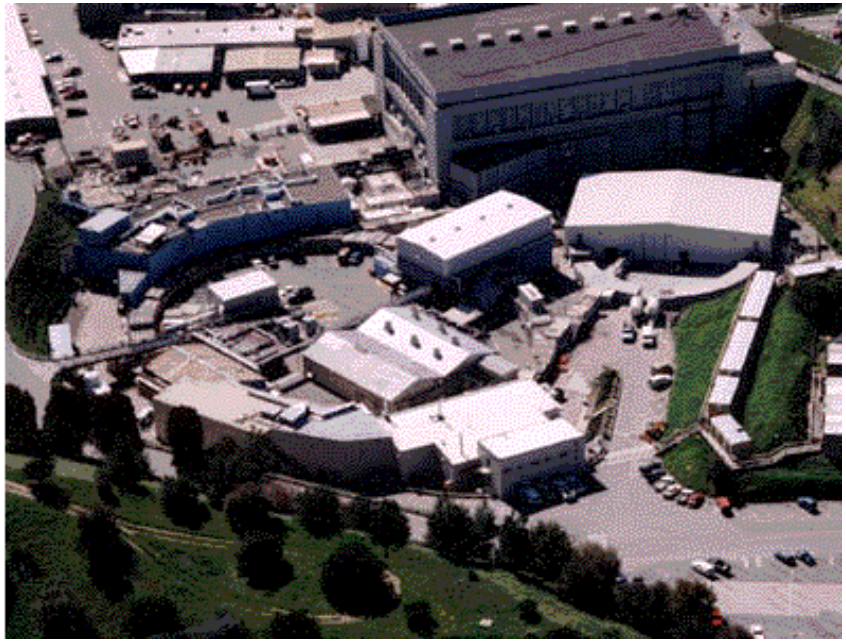
Beam-based Software for Light Sources

J. Safranek



HBSLS Workshop
Brookhaven National Laboratory
April 26-28, 2017

April 26, 2017

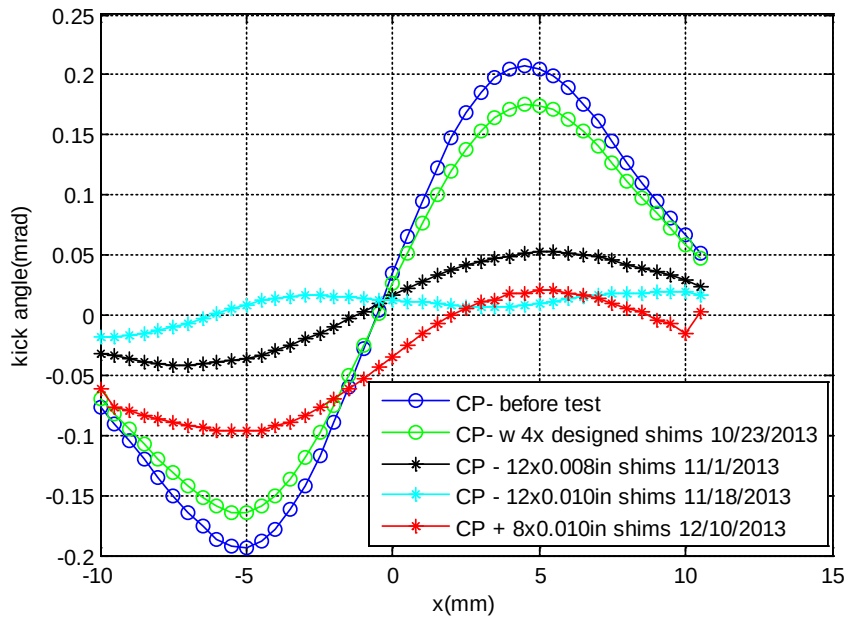
Introduction

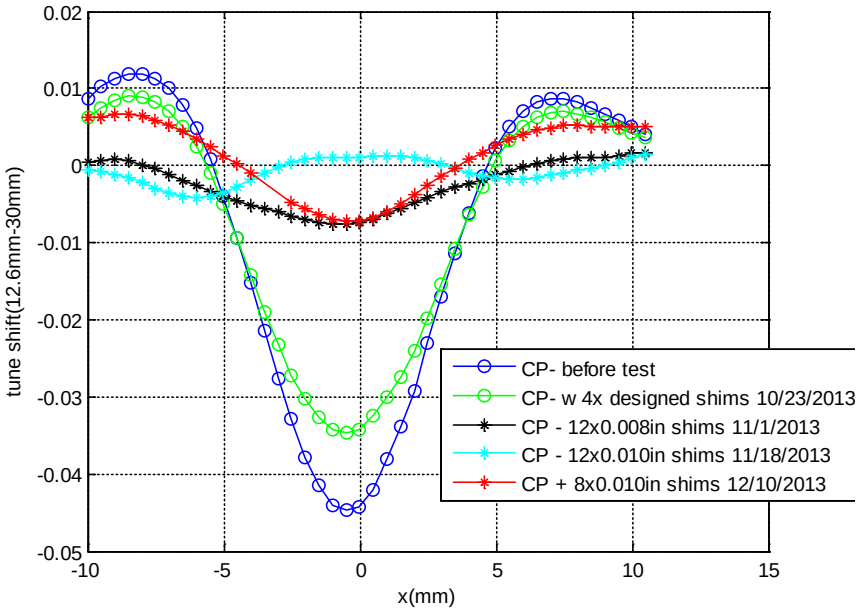
- Storage ring linear optics correction techniques are well advanced with both orbit response matrix analysis and various methods of turn-by-turn analysis
- Ultra-low emittance storage ring designs are pushing nonlinear dynamics hard. Need **beam-based nonlinear dynamics correction** algorithms
- For SPEAR3, we have went from 4 to 10 separate sextupole power supplies, and we wanted a beam-based algorithm to optimize the sextupole strength distribution

Widely used
Nonlinear dynamics measurements

- Nonlinear chromaticity
- Closed orbit bump probe of local nonlinearity

θ_x and/or ν_x vs. $x_{c.o.}$ measures B_y integral vs. x

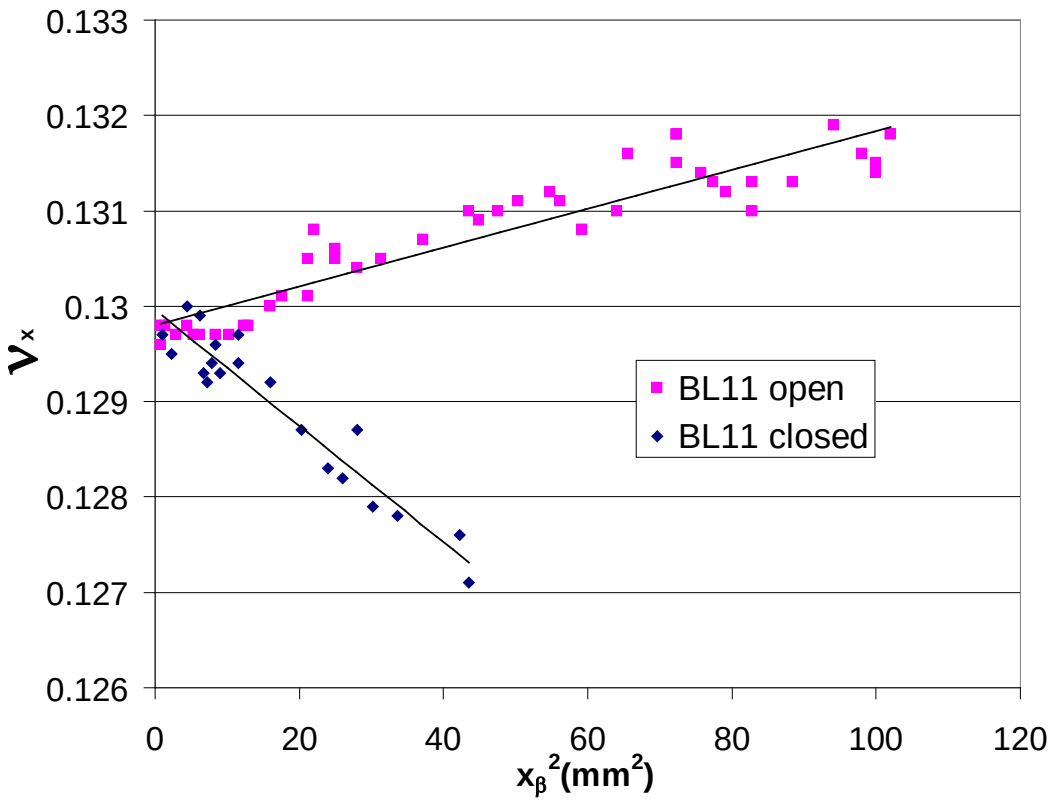




Measured nonlinear kick from a SPEAR3 EPU, X. Huang, K. Tian

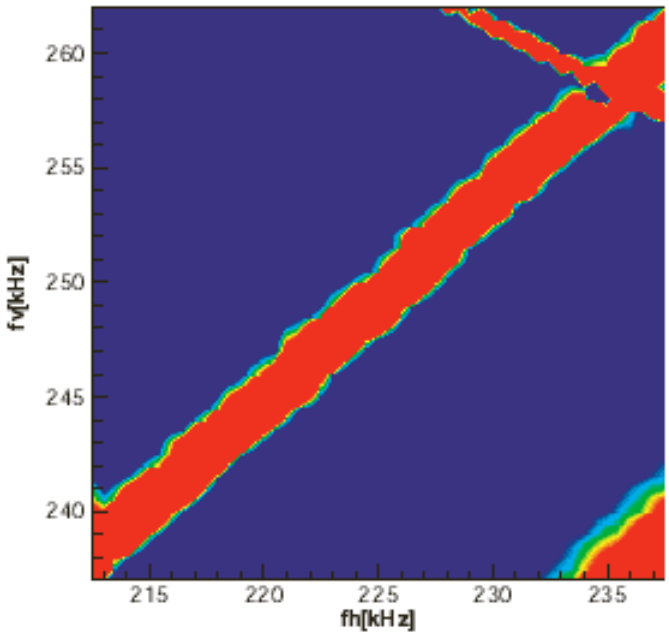
Widely used
Nonlinear dynamics measurements

- Nonlinear chromaticity
- Closed orbit bump probe of local nonlinearity
- Tune shifts with betatron amplitude, $d\nu_{x,y}/dJ_{x,y}$

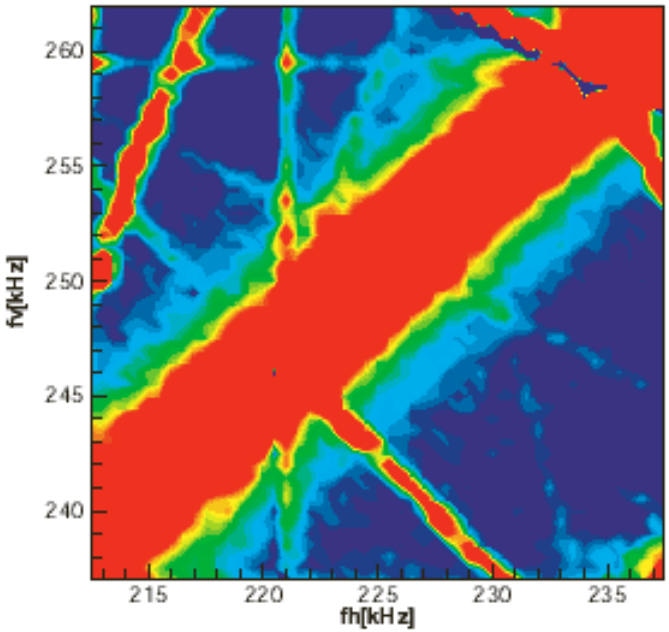


Widely used
Nonlinear dynamics measurements

- Nonlinear chromaticity
- Closed orbit bump probe of local nonlinearity
- Tune shifts with betatron amplitude, $d\nu_{x,y}/dJ_{x,y}$
- Tune scans, ($\sigma_{x,y}$, lifetime, DA, injection) vs. $\nu_{x,y}$



