

# Machine Based Optimization Using Genetic Algorithms in a Storage Ring

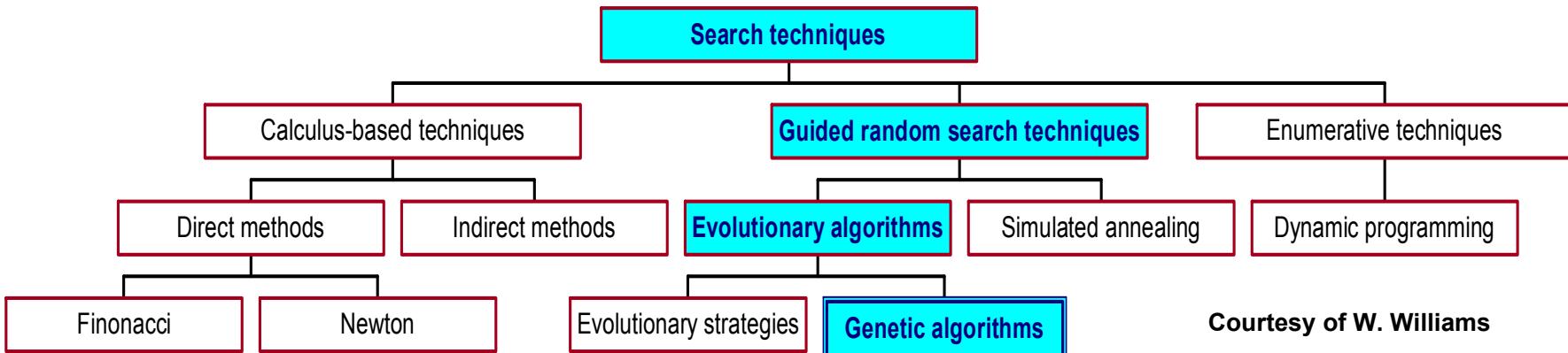
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# Genetic Algorithms

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- ❖ **Directed random** search algorithms based on the mechanics of biological evolution developed by Holland (1970's) and thoroughly reviewed by Goldberg (1980s).



