, M. Report on recalculation of Low-E beam lines, NSCL (2015).

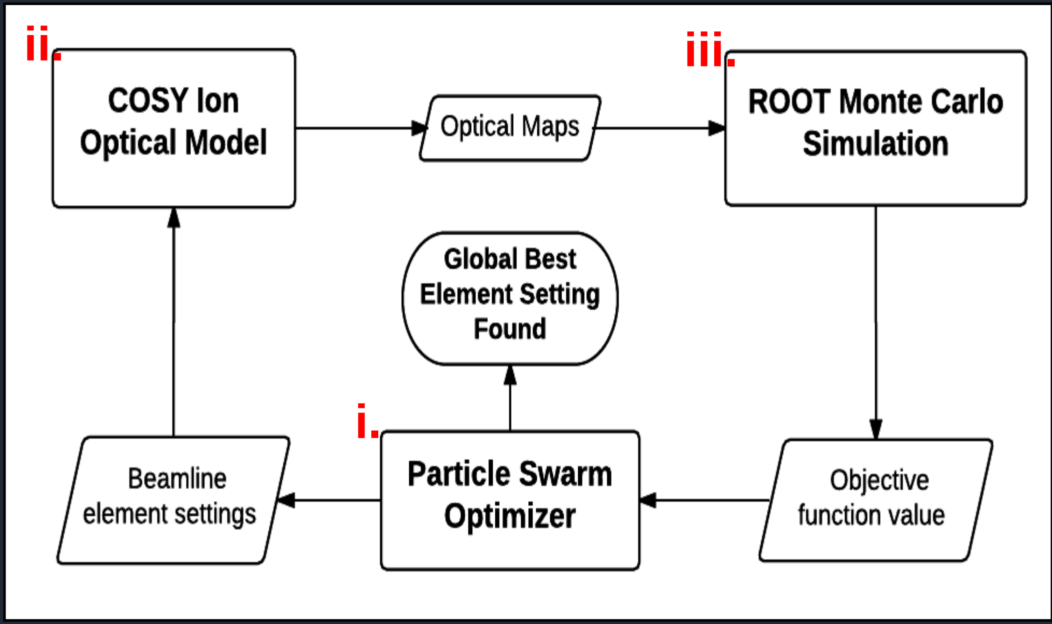
Computer Simulations
Test of the Experimental Approach

Continuous feedback loop consisting of:

i. Controlling optimization algorithm

ii. COSY model of beamline

iii. Monte Carlo simulation



Test Experiment on NSCL D-Line (Summer 2015)

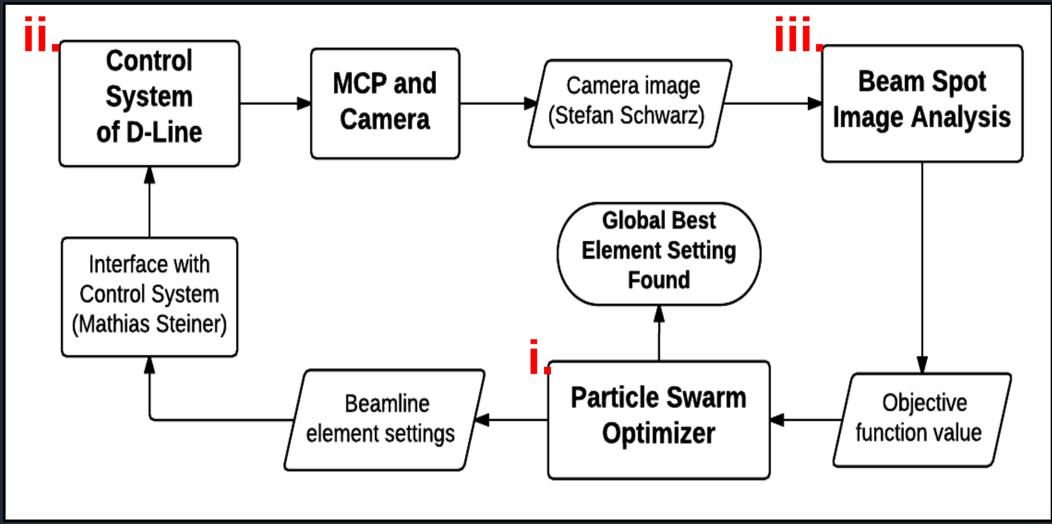
Goal: Test on-line optimization approach; reduce spot size (waist) while preserving transmission

Continuous feedback loop consisting of:

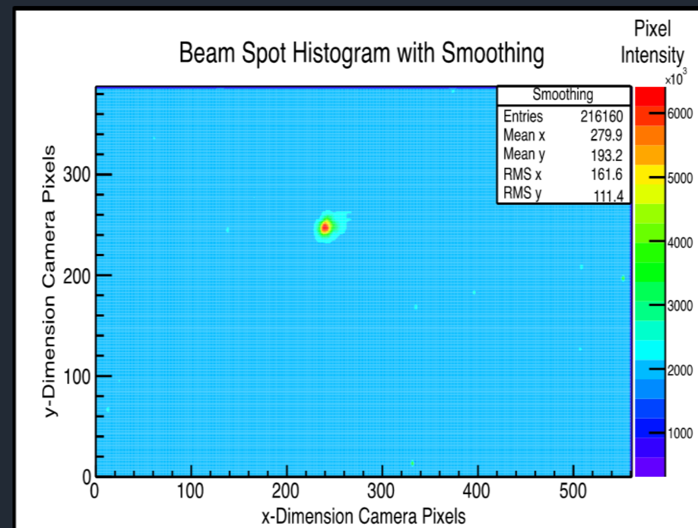
i. Controlling optimization algorithm

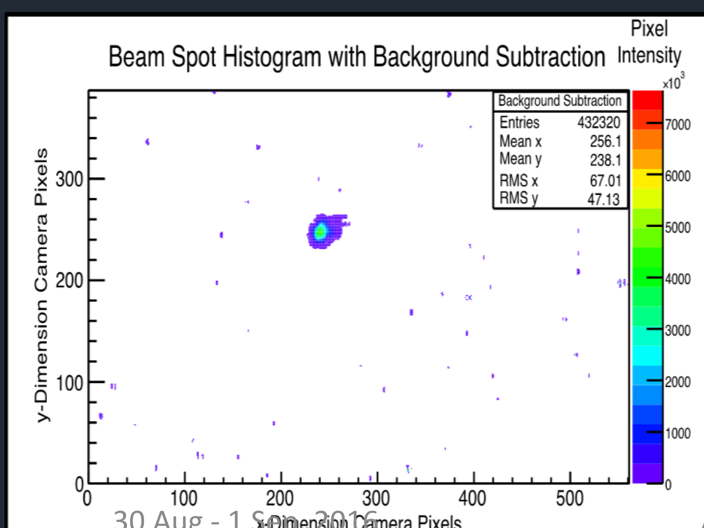
ii. Electrostatic D-Line

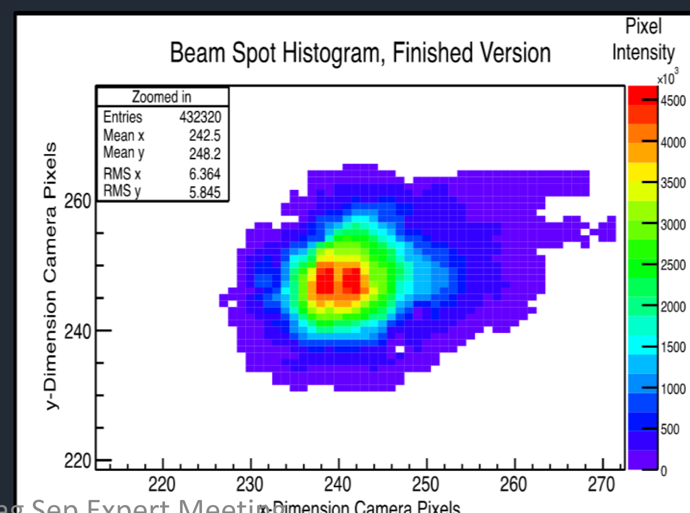
iii. Image analysis of beam spot after MCP/Camera



Automated Beam Spot Analysis MCP → Phosphor Plate → Camera







Measure

- σ_x and σ_y
- integral

Objective Function Definition

$$Obj = 20\sigma_x + 20\sigma_y + |\sigma_x - \sigma_y|$$

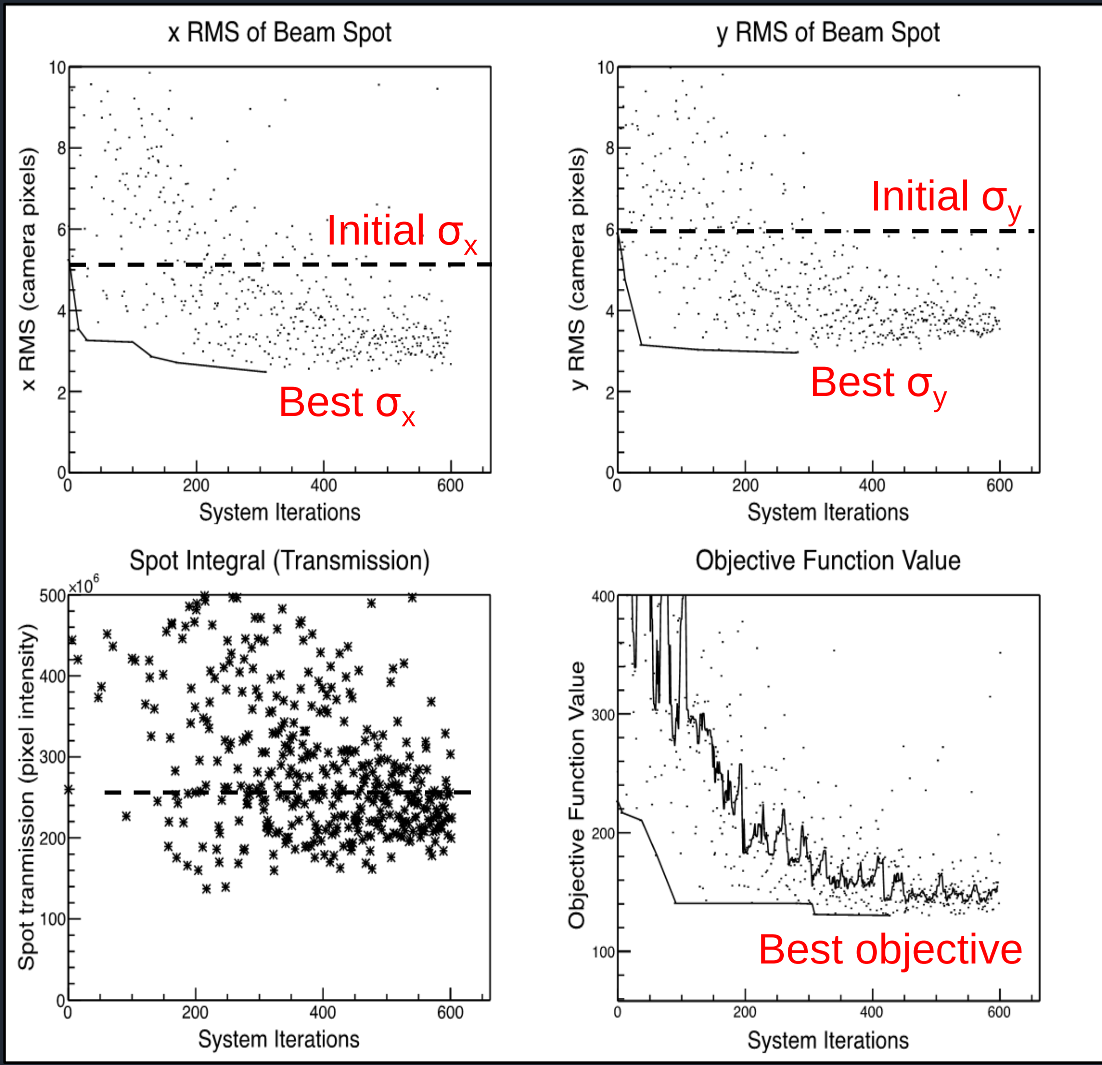
Objective function definition **(quality measure)** used in experimental runs (smaller is better)

- If transmission drops significantly (transmission threshold), objective function value is penalized (increased)

$$Obj_{new} = Obj_{old}\left(\frac{T_{Threshold}}{T_{Actual}}\right)$$

Results of Experiment (Run 12)

- Significant decreases in σ_x and σ_y over two hour period
  - Initial σ_x = 5.2 pixels
  - Best Tune σ_x = 2.8 p
  - Initial σ_y = 5.9 p
  - Best Tune σ_y= 3.4 p
- Transmission preserved, up to 90% of initial intensity (integrated pixel intensity)



$$Obj = 20\sigma_x + 20\sigma_y + |\sigma_x - \sigma_y|$$

Experimental Runs of Optimizer

- Several experimental optimization runs (~2 hours each)
- Tuning nine quadrupoles with transmission requirement

Table: Production run details.