CESR wiggler off



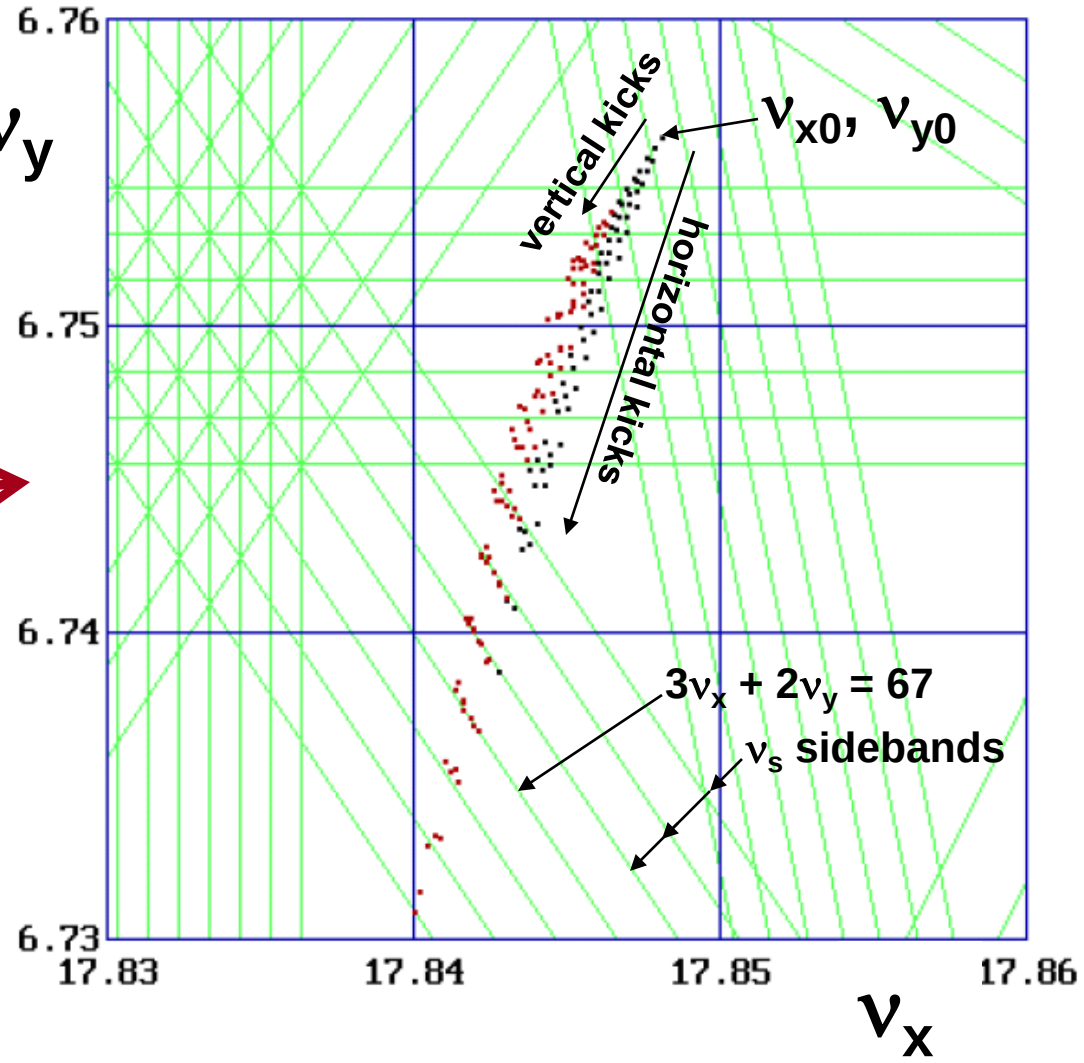
CESR wiggler on

Vertical beam size vs. (ν_x, ν_y) at CESR,Temnykh et al., PAC03

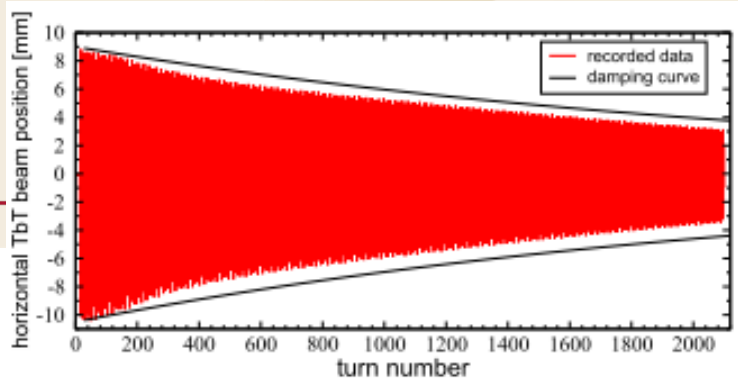
Widely used
Nonlinear dynamics measurements

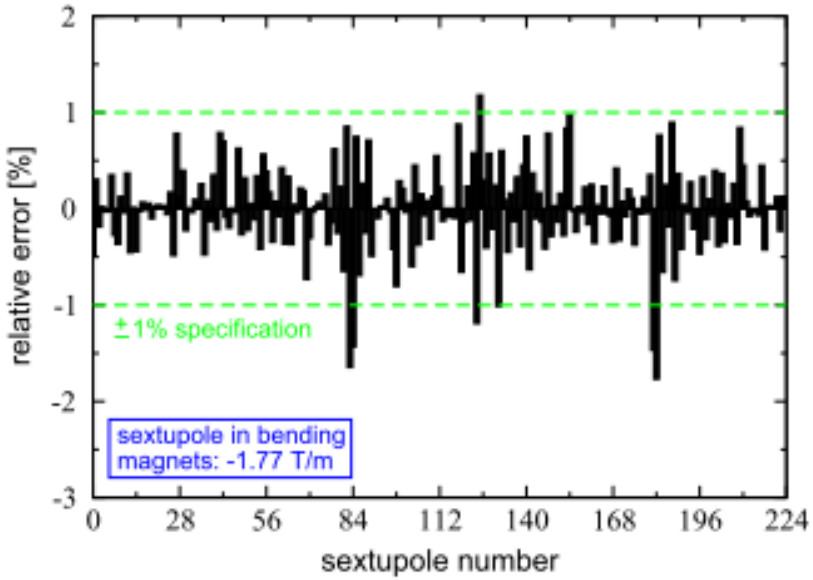
- Nonlinear chromaticity
- Closed orbit bump probe
- Tune shifts with betatro ν_y
- Tune scans, ($\sigma_{x,y}$, lifetime
- Energy acceptance (τ vs
- Dynamic aperture
- Tune maps

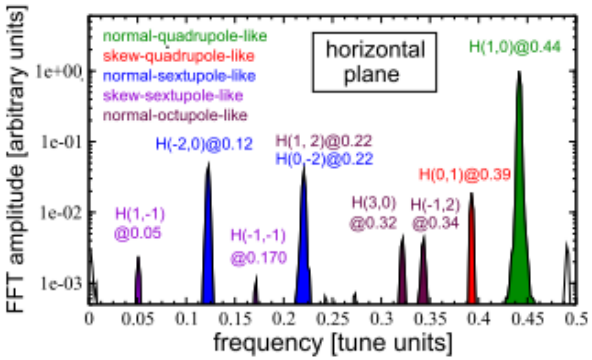
P. Kuske, Tune map at BESSY-II

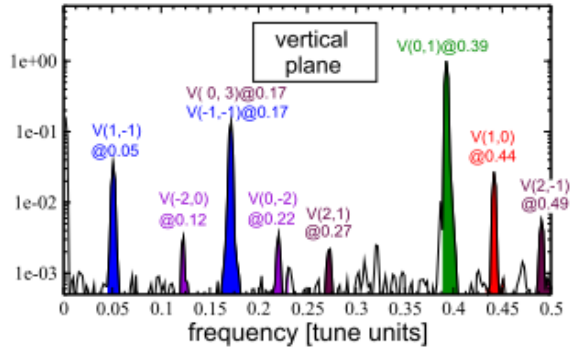


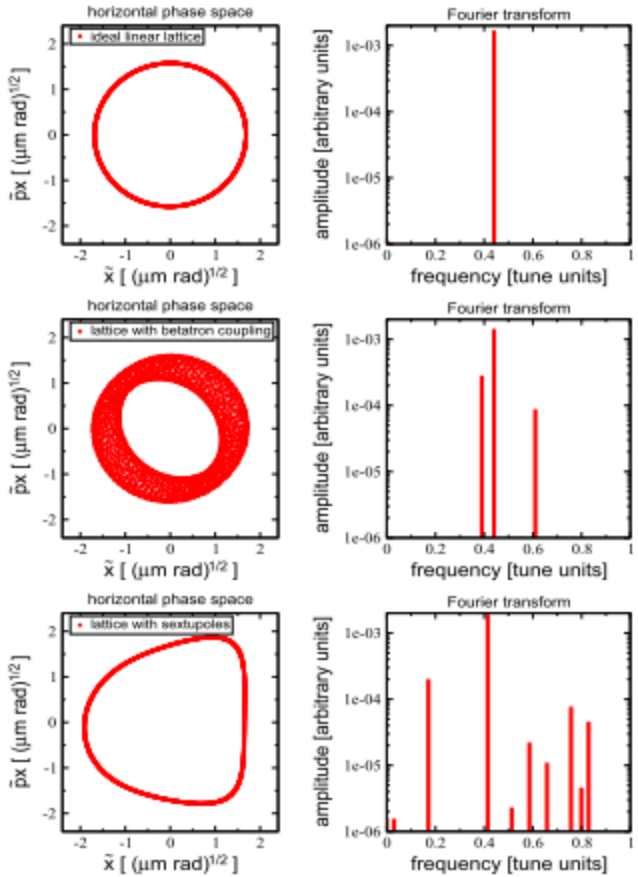
Resonance Driving Term (RDT) measurements







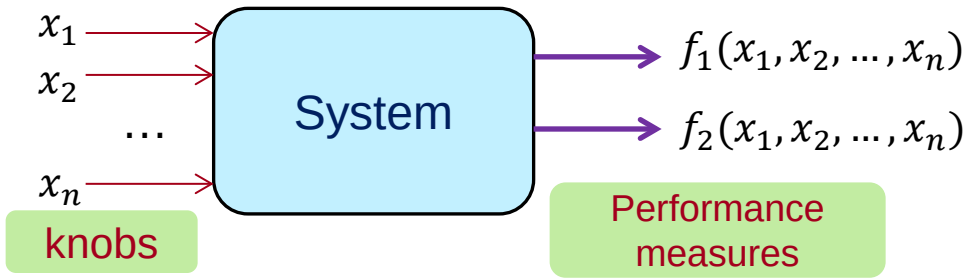




A. Franchi et al., http://arxiv.org/abs/1402.1461, Feb, 2014

Beam based optimization – tuning

Beam based optimization (tuning): adjust the operating condition to optimize machine performance directly.



We know the system works – changing input leads to performance responses. But we don't know **exactly** how it works – the functions are unknown.

Machine tuning is a multi-variable and (potentially) multi-objective optimization process. The function(s) is evaluated through the machine.