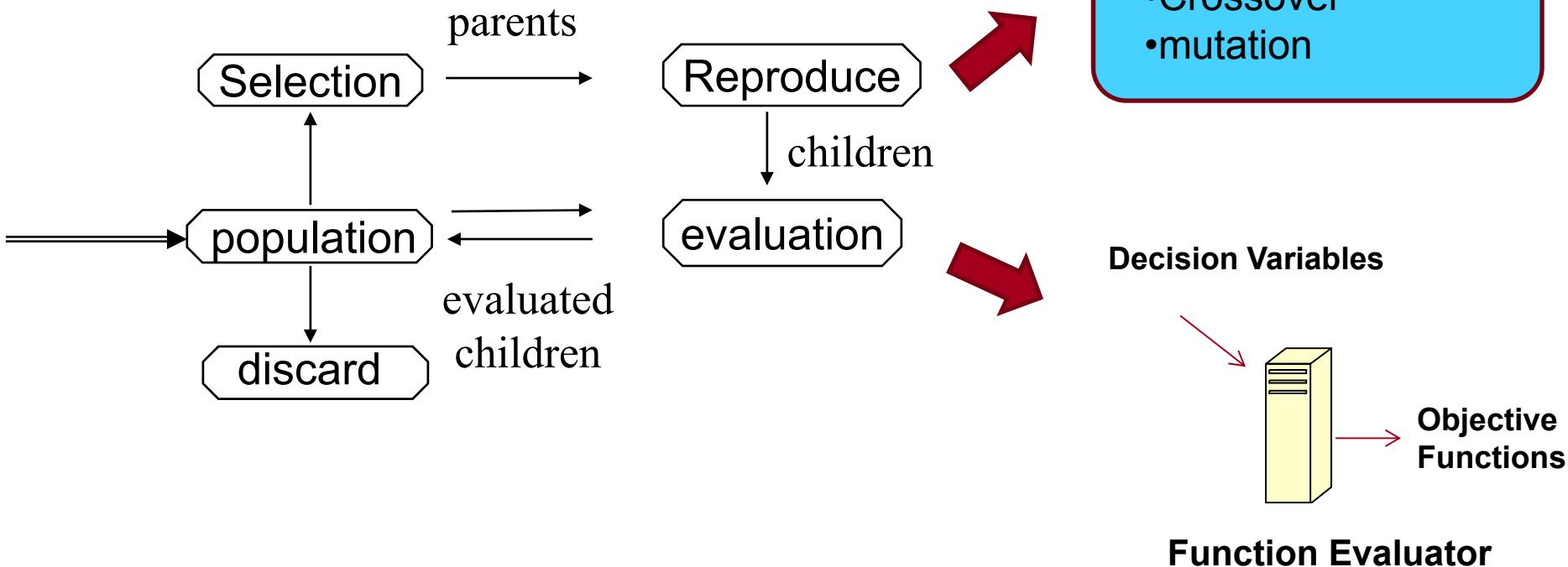
- ❖ **Features**

- ❖ Global search toward the optimum but usually computationally expensive;
- ❖ For multiple objective optimization, it provides a pool of solutions with trade off between different objectives;
- ❖ Especially suitable for problems with complex objectives functions.

# Machine Based Genetic Algorithm

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## Reproduction Cycle

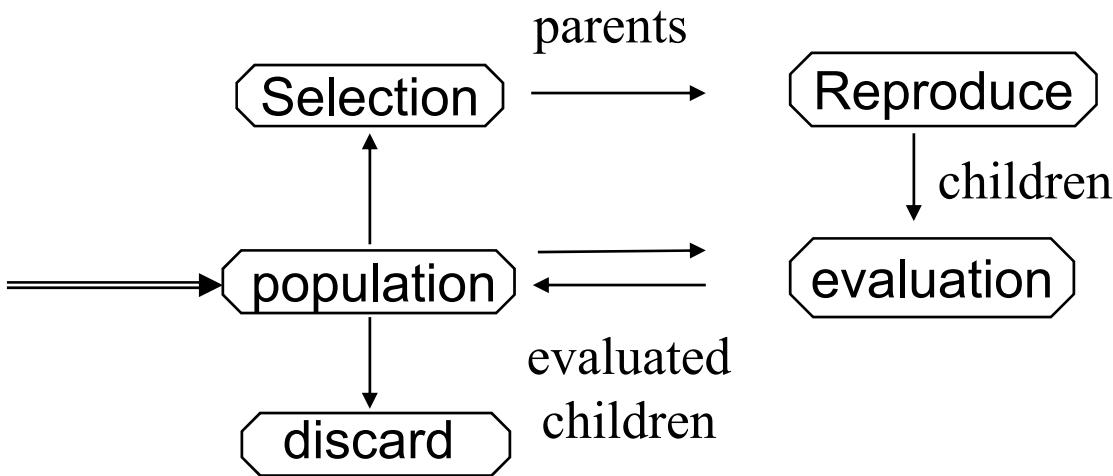


**Goal:** Experimental demonstration of the machine based Genetic Algorithm by minimizing vertical beam size by optimizing the 13 skew quads in SPEAR3.

# Machine Based Genetic Algorithm

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## Reproduction Cycle



Genetic Operations:

- Crossover
- mutation

Decision Variables



Function Evaluator

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

# Touschek Beam Loss and Vertical Beam Size

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

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

Minimize vertical beam size = Maximize Touschek beam loss

# Algorithm Formation (Derived from NSGA-II\*)

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population

120 individuals (chromosomes) per generation

*Chromosome= Decision Variables + Objective function +rank (15x1 array)*

Selection

Rank each individual according to the sole objective function

Reproduce

Real-coded Simulated Binary Crossover (SBX) and polynomial mutation

- ❖ *Mutation Ratio;*
- ❖ *Tuning parameter for crossover*
- ❖ *Tuning parameter for mutation*

evaluation

Direct measurement from BLM; the whole population is reevaluated every 10 generations.

\* K. Deb, A.Pratap, S. Agarwal, and T. Meyarivan, IEEE Transactions on Evolutionary Computation, Vol.6, No. 2, April 2002;  
<http://www.mathworks.com/matlabcentral/fileexchange/10429-nsga-ii-a-multi-objective-optimization-algorithm>