Run	Run Time (min)	Total Trial Tunes	Plot Colors	Swarm Solutions	Field Start Width (+/-)	Velocity Start Width (+/-)	Accel. and Inertia †	Trans. Thresh.	Random Gen. Seed	σ_x spot change %-diff	σ_y spot change %-diff
9	112	526	Red	15	25V Gaus	25V Unif	1.4, 0.8	0.60	1	-43%	34%
10	78	385	LtGreen	15	40V Gaus	40V Unif	1.6, 0.6	0.75	1	-36%	29%
11	103	494	Blue	15	40V Gaus	40V Unif	1.5, 0.7	0.90	1	-23%	29%
12	123	602	Pink	30	80V Gaus	80V Unif	1.5, 0.7	0.90	1	-47%	42%
13	115	421	Cyan	30	80V Gaus	80V Unif	1.5, 0.7	0.90	20000	-23%	38%
14	165	561	Green	30	300V Unif	100V Unif	1.5, 0.7	0.90	1	-26%	30%

†Trelea, I.C. (2003). "The Particle Swarm Optimization Algorithm: convergence analysis and parameter selection". Information Processing Letters 85 (6): 317–325.

Experimental Runs of Optimizer

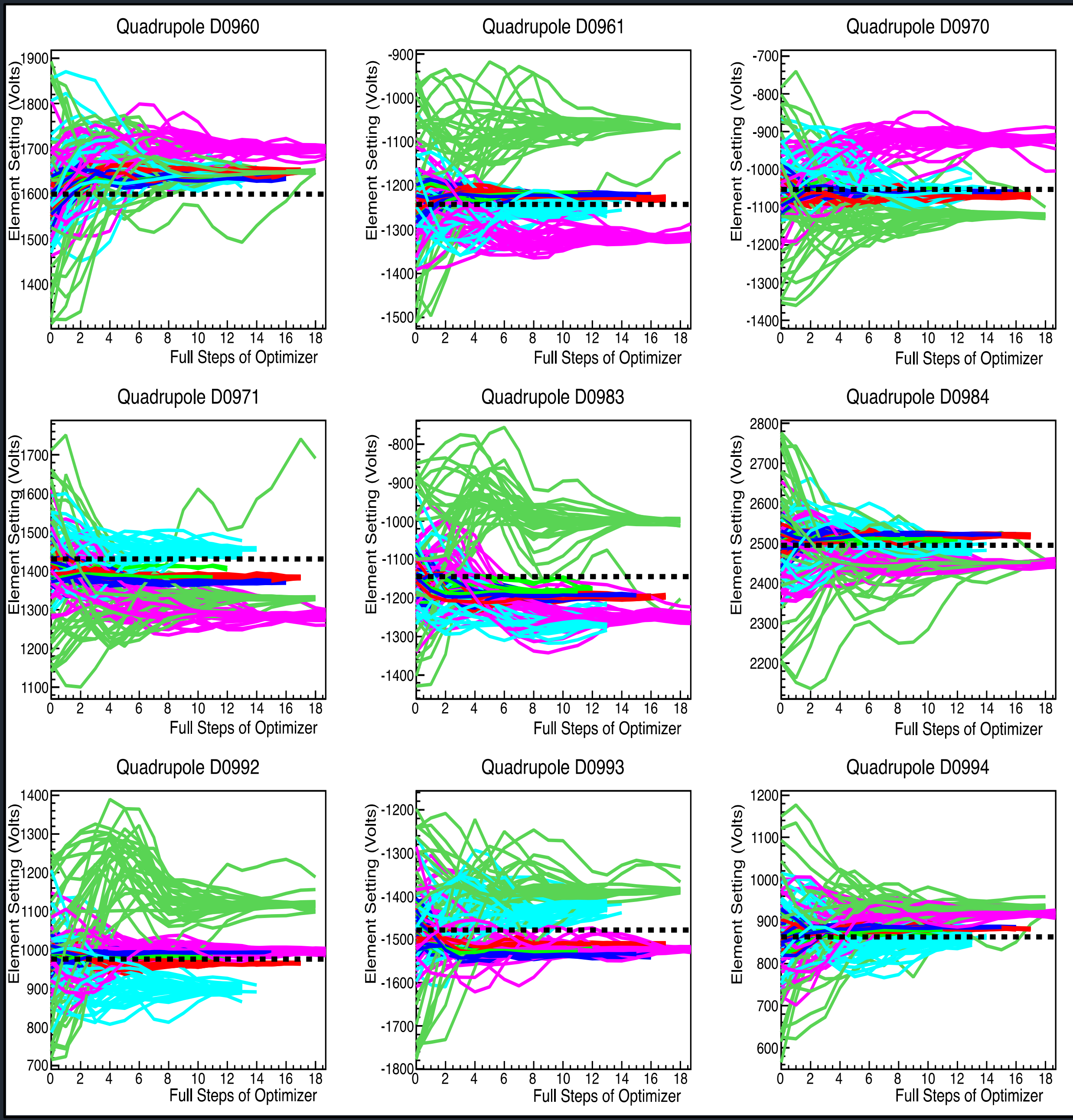
Run 12

Run 13

Identical optimizer parameters, different random seed (for random number generation) for run 13

Visualizing the swarm:

Element setting plots of nine quadrupoles over different runs (dashed = initial setting)



Key:

Run 9:
small region, slow convergence

Run 10:
faster convergence

Run 11:
mid-convergence rate

Run 12:
larger start region,
more swarm particles

Run 13:
same as run 12 with different random numbers

Run 14:
large start region (quasi-global)

D-Line Experiment: Summary

- Over several runs the experimental optimizer succeeded:
  - Significantly decreased beam spot size,
    - Roughly x2 in both dimensions, thus x4 in spot area.
    - Preserved transmission
  - Found new, unique tunes away from the initial tune
  - Successful in local (small) and quasi-global (large initialization ranges)