Beam-based nonlinear optimization

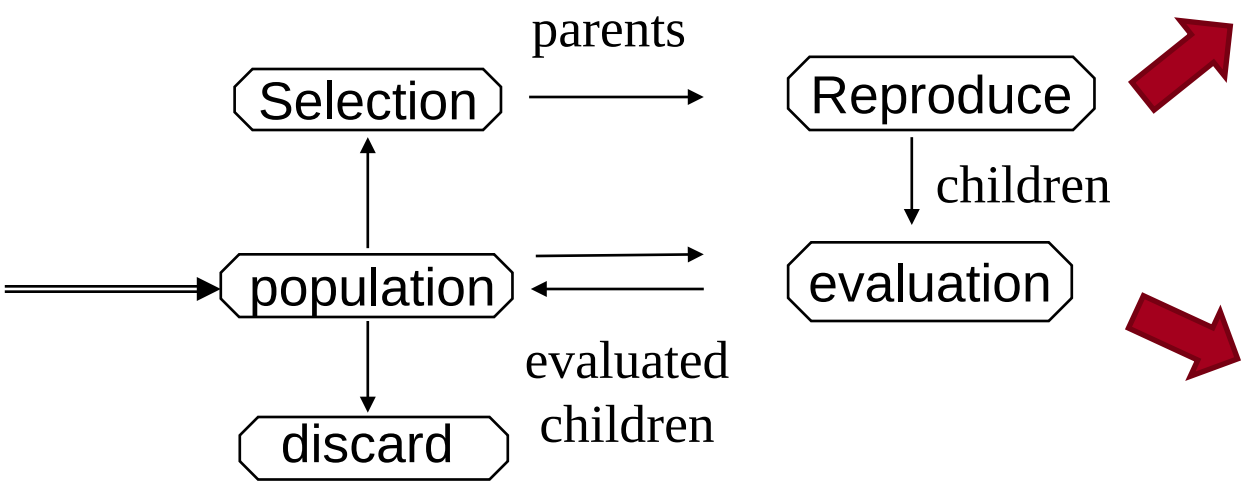
- MOGA & PSO: powerful tools for accelerator design
  - Directly optimize numerical DA & lifetime
- As-built low emittance rings will need nonlinear tuning
  - Directly optimize measured DA & lifetime? (or injection efficiency & loss rate).
- Challenges
  - Noisy function evaluation (measurement)
  - Need fast, accurate measurement
  - Standard optimizer (Simplex, minimum gradient …) algorithms often fail due to measurement noise
  - Minimize # of function evaluations (i.e. measurements)
- Previous beam-based optimization work includes
  - L. Emery et al., PAC2003.
  - M. Aiba et al., NIMA, 2012

Optimization algorithm development at SSRL/SPEAR3

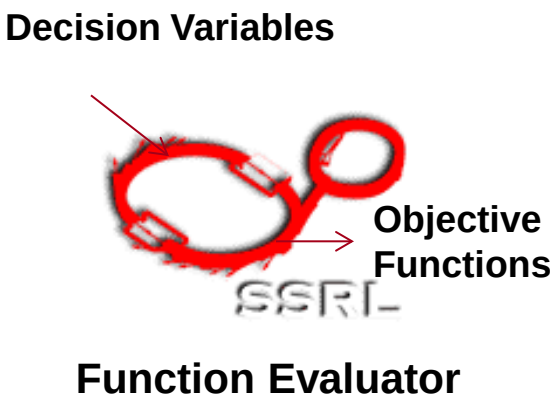
- **Multi-Objective Genetic Algorithm (MOGA or SOGA)**
  - Applied to minimize coupling using 17 skew quadrupoles
  - *K. Tian, J. Safranek, and Y. Yan, Phys. Rev. ST-AB (2014)*
- **Robust Conjugate Direction Search (RCDS)**
  - Applied to coupling, top-off transient, LCLS undulator taper, etc...
  - *X. Huang, J. Corbett, J. Safranek, J. Wu, NIMA (2013*)
- **Particle Swarm Optimization (PSO)**
  - Applied to numerical dynamic aperture optimization (see Xiaobiao's presentation later today)
  - Applied to SPEAR3 coupling correction
  - *X. Huang, J. Safranek, NIMA-D-14-00356 (2014)*

Machine Based Genetic Algorithm

Reproduction Cycle



Genetic Operations:
- Crossover
- mutation



Goal: Experimental demonstration of the machine based Genetic Algorithm by minimizing vertical beam size by optimizing the 13 skew quads in SPEAR3.

K. Tian

Touschek Beam Loss and Vertical Beam Size

Beam loss in modern electron storage ring is dominated by Touschek scattering, so vertical beam size is inverse proportional to normalized beam loss:

$$\frac{\left|\frac{dI}{dt}\right|}{I^2} \propto \frac{1}{\bar{\sigma}_y}$$

Minimize vertical beam size = Maximize Touschek beam loss

Objective Function: -|dI/dt|/I^2

Decision Variables : strengths of the 13 skew quads

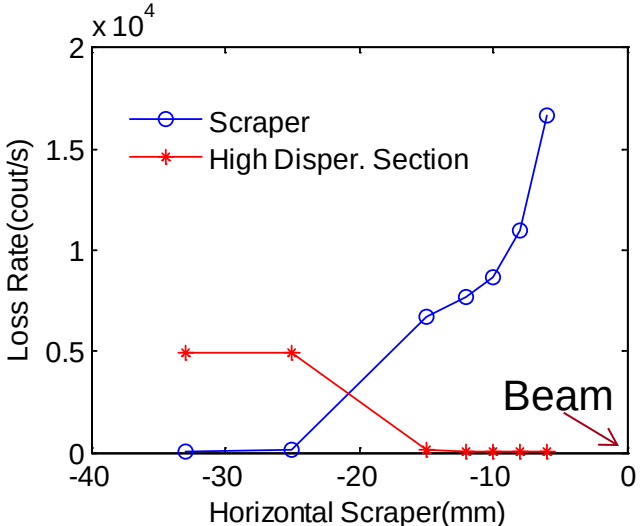
Beam Loss Measurement

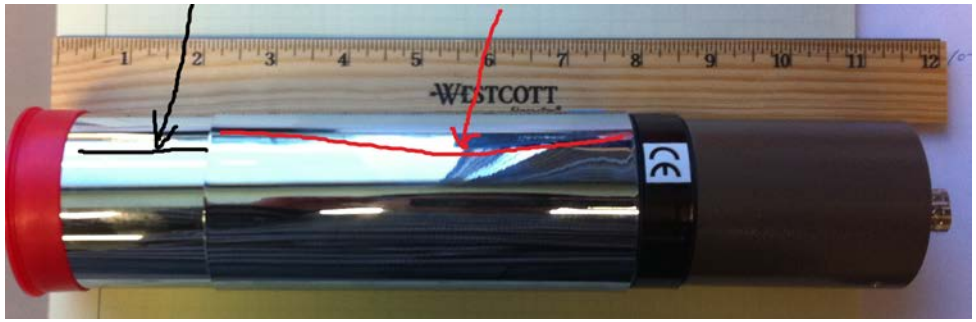
❖dc current transformer (DCCT):

- ✓Direct measurement of the global beam loss;
- ✓~10% uncertainty for 6 second integration with 500mA stored current

❖Beam Loss Monitor:

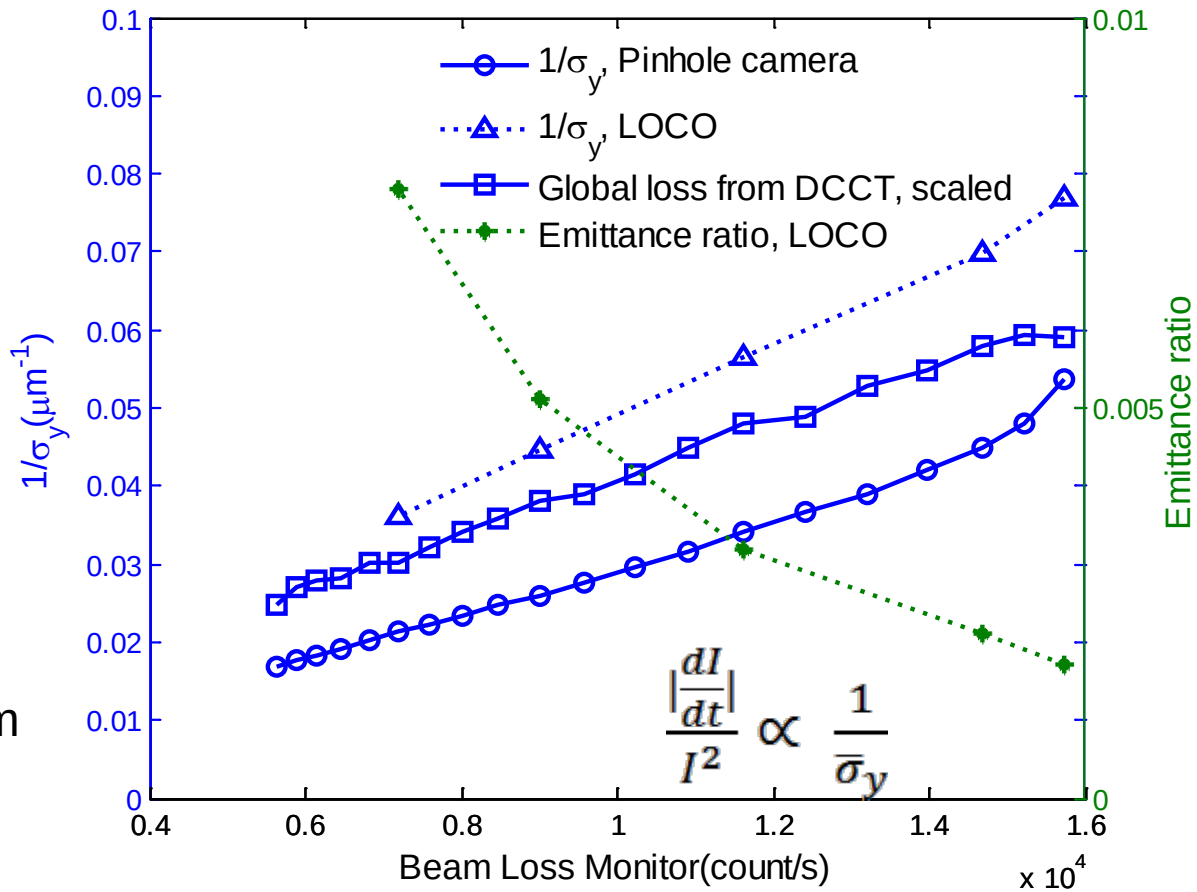
- ✓NaI Scintillator with PMT tube;
- ✓High SNR;
- ✓Fast 1Hz rate;
- ✓Local beam loss;
- ✓ Insert scraper to capture most of the beam loss at one location.





Experimental Verification

- ❖20 different setting of skew quads;
- ❖ Vertical beam size measure at one location;
- ❖ Global beam loss from DCCT
- ❖ LOCO analysis for 4 cases
  - ❖Average vertical beam size;
  - ❖Emittance ratio



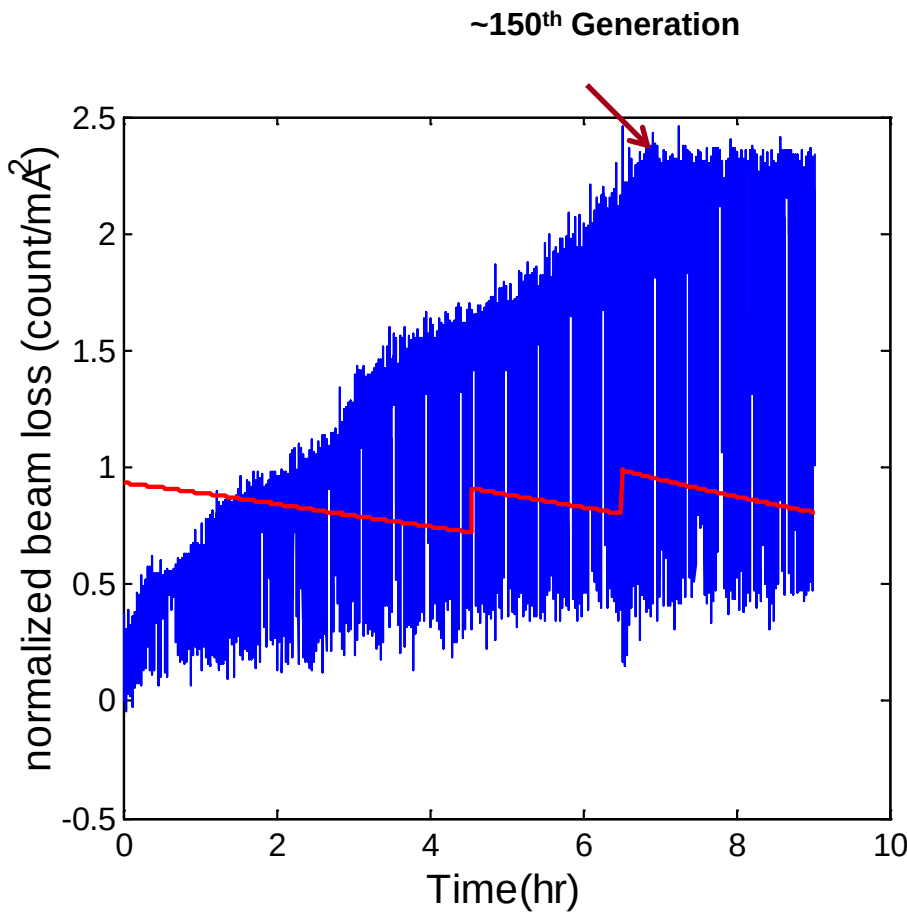
Beam loss caused by tune shift or reduction of energy acceptance is not a major concern when varying the skew quads in SPEAR3.