# Beam Loss Measurement

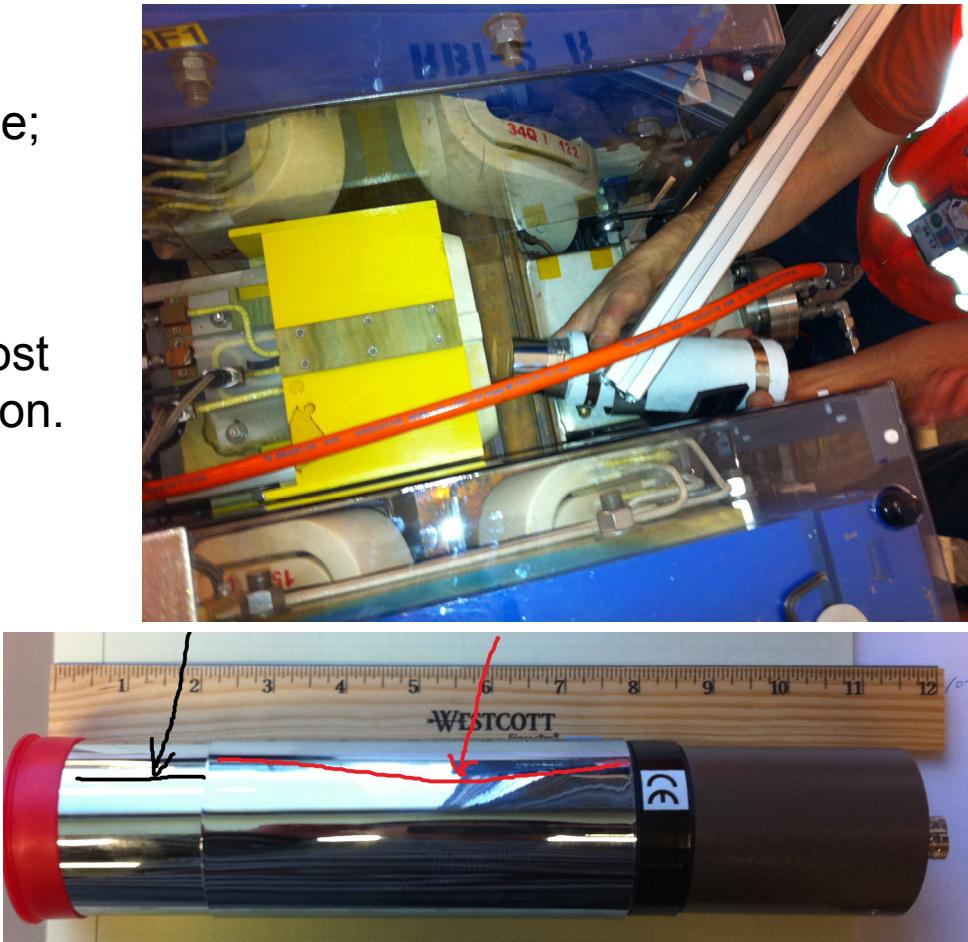
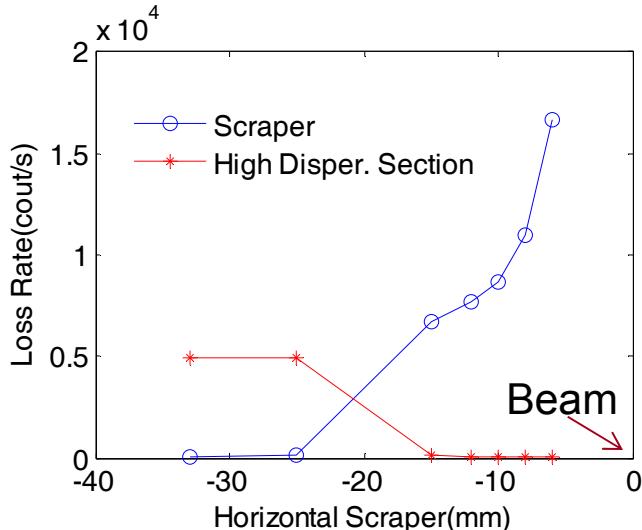
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## ❖ dc current transformer (DCCT):