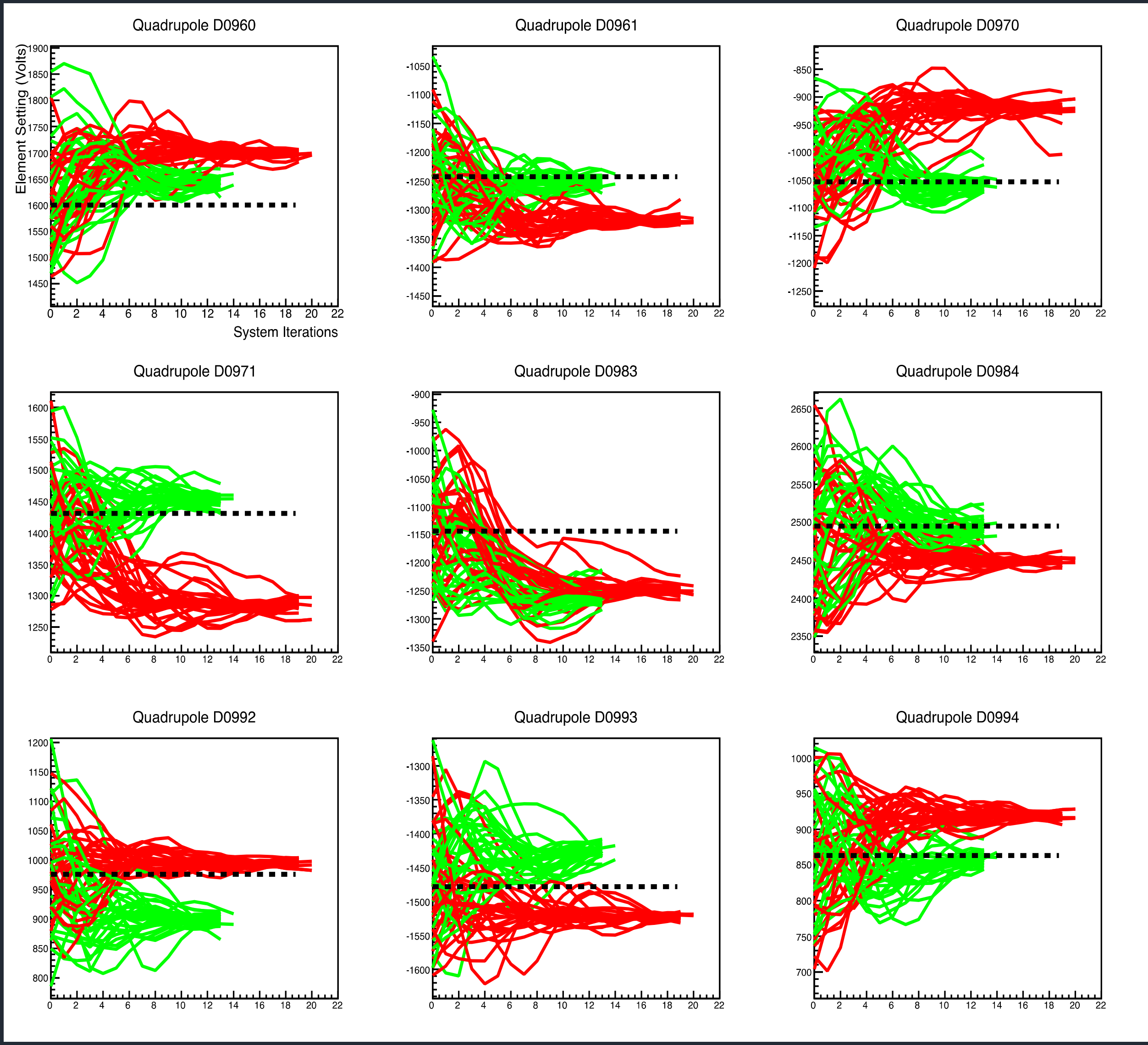
Large separators will be more challenging...

How do we “ensure” success?

A Stochastic Process

Tune evolution for Run 12 and Run 13.

Run 12
Run 13



Same optimization but different random initialization (and beam fluctuations)

Different results

Different performance

Hybrid Algorithm

Goal: Improve the performance of the optimizer

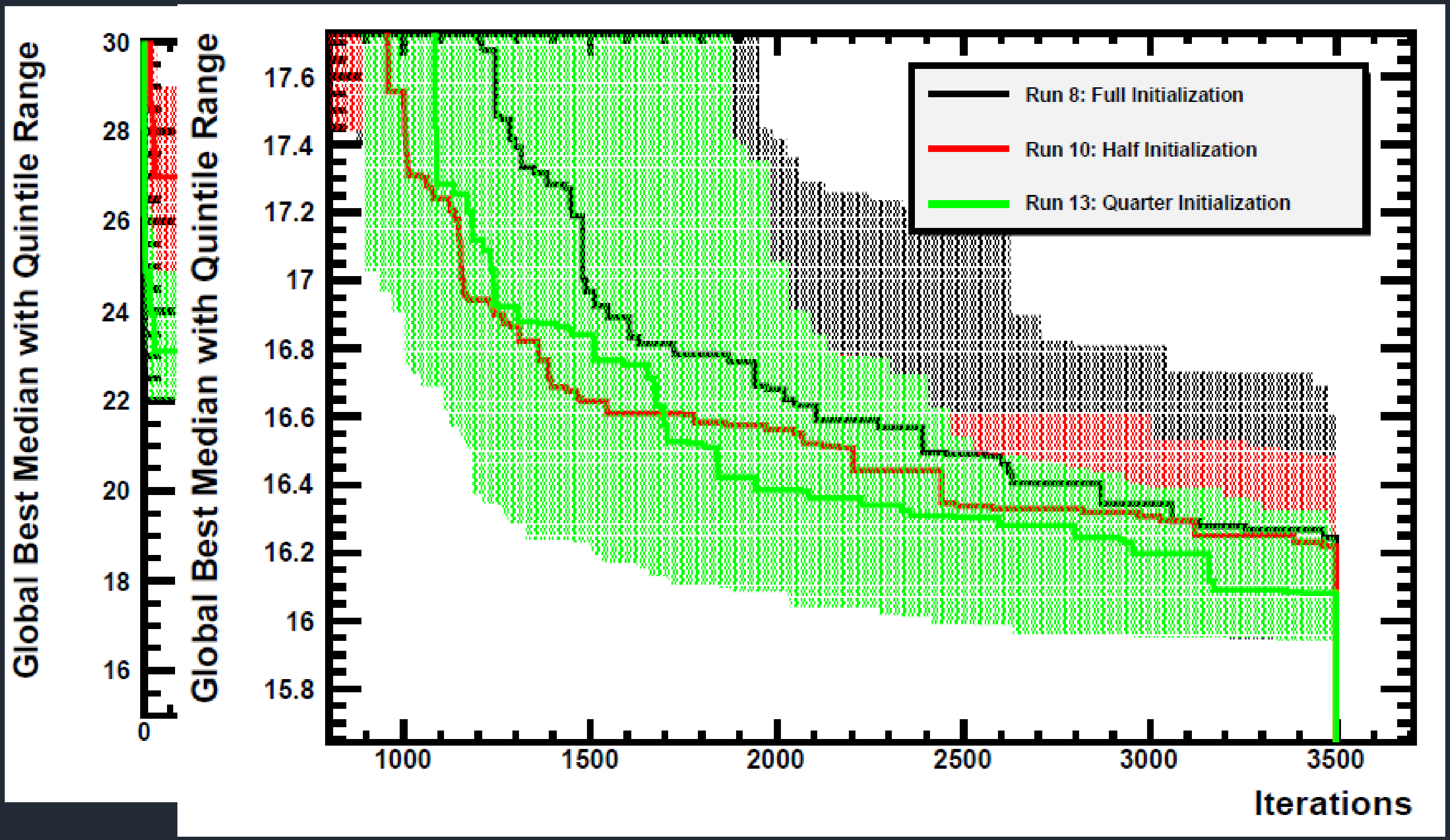
- Define Performance:
  - Production of good tunes
  - RELIABLE production of good tunes (unlikely to fail)
- Hybrid Particle Swarm & Differential Evolution
  - Both act by evolving a population of solutions