MOGA coupling correction, SPEAR3

❖211 generations and about 9 hours in total (<3 minutes /generation);

❖ Refill the stored current to 100mA twice;

❖ The optimization was paused during the fill and restarted by loading the dumped data after the fill

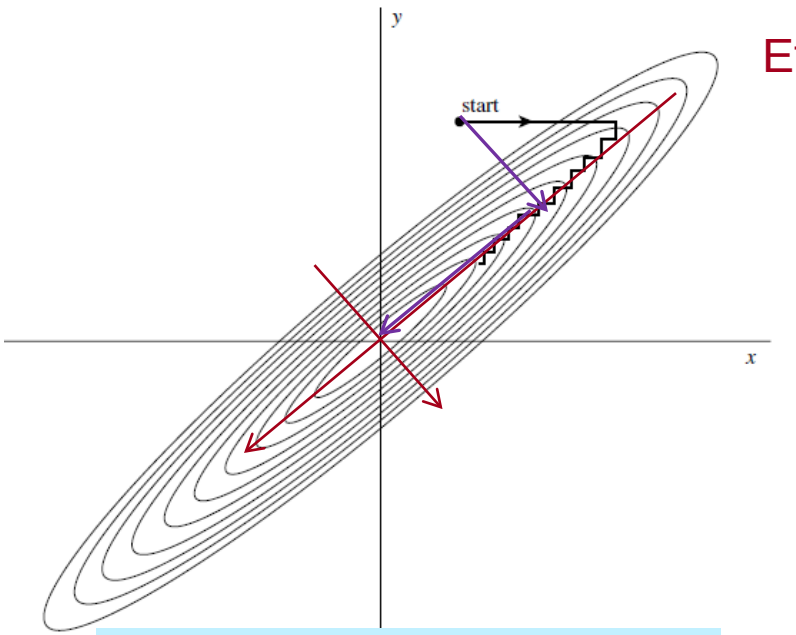


The development of the RCDS algorithm

- The development was motivated by the need to optimize storage ring nonlinear beam dynamics.
  - Correction of nonlinear dynamics is difficult – lack of direct diagnostics, deterministic method, and even target.
- Robust conjugate direction search (RCDS)* performs iterative search over conjugate directions with a robust (against noise), efficient line (1D) optimizer.
  - The conjugate direction set may be updated with Powell's method.
  - The 1D robust optimizer is designed to deal with noise.

*X. Huang, J. Corbett, J. Safranek, J. Wu, "An algorithm for online optimization of accelerators", Nucl. Instr. Methods, A 726 (2013) 77-83.

Search over conjugate directions



Inefficient search directions

It takes many tiny steps to get to the minimum when searching along x and y directions.

Efficient search directions: conjugate directions

A search over conjugate direction does not invalidate previous searches.

Directions $\mathbf{u}$ and $\mathbf{v}$ are conjugate if

$$\mathbf{u}^{\mathrm{T}} \cdot \mathbf{H} \cdot \mathbf{v} = 0$$

with $\mathbf{H}$ being the Hessian matrix of function $f(\mathbf{x})$,

$H_{ij} = \frac{\partial^2 f}{\partial x_i \partial x_j}$.

Around the minimum

$$f(\mathbf{x}_m + \Delta\mathbf{x}) = f(\mathbf{x}_m) + \frac{1}{2}\Delta\mathbf{x}^{\mathrm{T}} \cdot \mathbf{H} \cdot \Delta\mathbf{x}.$$

Powell's method can update the directions using past search results to develop a conjugate set.

*W.H. Press, et al, Numerical Recipes

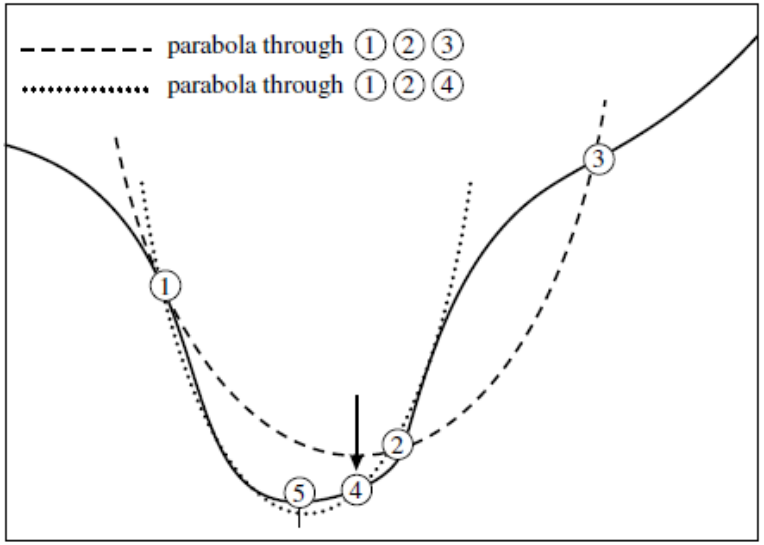
*M.J.D. Powell, Computer Journal 7 (2) 1965 155

Anatomy of a line optimizer that is sensitive to noise

Line optimizer – Brent's method

Step 1: Initially bracketing the minimum.

Step 2: Successive interpolation to converge to the minimum.



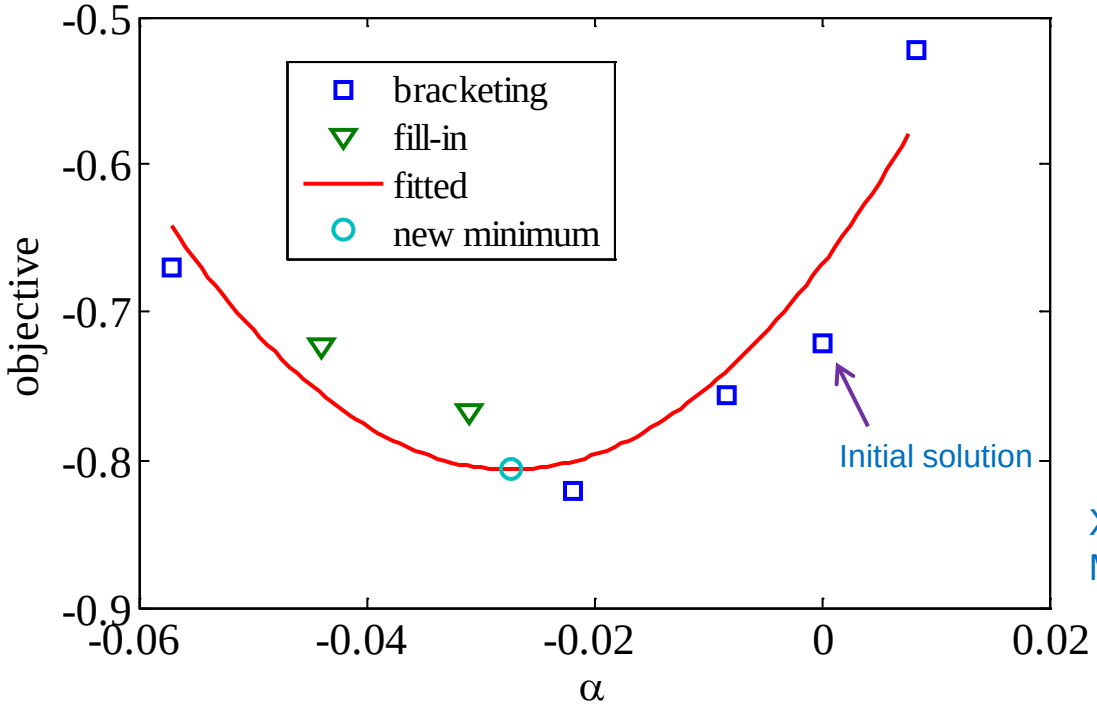
Inverse quadratic interpolation (figure from Numeric Recipes*.)

With noise, the comparison of values in both steps can go wrong and the algorithm won't converge.

*W.H. Press, et al, Numerical Recipes

The robust 1D optimizer

The robust optimizer is aware of noise in bracketing and uses noise level to filter out outliers. Noise level is detected before optimization.

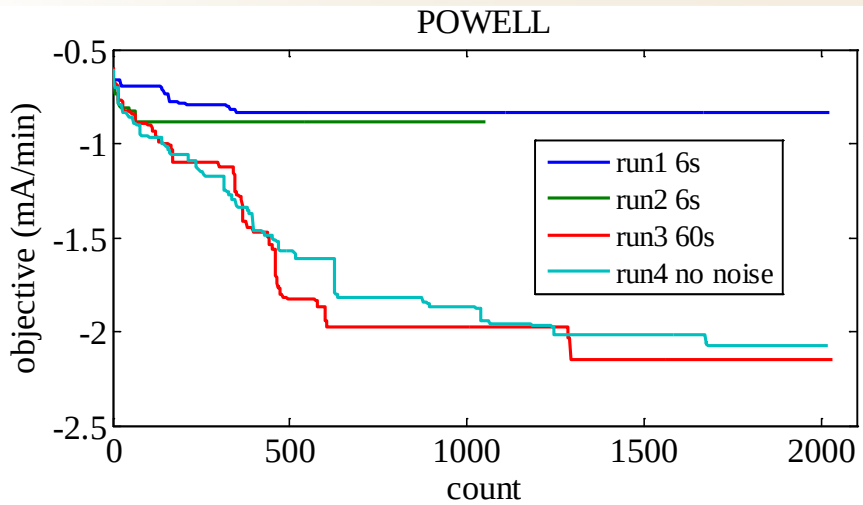


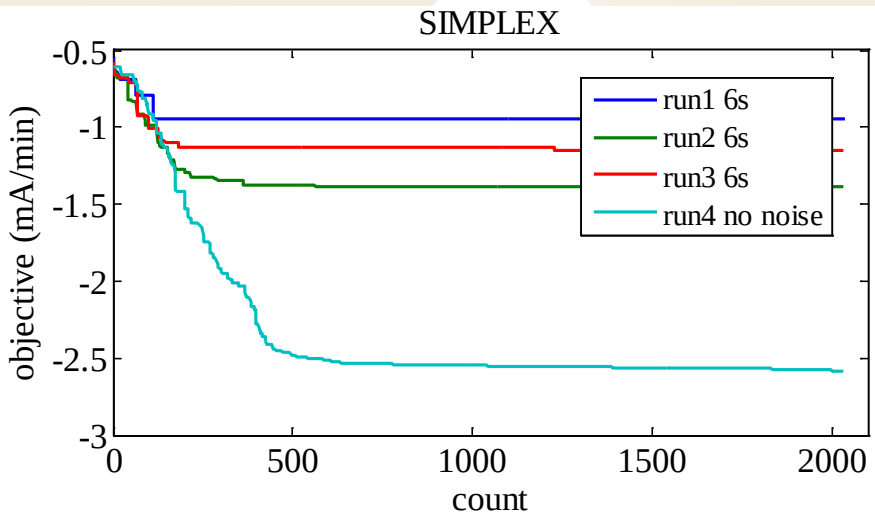
X. Huang et al, Nucl. Instr. Methods, A 726 (2013) 77-83.

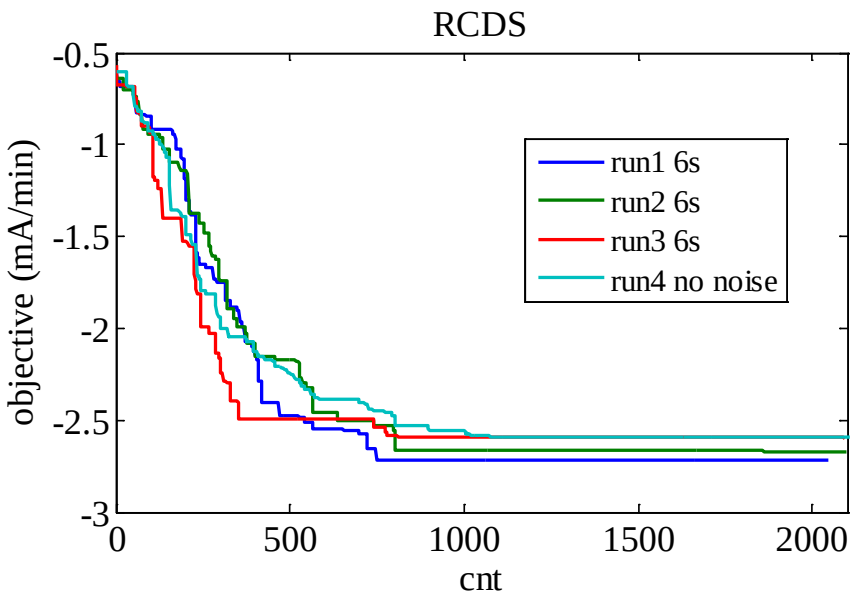
Bracketing: step size is increased in the search. Bracket ends are higher than minimum by 3 noise sigma.