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

## ❖ Beam Loss Monitor:

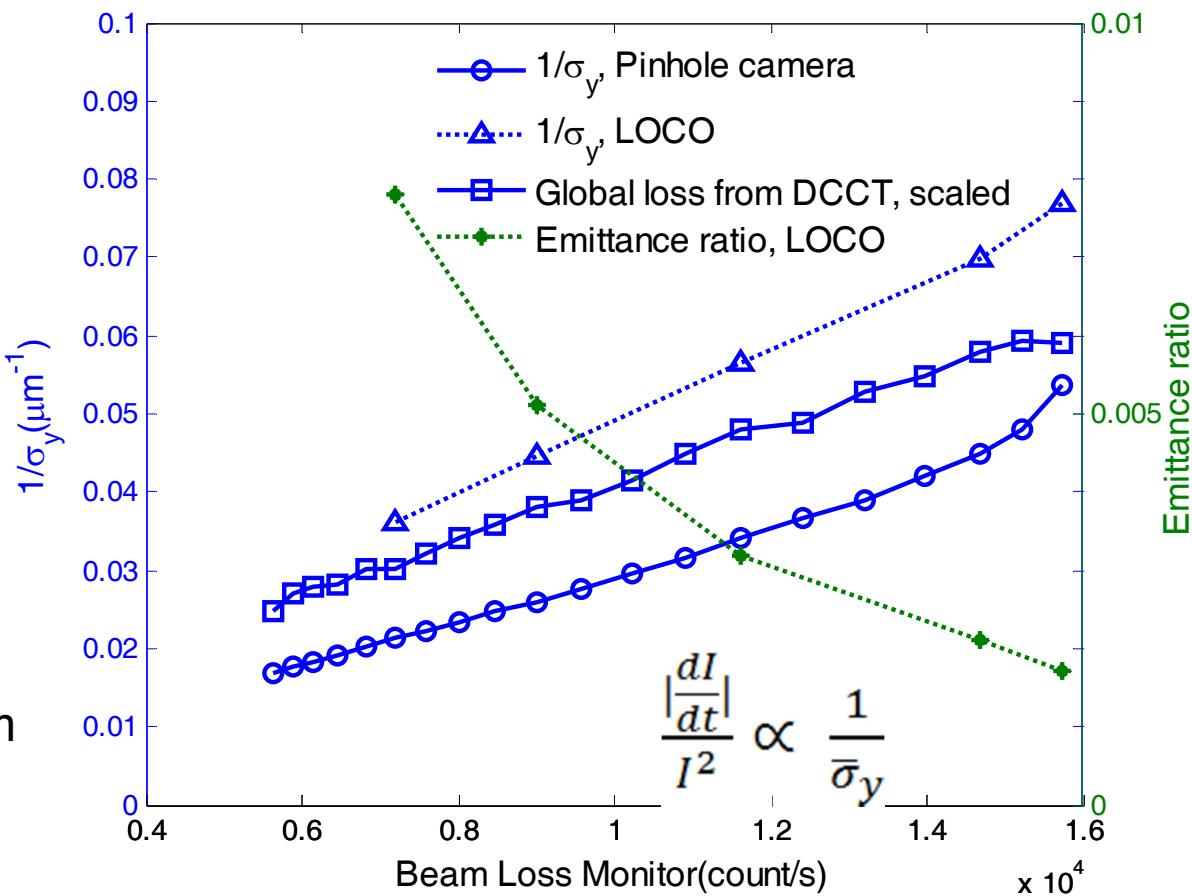
- ✓ NaI Scintillator with PMT tube;
- ✓ High SNR;
- ✓ Fast 1Hz rate;
- ✓ Local beam loss;
- ✓ Insert scraper to capture most of the beam loss at one location.



# Experimental Verification

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- ❖ 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