Differential Evolution

For some swarm solution $\vec{x}$, replace the components, x_i, (with probability C_r) with new values $a_i + F(b_i - c_i)$, where $\vec{a}$, $\vec{b}$, and $\vec{c}$ are other solutions (randomly selected) from the swarm.

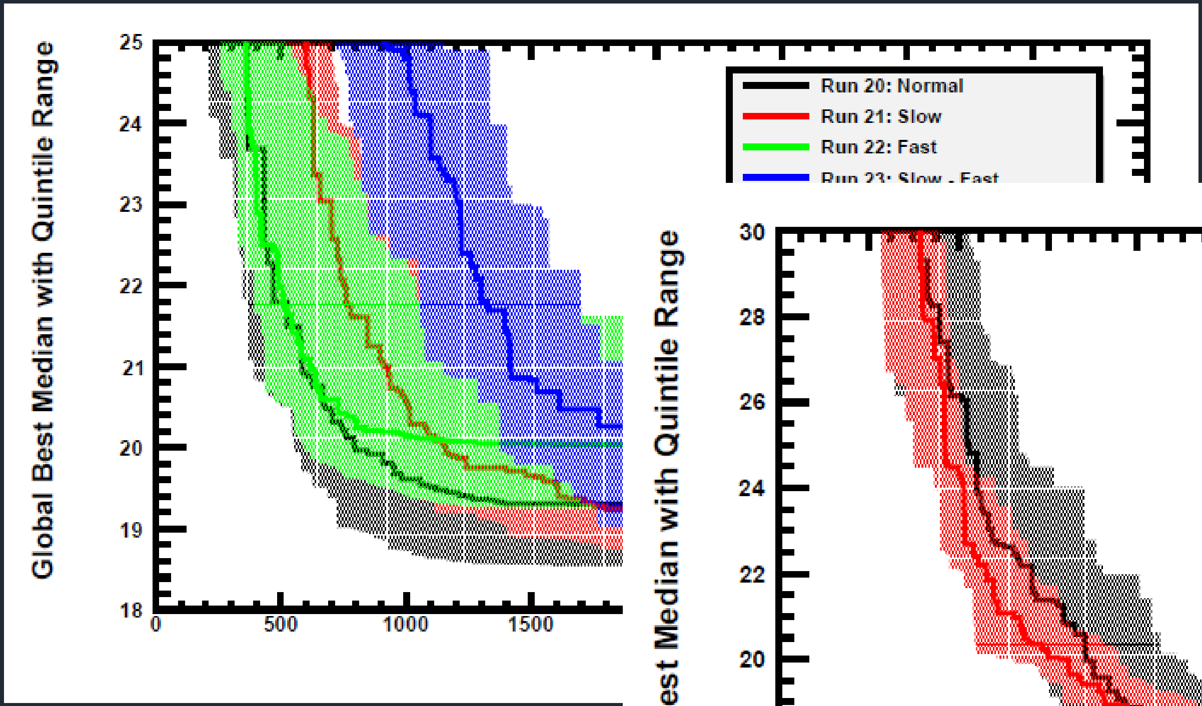
Develop based on A1900 3rd order optimizations (quad + sext)

Performance & Reliability Initialization Range

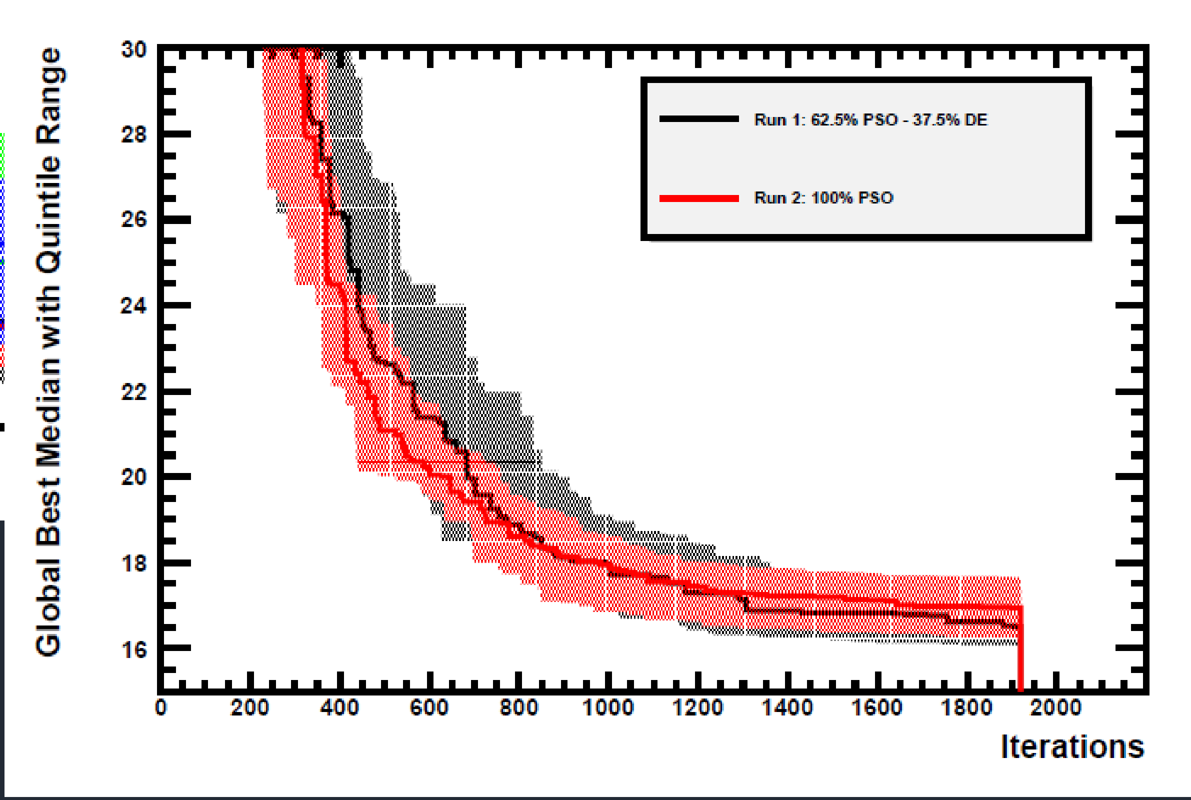


Best *not* to initialize multipoles over full available strength.