Fitting: fill in additional points when necessary to better sample within the bracket and then fit a parabola.

Simulation results for three direct search methods







(1) Showing history of the best solution.

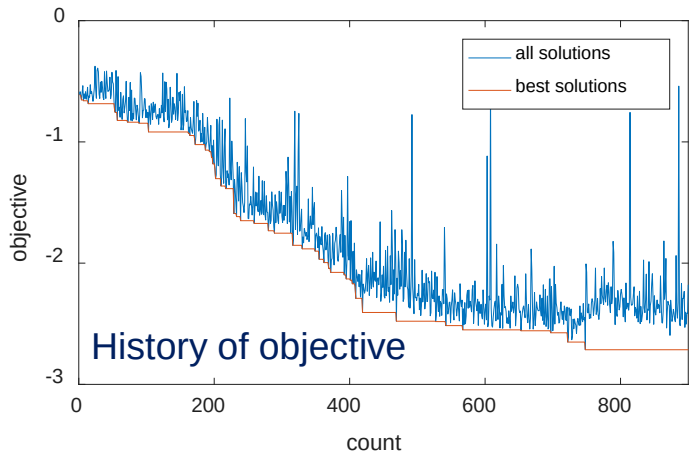
(2) The simplex method is efficient without noise, but fails to reach the minimum with noise.

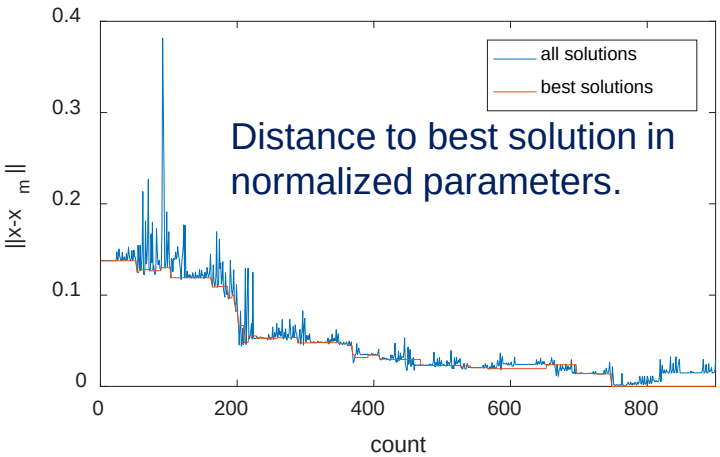
(3) Powell's method works without noise, but fails with noise. The initial direction set are individual skew quads.

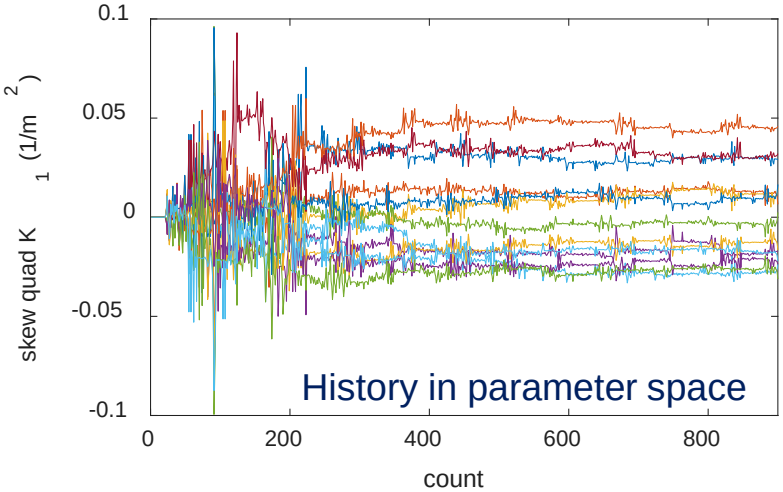
(4) The RCDS method is efficient with or without noise.

The performances of algorithms for noisy problems depends on the problems.

Detailed look of an RCDS run, SPEAR3 coupling correction





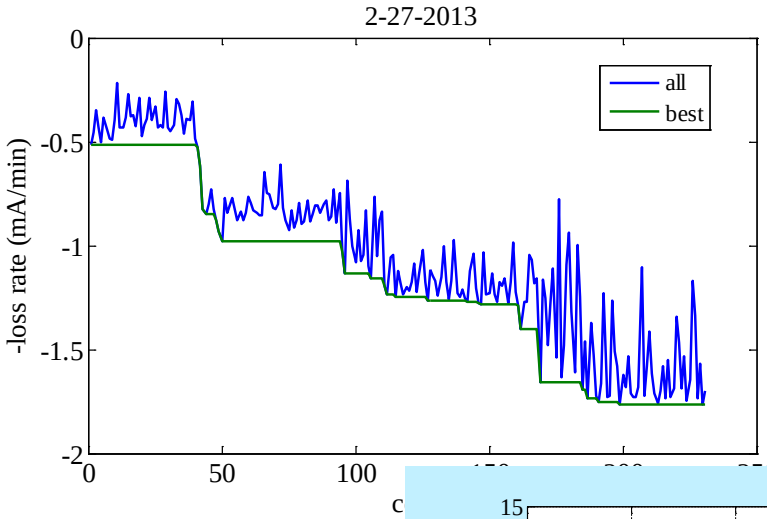


The algorithm converges fast but it does not stay right at the minimum – it keeps probing around.

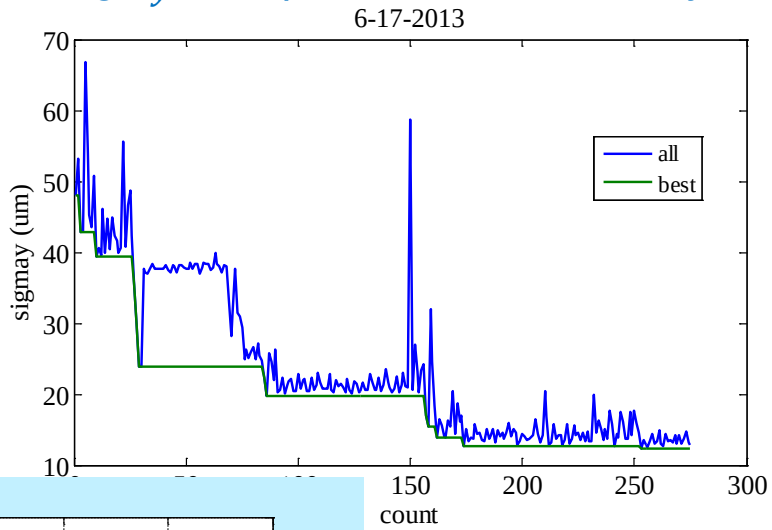
So usually we need to sort the solutions and apply the best one to the machine.

Coupling correction experiments on SPEAR3 with RCDS

Using loss rate (normalized) as objective

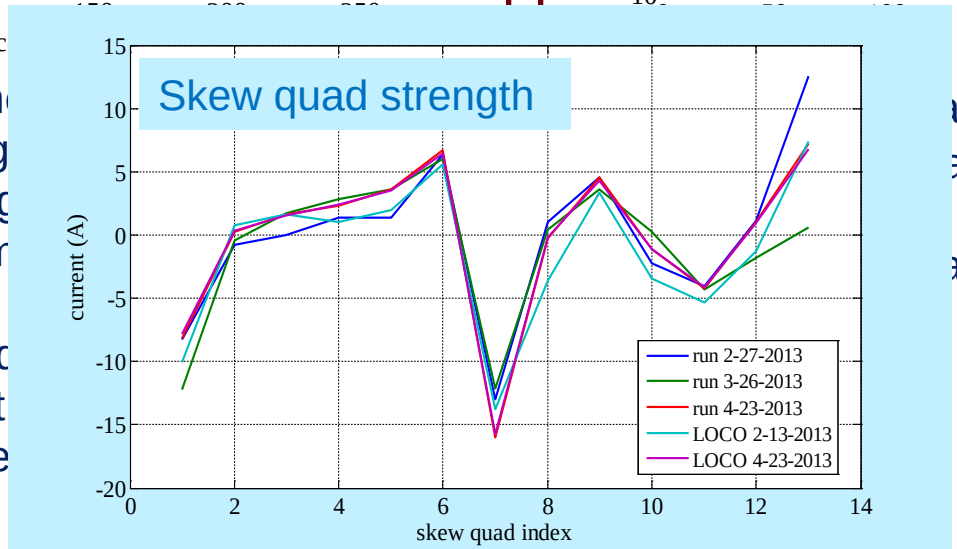


Using σ_y from pinhole camera as objective



Beam loss rate is m
beam current chang
(no fitting). Noise sig
were taken at 500 m

Initially all 13 skew c
At 500 mA, the best
4.6 hrs. This was be
correction (5.2 hrs)



at 0.3 micron.
ads were off initially.

a resolution is limited.

Applications of RCDS on real-life problems

- SPEAR3
  - Kicker bump matching
  - Transport line optics
  - Transport line steering
  - GTL steering and optics
  - Injection efficiency w/ sextupoles

X. Huang, J. Safranek, PRSTAB 18, 084001 (2015)

- LCLS
  - Undulator taper optimization

J. Wu, K. Fang, X. Huang, 2014-2016

- BEPC-II luminosity optimization
  - Steering and coupling
  - Interaction point beta

H. Ji, et al, Chinese Physics C 2015 Vol. 39 (12)

- ESRF
  - beam lifetime w/ sextupoles

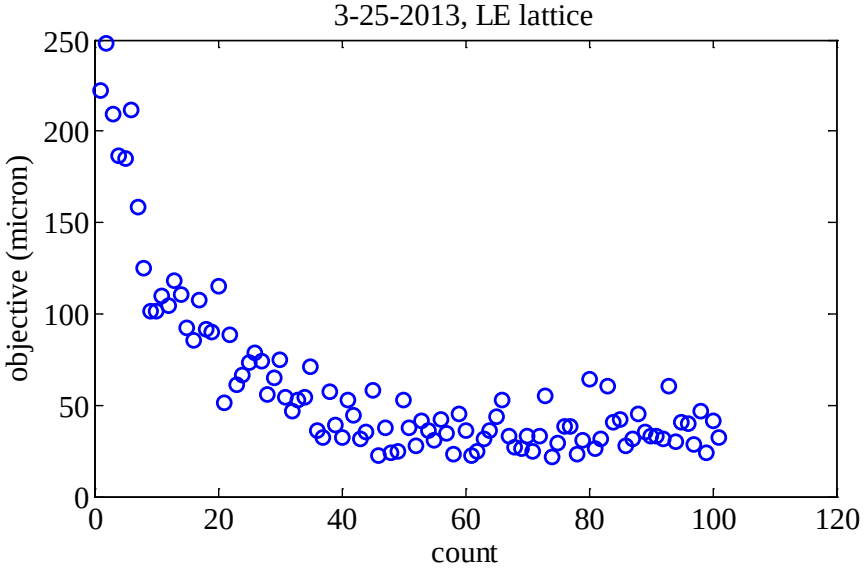
S. M. Liuzzo, et al, IPAC'16, THPMR015

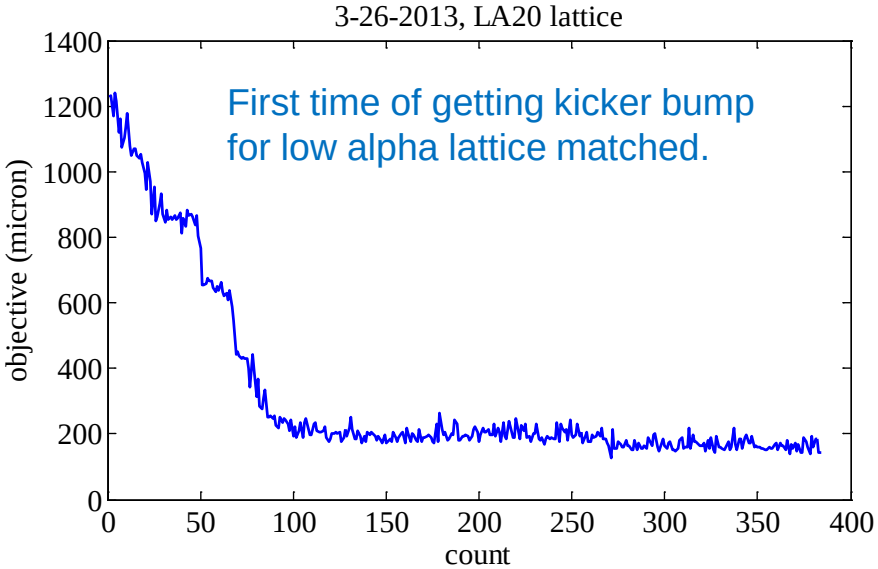
  - Injection steering

RCDS Top-off kicker bump matching, SPEAR3

Parameters: Adjusting pulse amplitude, pulse width and timing delay of K1 and K3 (with K2 fixed) and two skew quads for vertical plane; 8 parameters total.