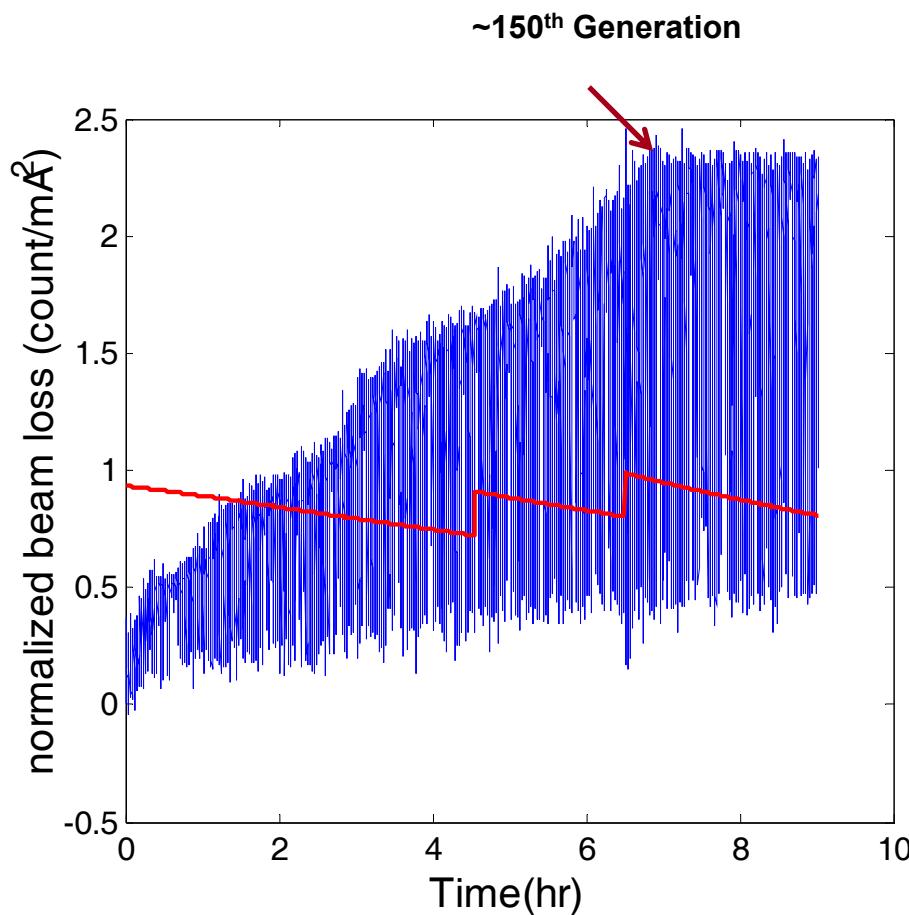


**Beam loss caused by tune shift or reduction of energy acceptance is not a major concern when varying the skew quads in SPEAR3.**

# Results

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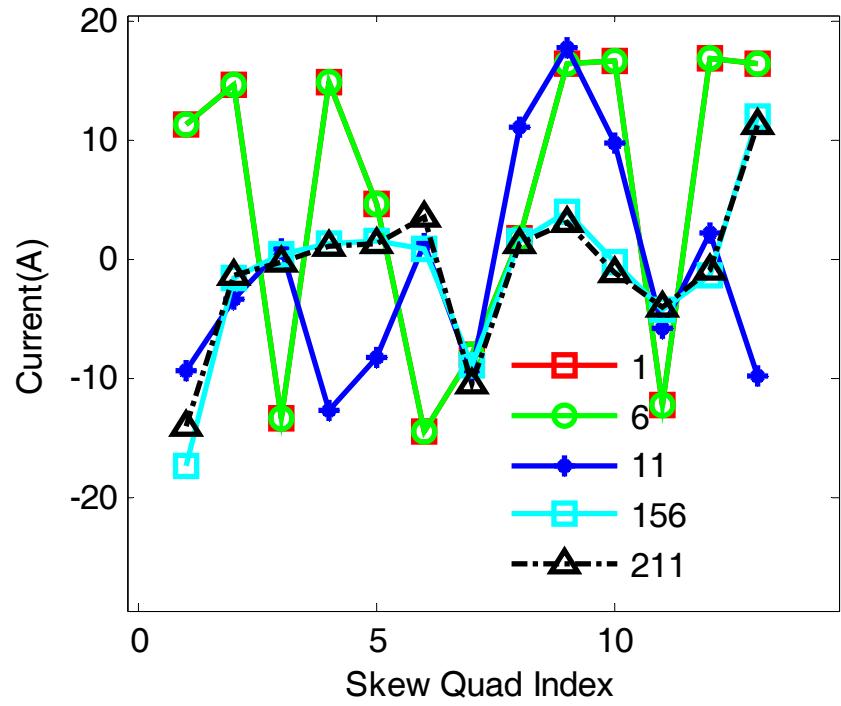
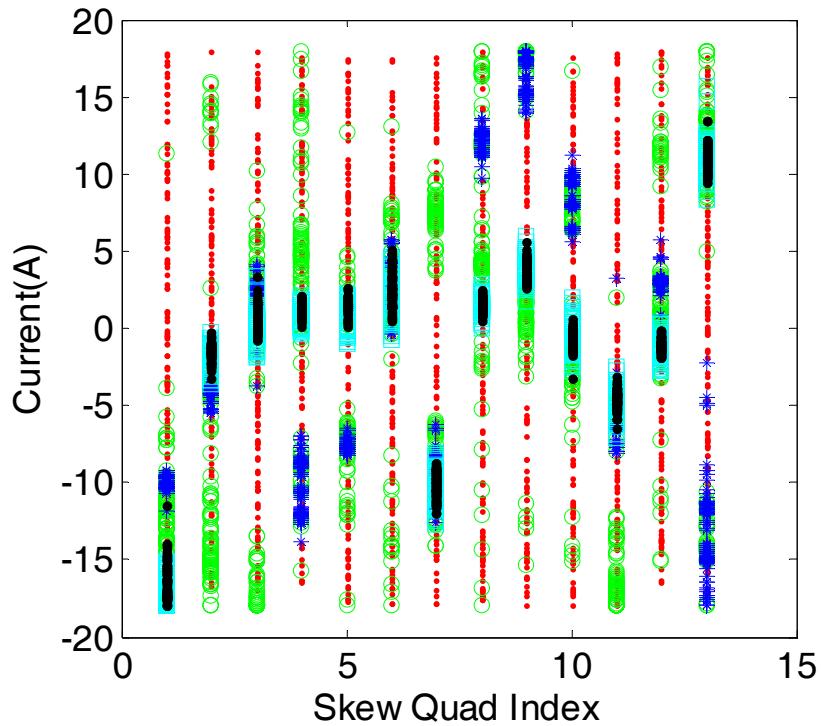
- ❖ 211 generations and about 9 hours in total (<3 minuets /generation);
- ❖ Refill the stored current to 100mA twice;
- ❖ The optimization was paused during the fill and restarted by loading the dumped data after the fill