Performance & Reliability Optimizer Parameters

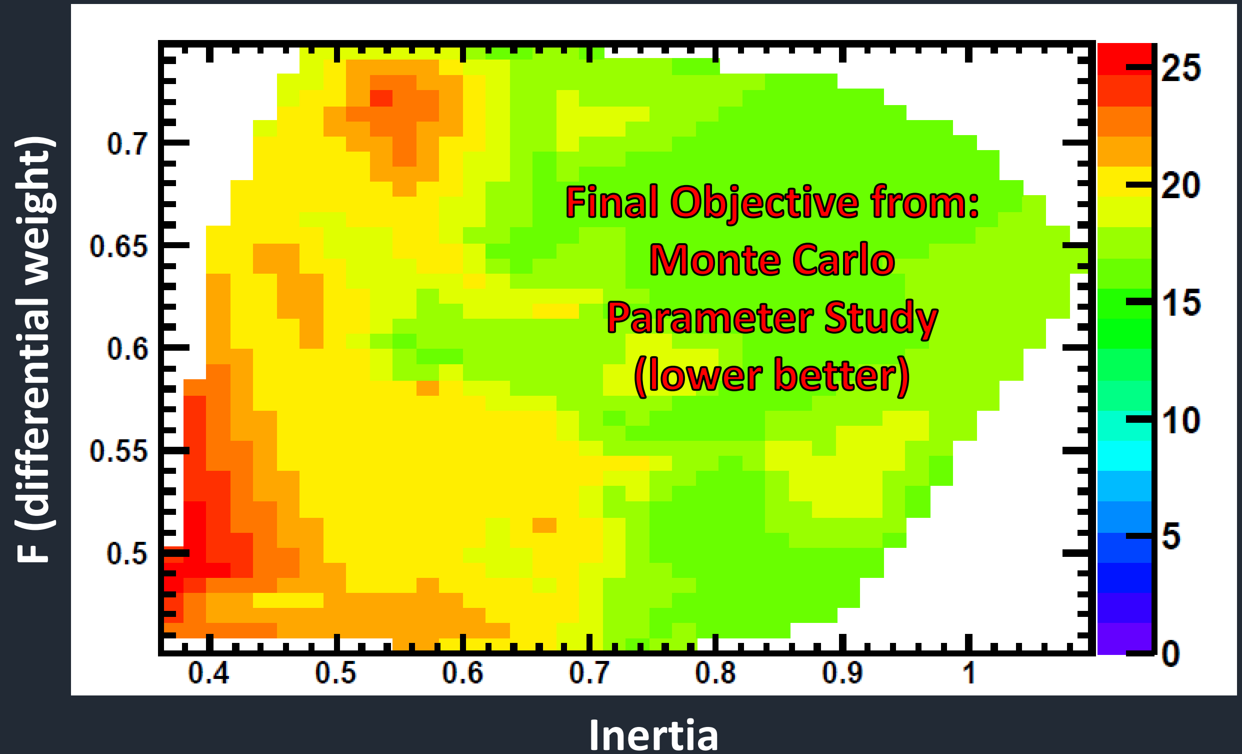


100 Optimizations per curve



Median objective and central 60% band

Performance & Reliability Coupled Parameter Analysis



Hybrid optimizer has more internal parameters:

2 – Particle Swarm
Acceleration, Inertia

2 – Differential Evolution
Diff. weight, Cross. Prob.

1 – Coupling
Steps per A/B

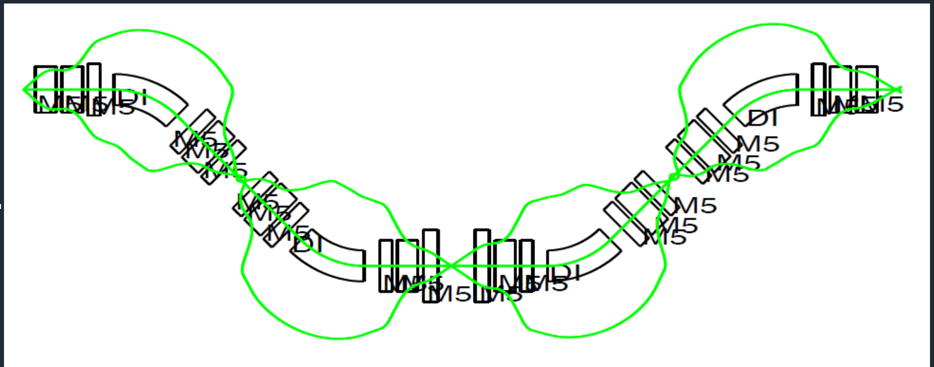
Summary & Outlook

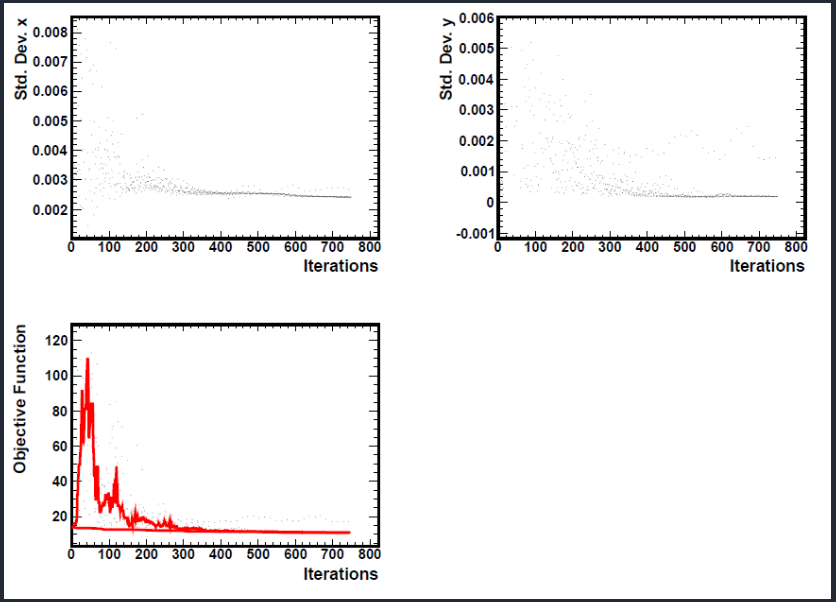
- First experimental test was a success.
- For slower-tuning magnetic systems. (e.g. A1900, quadrupoles ~10 seconds, sext & oct faster) analyze histograms rather than images.