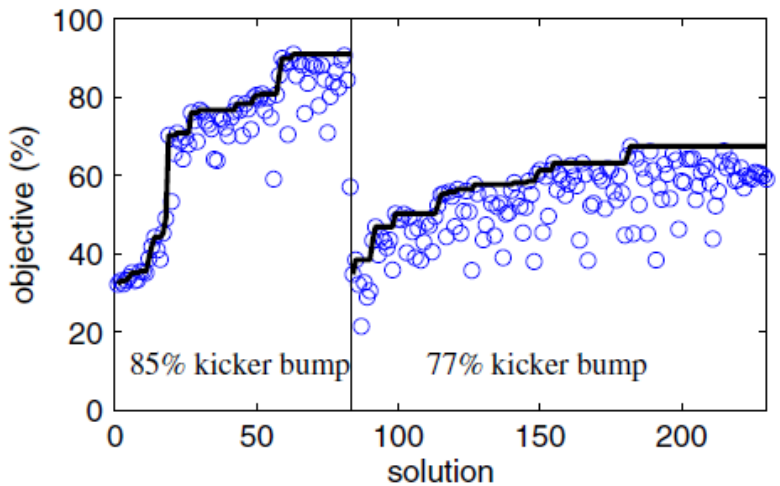
Objective: sum of rms(x) and rms(y) of turn-by-turn orbit (for 30~300 turns).

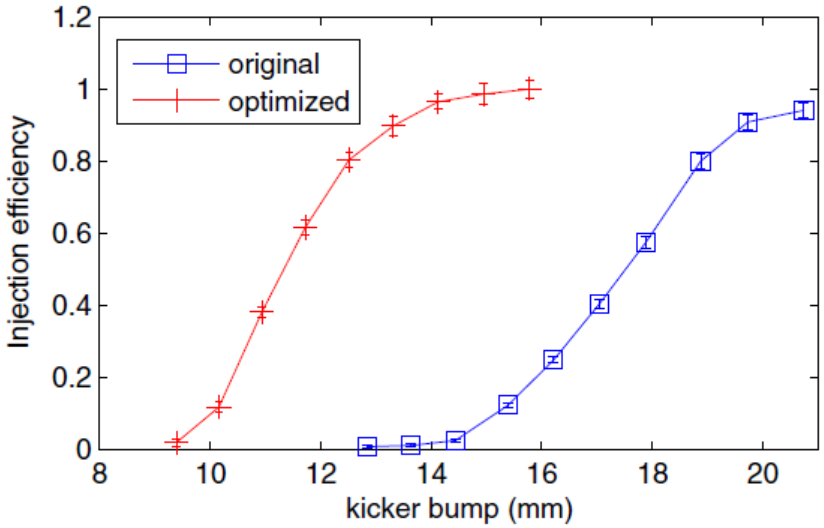




X. Huang

Online dynamic aperture optimization for SPEAR3





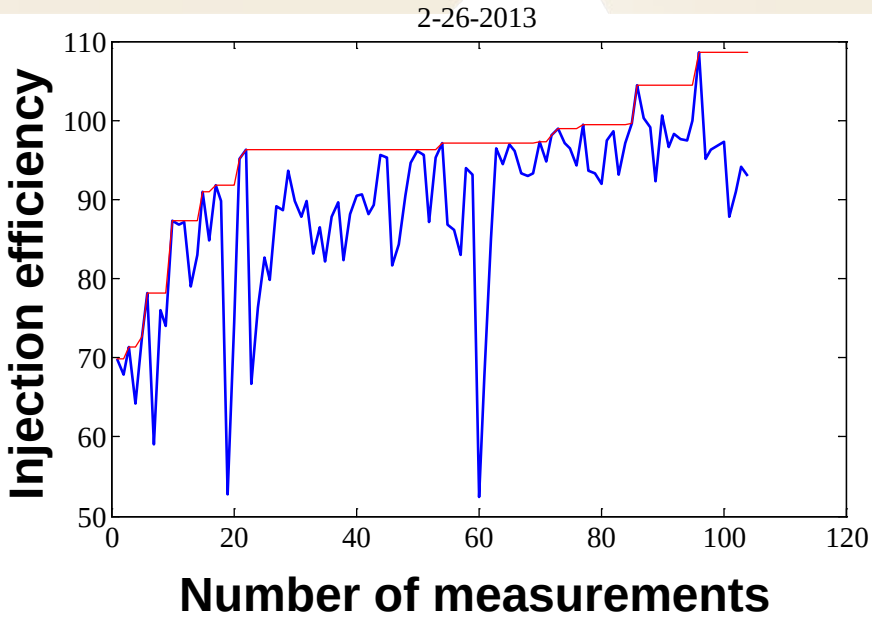
Optimizing injection efficiency with reduced kicker bump.
Knobs: 8 sextupole knobs – each knob is a pattern of 10 sextupole families that do not change chromaticities.

DA was increased from 15.1 mm to 20.6 mm by optimization.
Momentum aperture (MA) was not affected.

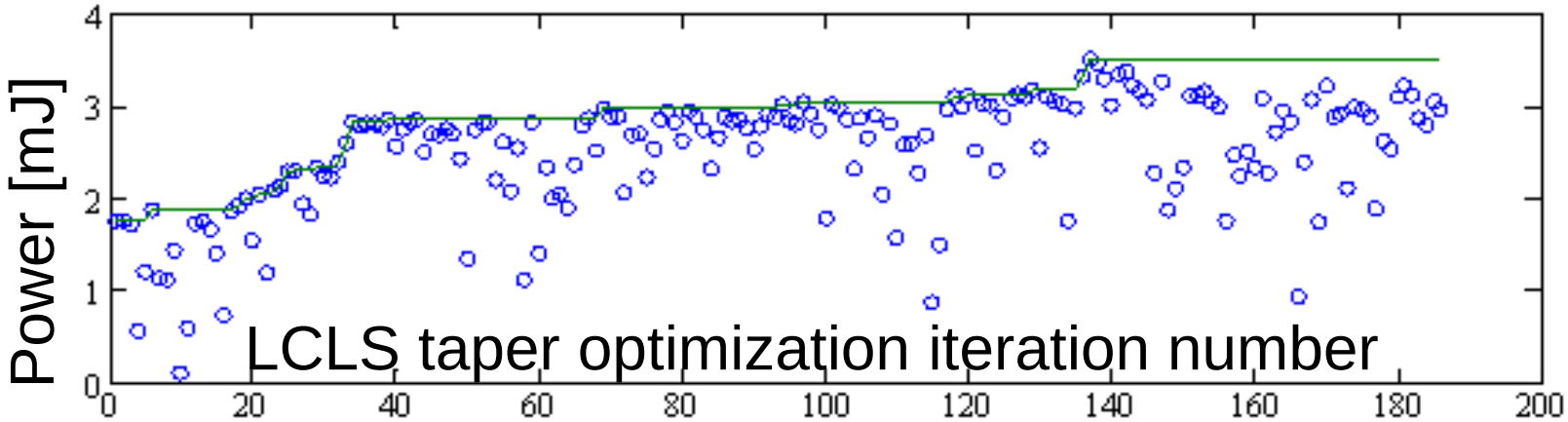
X. Huang, J. Safranek, PRSTAB 18, 084001 (2015)

RCDS beam-based optimization, additional examples

- **Beam-based optimization of SPEAR3 injection efficiency with four transport line steering magnets (x, x', y, y')**



- **LCLS: Maximize measured energy/pulse as a function of undulator gaps**

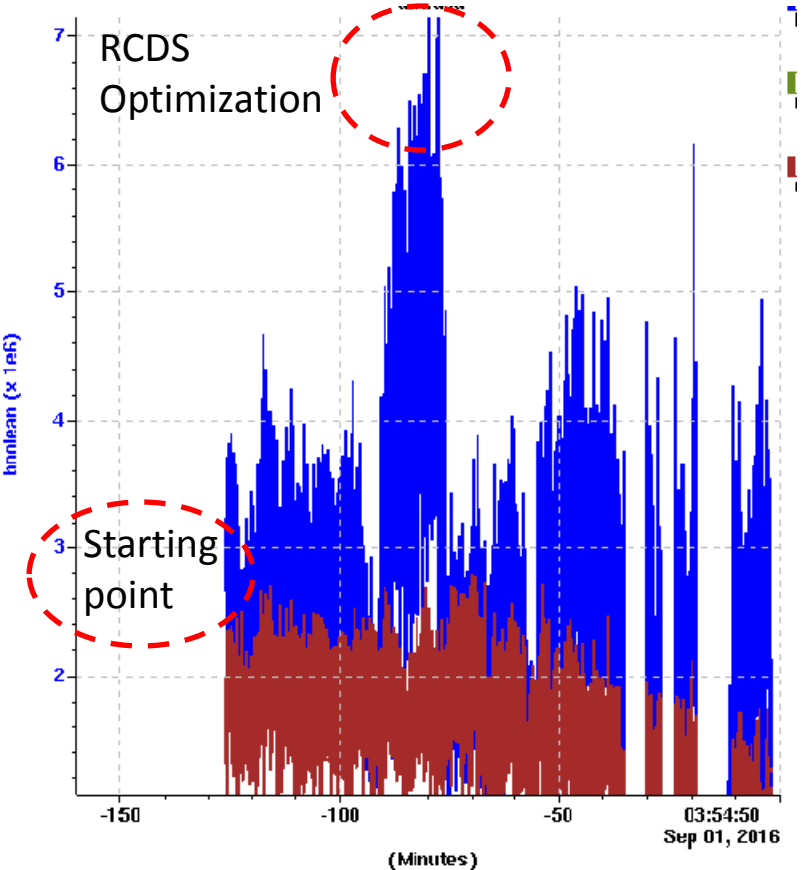


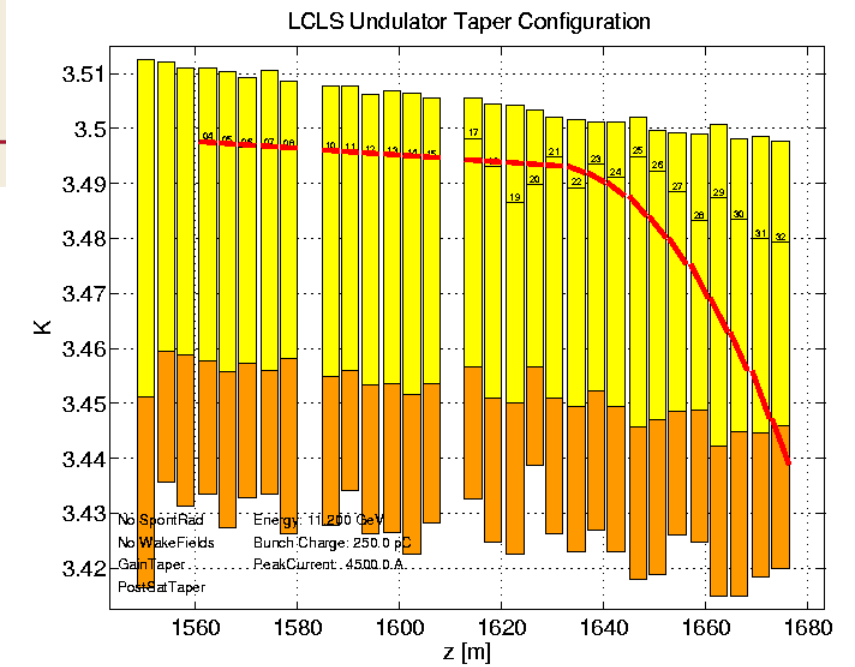
X. Huang

Recent result by Juhao Wu, 9/1/2016

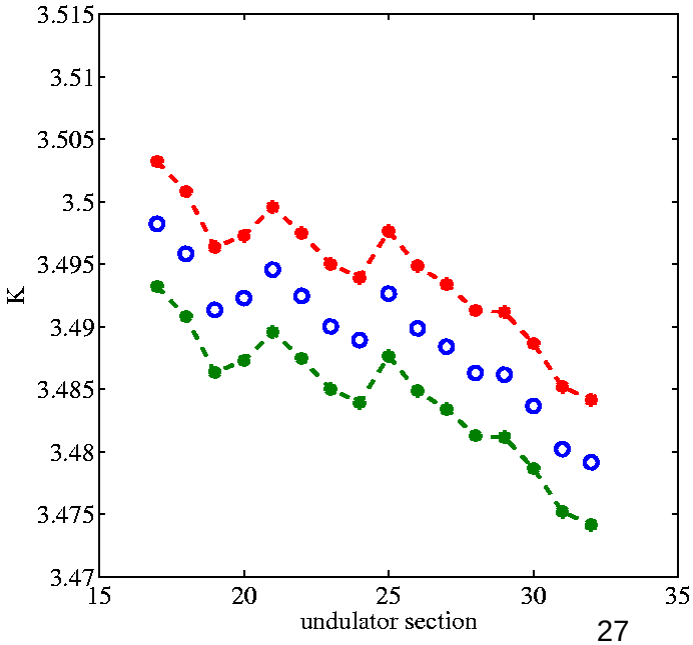
SELF-SEEDING FEL OPTIMIZATION

- 5.5 KeV Self-seeding FEL
  - More than doubled
  - U17-U32 continuous function: does not work well
  - Zig-zag taper profile: ~ 1 mJ in 10 fs





Knobs: 16 parameters that control the taper profile. For U17-U32: *each K is freely optimized with bounds*.
Objective: FEL photon beam intensity.