# Results(cont.)

Red: 1; Green: 6; Blue: 11; cyan: 156; black: 211.

the best at selected generations

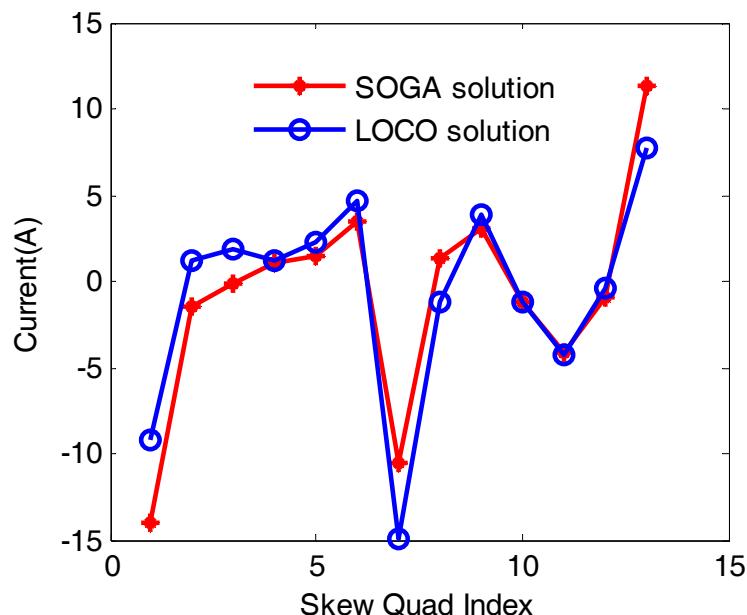


The solutions start to cluster at several regions rather than spread out in the whole hyperspace in the 6th and 11th generation. It appears that the final region of the solution is found in the 156<sup>th</sup> generation.

# Results(Cont.)

LOCO results vs. GA results

	LOCO	GA
$\bar{\sigma}_y$ ( $\mu\text{m}$ )	7.9617	7.087
Emittance Ratio	0.0605%	0.0461%
Normalized Loss rate	2.07	2.44



- ❖ LOCO results: LOCO correction to minimize the off diagonal terms in ORM and the vertical dispersion;
- ❖ GA results are better but cost a lot of time: 9 hours vs. 30 minutes;
- ❖ LOCO results could be improved;
- ❖ GA will show more advantage for bigger machine with more magnets or more complex problems.

# Summary

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- ❖ Benefit from the fast ramping power supply of the skew quads and instantaneous beam loss measurement from BLM, we have successfully demonstrated machine based GA;
- ❖ Future refinement to the algorithm may improve the speed and performance:
  - ❖ Hybrid technique to improve the local optimization speed;
  - ❖ MOGA based GA;
- ❖ Machine based GA can be more useful for optimizing objectives expensive for simulation but easy to measure in large machines such as the luminosity of LHC or DA optimization of PEPX using sextupoles.