- Simulations are underway to study the case of the A1900 in higher order optimizations.
  - Take data while retuning and analyze all intermediate tunes
  - Hybrid algorithm development to reduce failure rate. (optimize the parameters)

- Preliminary conclusion: Higher order optimization of modern, large separators is feasible with a good chance for success in runs on the timescale of 8 hours.
  - First order tunes would be faster
  - Local optimizations would be faster

Early A1900 simulated 1st order optimization





Acknowledgments

Collaborators:

Zach Schillaci[1], Dave Morrissey[2], Mauricio Portillo[3], Stefan Schwarz[2], Mathias Steiner[2], Antonio Villari[2] , Chandana Sumithrarachchi[2]

[2]National Superconducting Cyclotron Laboratory, East Lansing, MI, USA
[3]Facility for Rare Isotope Beams, East Lansing, MI, USA

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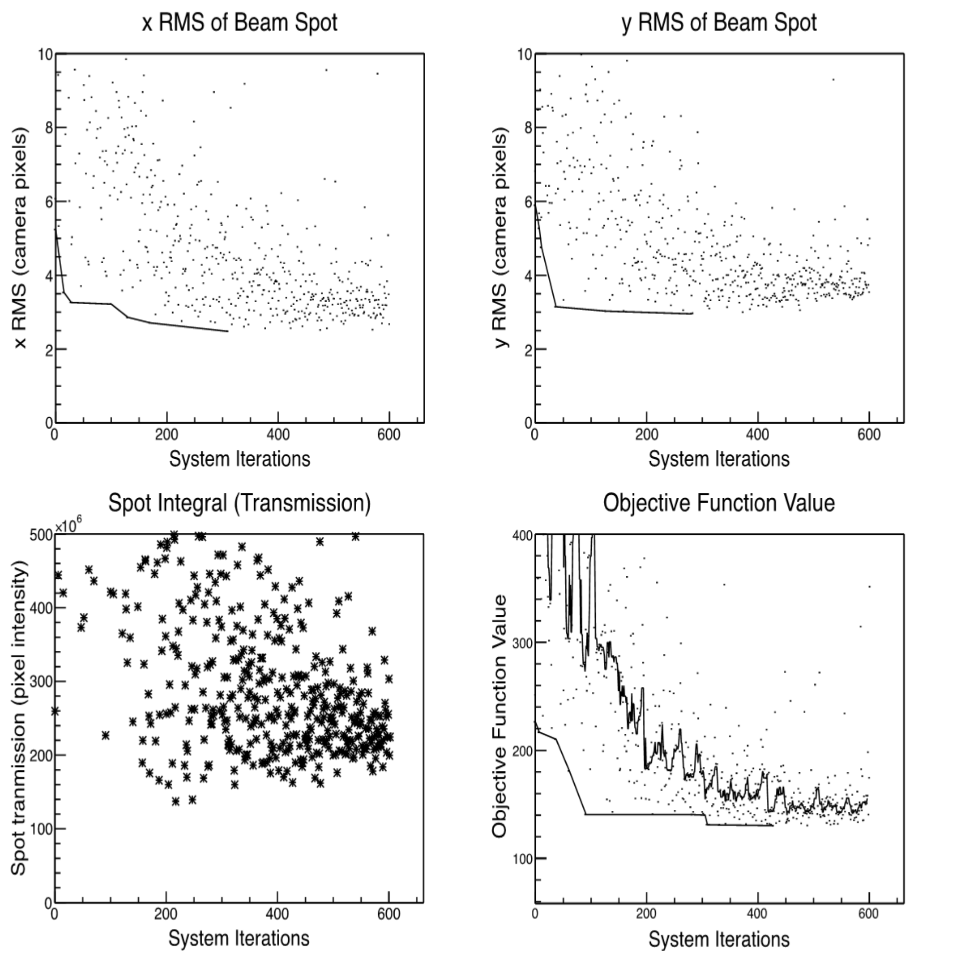
With particular thanks to Zach Schillaci for the slides.

Issues with measuring Transmission

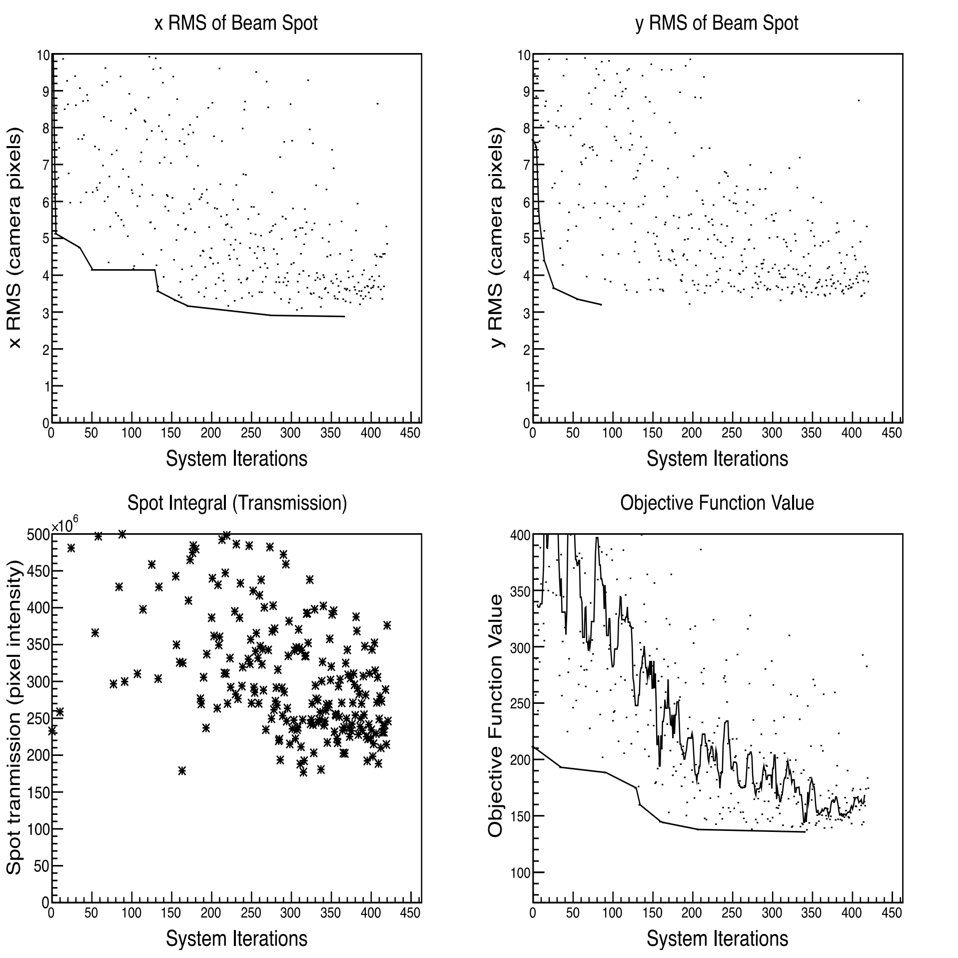
- Beam spot image has tendency to dim even though transmission is not lost
  - Camera may automatically adjust based upon saturation as beamline is focused
  - Focusing beam spot wears out MCP (micro-channel plate)
- MCP and camera not ideal detectors for measuring transmission