ESRF optimization of beam lifetime with sextupoles

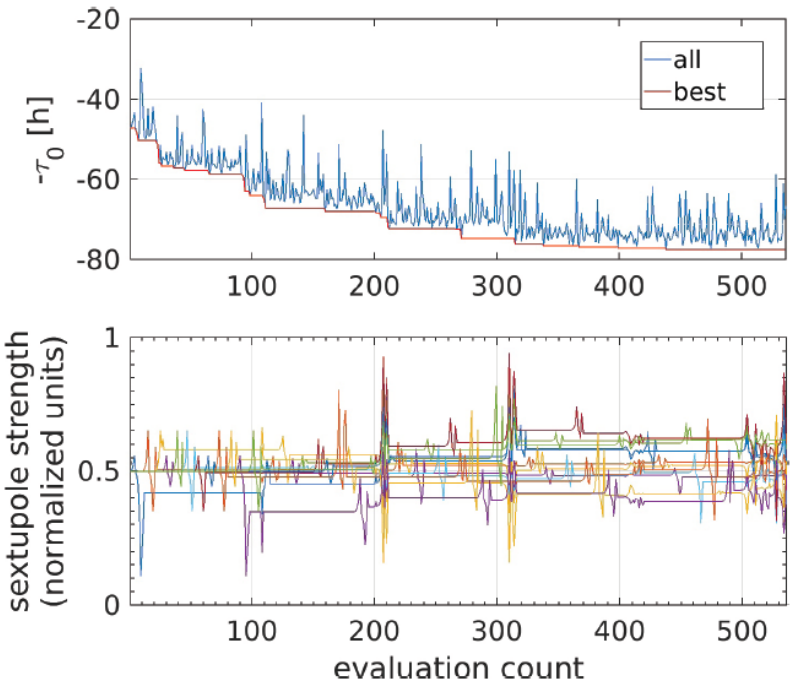
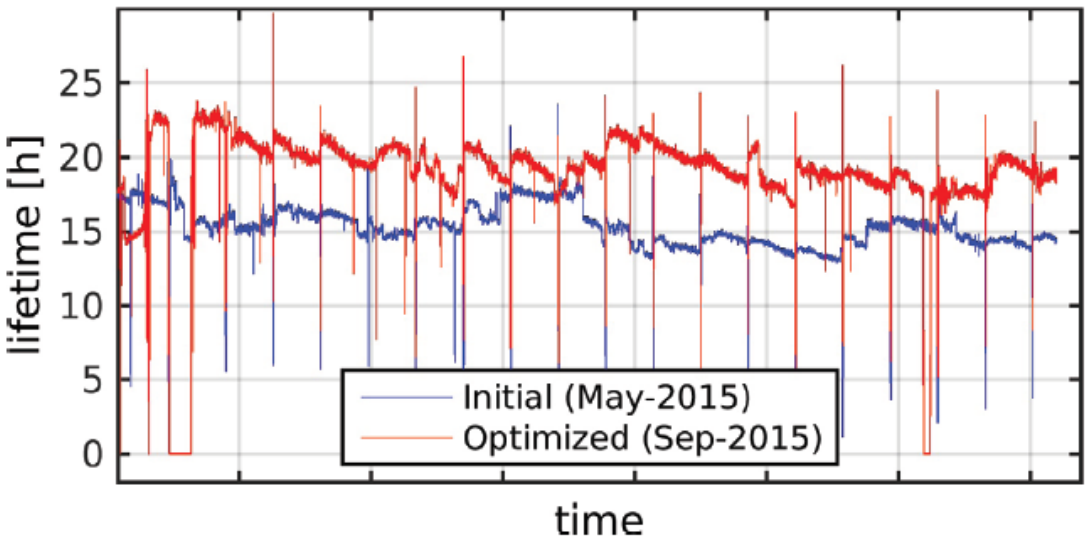


Figure 2: Optimization of lifetime using 12 sextupole correctors in 7/8+1 mode.



Lifetime for the 16-bunch mode in one month before and after optimization.

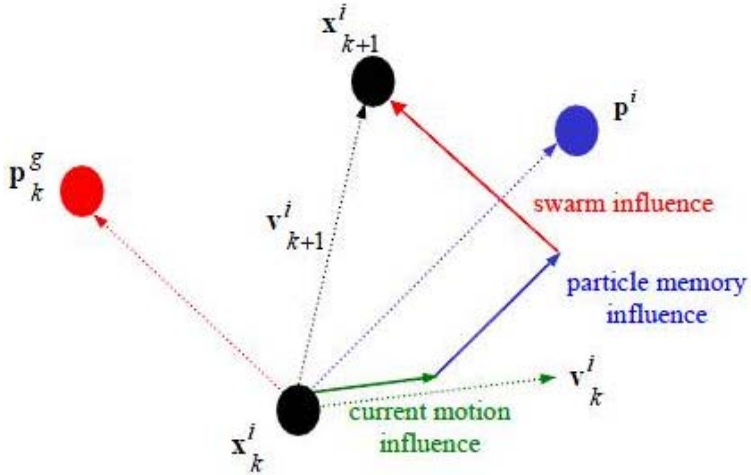
Objective: lifetime normalized by current, bunch length, and vertical size (average over 13 beam size monitors)

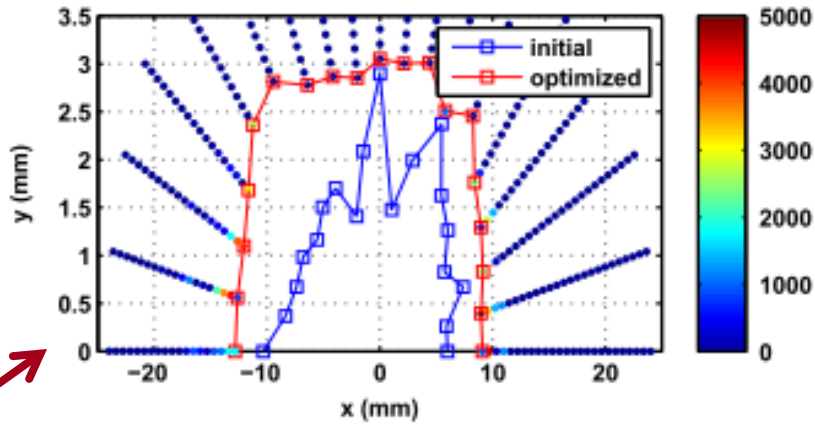
$$\tau_0 = \tau \frac{I}{I_0} \frac{BL(I_0)}{BL(I)} \frac{\sigma_{y,0}}{\sigma_y}$$

S. M. Liuzzo, et al, IPAC'16, THPMR015

Particle Swarm Optimization (PSO)

- Invented ~1995; first accelerator application ~2014[1]
- Multiple solutions swarm through parameter space
- Individual solution velocity evolves from
  - **Solution present velocity**
  - **Best past individual solution**
  - **Best past swarm solution**



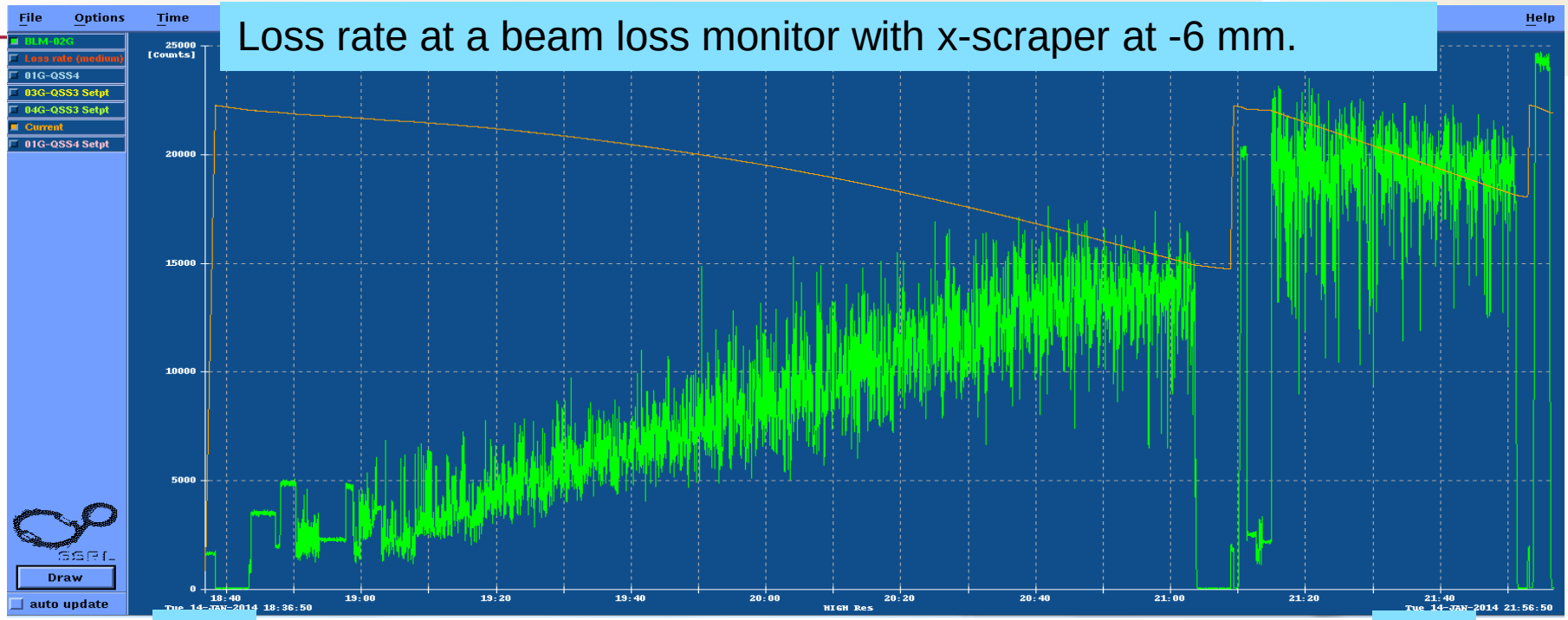


- X. Huang applied to numerical dynamic aperture optimization

[1]*X. Pang, L.J. Rybarcyk, NIMA, 2014*

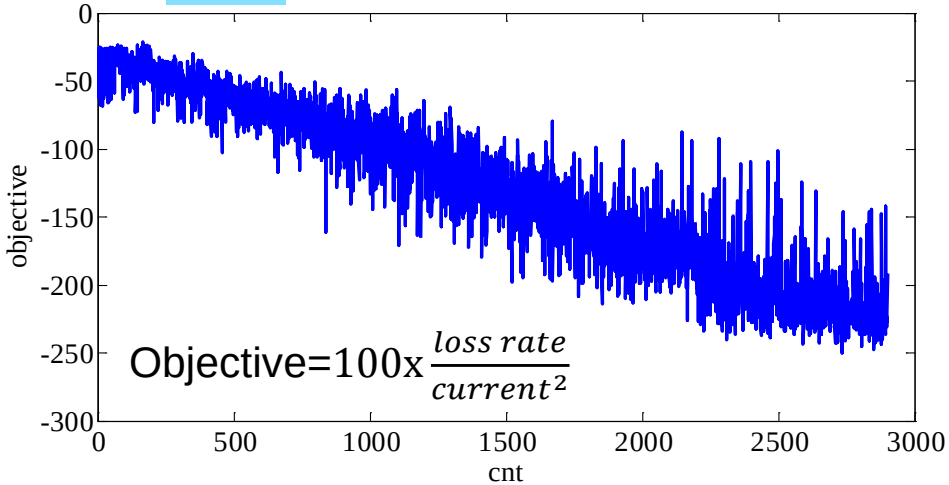
Coupling correction with PSO – experiment

Loss rate at a beam loss monitor with x-scraper at -6 mm.



18:40

21:40



After optimization, for the best solution, at 500 mA, the lifetime is 3.78 hrs.
LOCO data showed that coupling ratio is 0.029%, lowest on SPEAR3.

The experiment took less than 3000 evaluations.

The Extremum Seeking (ES)* method

- The ES method is theoretically elegant.

$$p_1(n+1) = p_1(n) + \Delta\sqrt{\alpha\omega_1}\cos\left(\omega_1\Delta n + k\hat{C}(n)\right)$$

$$p_2(n+1) = p_2(n) + \Delta\sqrt{\alpha\omega_2}\cos\left(\omega_2\Delta n + k\hat{C}(n)\right)$$

$$\vdots$$

with $\hat{C}(n) = C(\mathbf{p}(n), t) + \nu(t)$ ← noise

The optimization parameters (knobs) are rotated with various frequencies and amplitudes, and subject to modulation by the cost function.

At the high frequency limit, the behavior approaches that of a gradient descent method

$$\frac{d\mathbf{p}(t)}{dt} = -\frac{k\alpha}{2}\nabla C^T(\mathbf{p}(t), t)$$

Pros: (1) noise is averaged out; (2) a simple and general framework; (3) can dynamically track the optimum.

Cons: (1) algorithm control parameters are problem specific and need tuning;

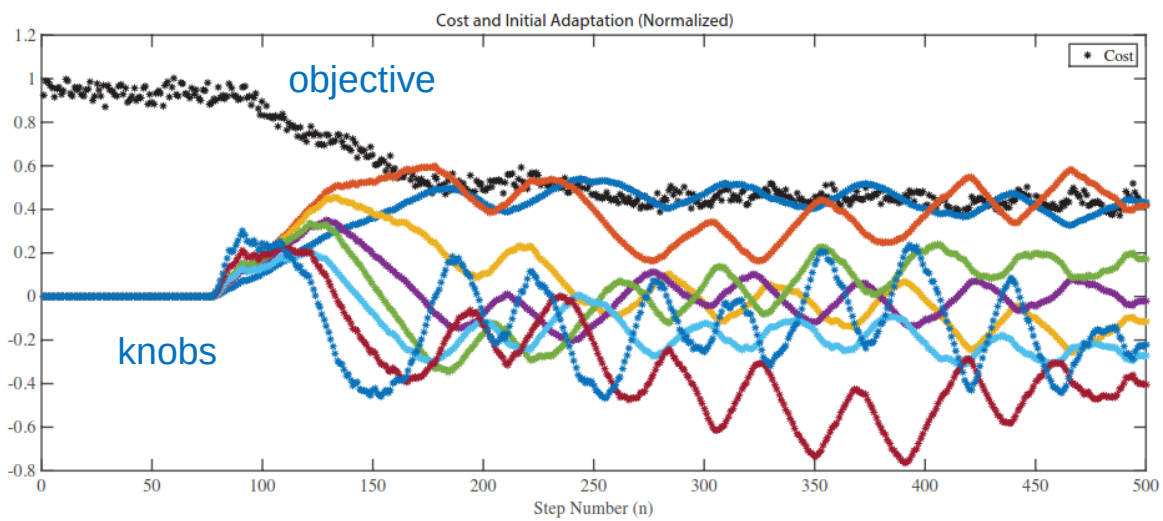
(2) may not be as efficient as other direct search method (e.g. RCDS, simplex);

(3) Parameter update rate is bounded, but parameters are not.

*A. Scheinker, M. Krstic, IEEE Trans. Automatic Control, 58, 1107 (2013).
A. Scheinker, M. Krstic, Systems & Control Letters, 63, 25 (2014)

Test of the ES method on SPEAR3*

The problem: injection kicker bump matching
Knobs: pulse amplitude, width, and delay of K1 and K2, and two skew quads – 8 knobs total.
Objective: residual oscillation of stored beam



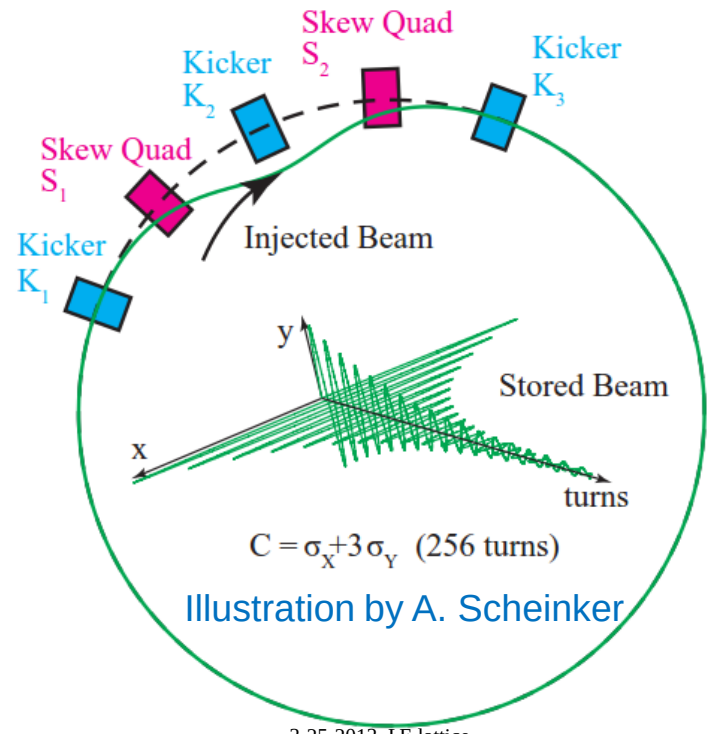
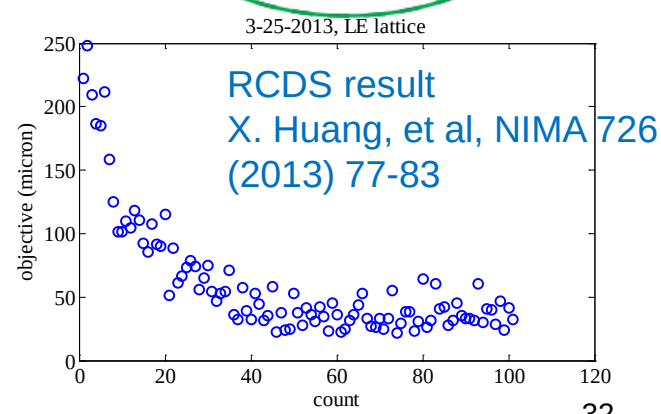


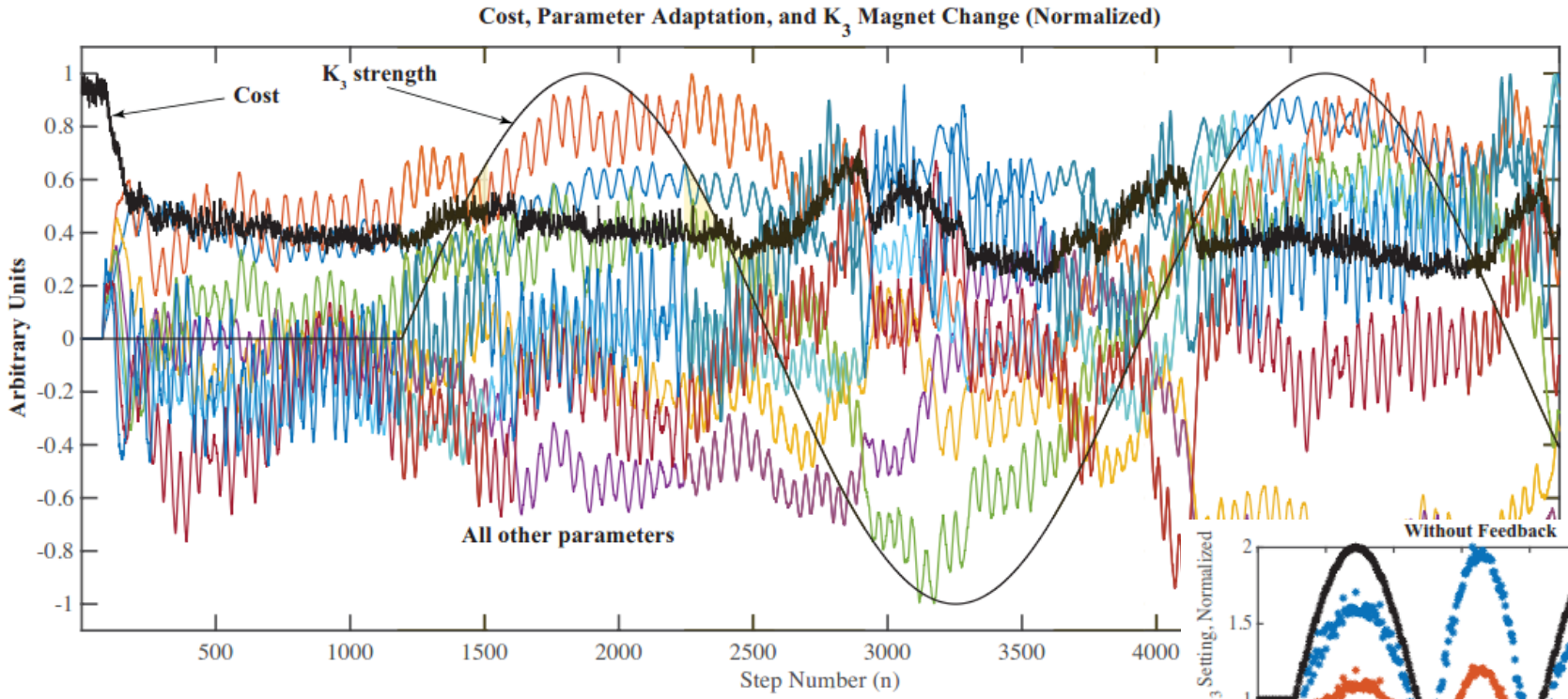
Illustration by A. Scheinker



*A. Scheinker, X. Huang, J. Wu, SLAC-PUB-16508 (2016)

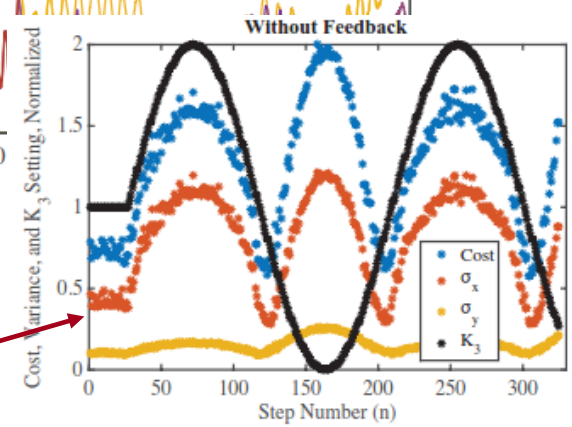
ES – dynamic tracking of the objective

In this test one parameter (K3 voltage, not an optimization variable) is varied, while the ES algorithm serves as a feedback to make compensation.



The ability to maintain performance with a drifting system is important.

If there is no ES feedback



Summary

- We are making good progress on beam-based nonlinear dynamics optimization which could be helpful with the commissioning and operation of ultra-low emittance storage rings. There are still some interesting challenges.

- **Thanks** to X. Huang & K. Tian for many of the powerpoint pages.

THAT'S ALL FOLKS!