Run 12 and Run 13 Comparison

Run 12



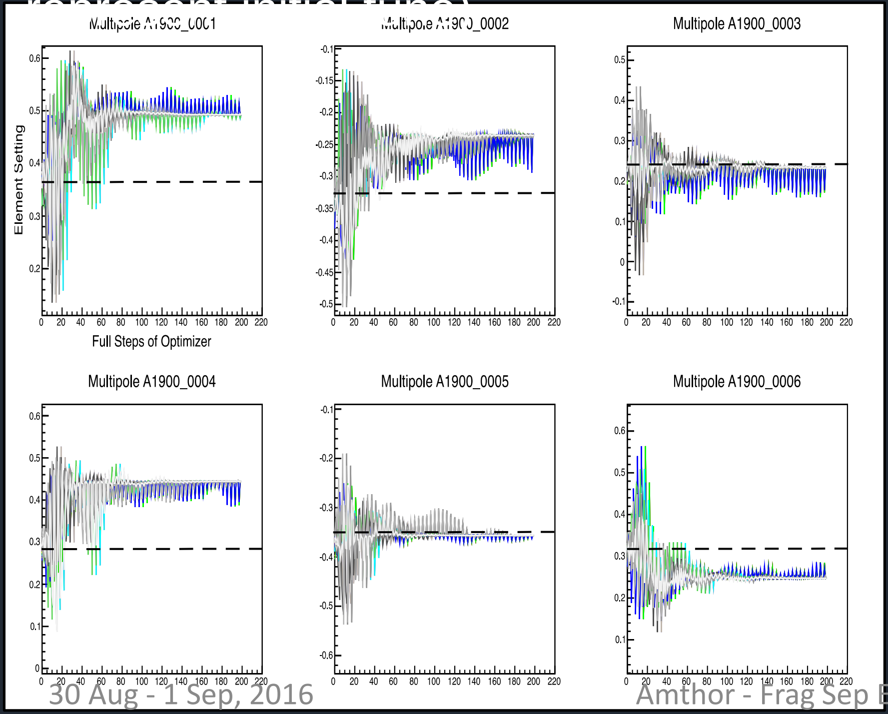
Run 13



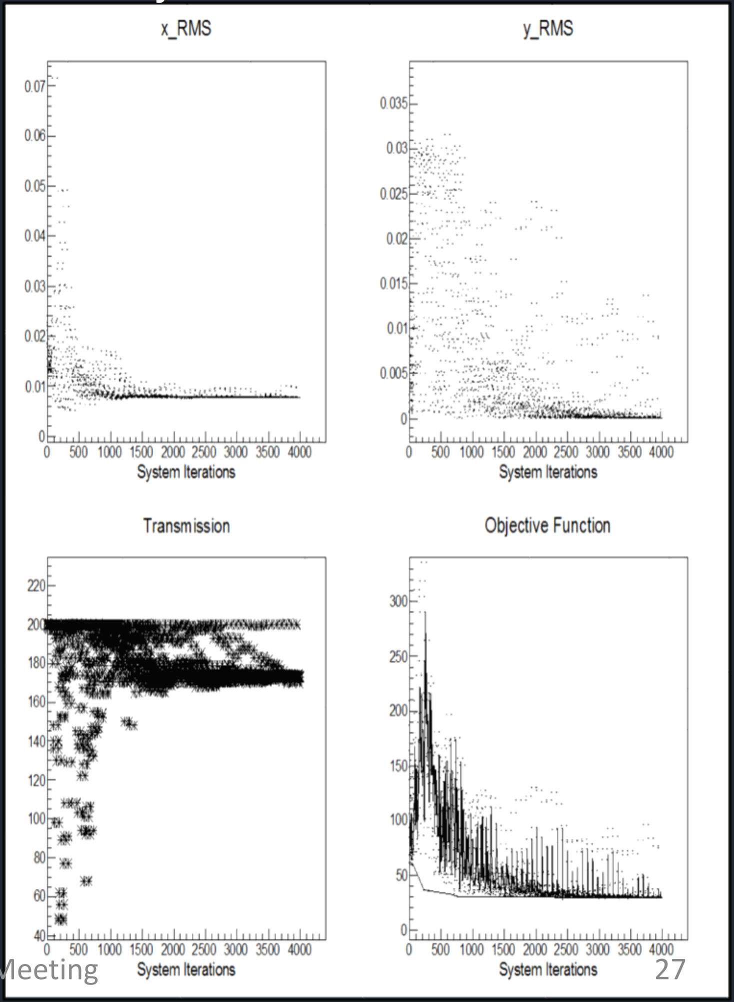
A1900 Computer Simulation Results

Results of a successful optimization run on model of A1900

Beam element settings plots of six optimized quadrupoles (dashed lines represent initial tune)



Plots of σ_x and σ_y , transmission, and objective function value



Particle Swarm Optimizer

Equations of motion for swarm particles

$$v_{i,n} = av_{i,n} + b\left(rand()(x_{i,n} - pbest_{i,n}) + rand()(x_{i,n} - gbest_n)\right)$$

$$x_{i,n} = x_{i,n} + v_{i,n}$$

a = Inertia coefficient

b = Acceleration coefficient

- Inertia drives in direction of current velocity
- Acceleration drives towards personal and global best

Objective Function Definition

Transmission Penalty

$$Objective\ Function\ =\ Objective\ Function \times \left(Transmission\ Fraction \times \frac{Initial\ Transmission}{Current\ Transmission} \right)$$

If transmission drops below set fraction of initial transmission, objective function value is penalized by the ratio