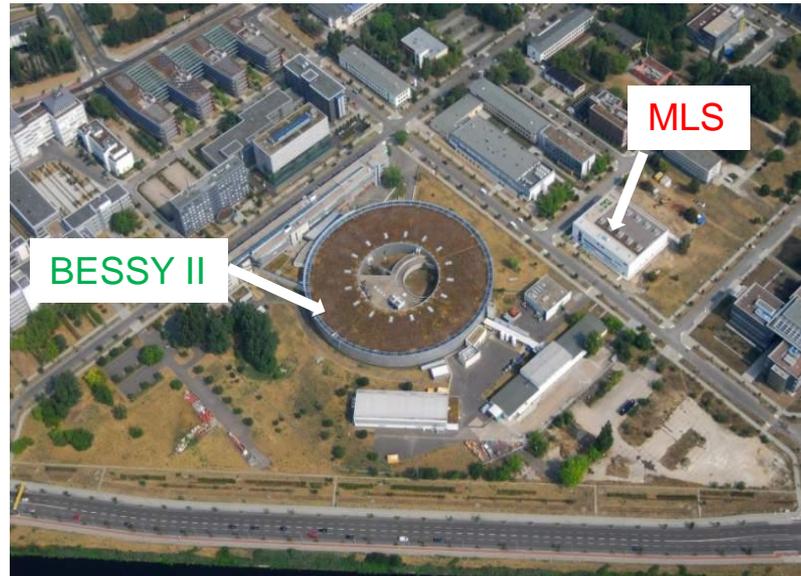


Lifetime improvement with Particle Swarm Optimization algorithm applied at the MLS and BESSY II

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- Motivation of lifetime optimization
- Possible methods to optimize lifetime
- Introduction of Particle Swarm Optimization(PSO)
- Experiments
- Conclusion and outlook



Main Parameters

MLS

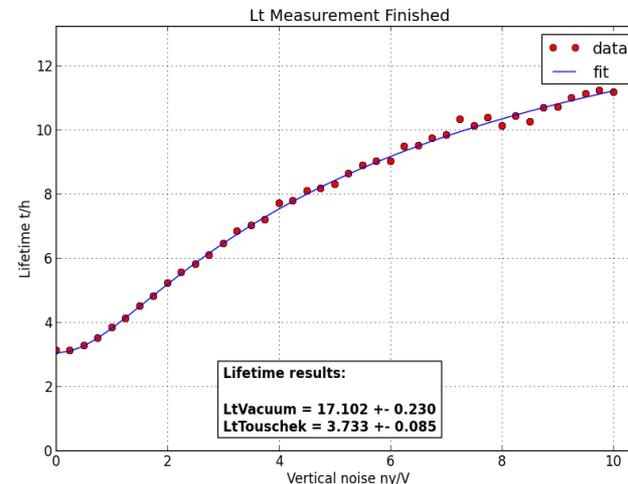
BESSY II

Lattice :	4 DBA	16 DBA
Circumference:	48 m	240 m
Electron energy:	630 MeV	1.72 GeV
RF frequency:	500 MHz	500 MHz
Injection energy:	105 MeV	1.7 GeV(top-up)
Emittance @ standard user :	~100 nm rad	5 nm rad
@ low emittance :	~25 nm rad	

- Low emittance mode of the MLS:
 - Lifetime: 1.5 h @ 150 mA due to small beam size
 - To have even smaller beam size
- BESSY II:
 - Lifetime: 5.7 h /3.7 h @250 mA standard w/o vertical excitation
 - Mandatory for top-up injection
 - Possibility to improve the brilliance
- How?:
 - To adjust the sextupoles to optimize the dynamic aperture

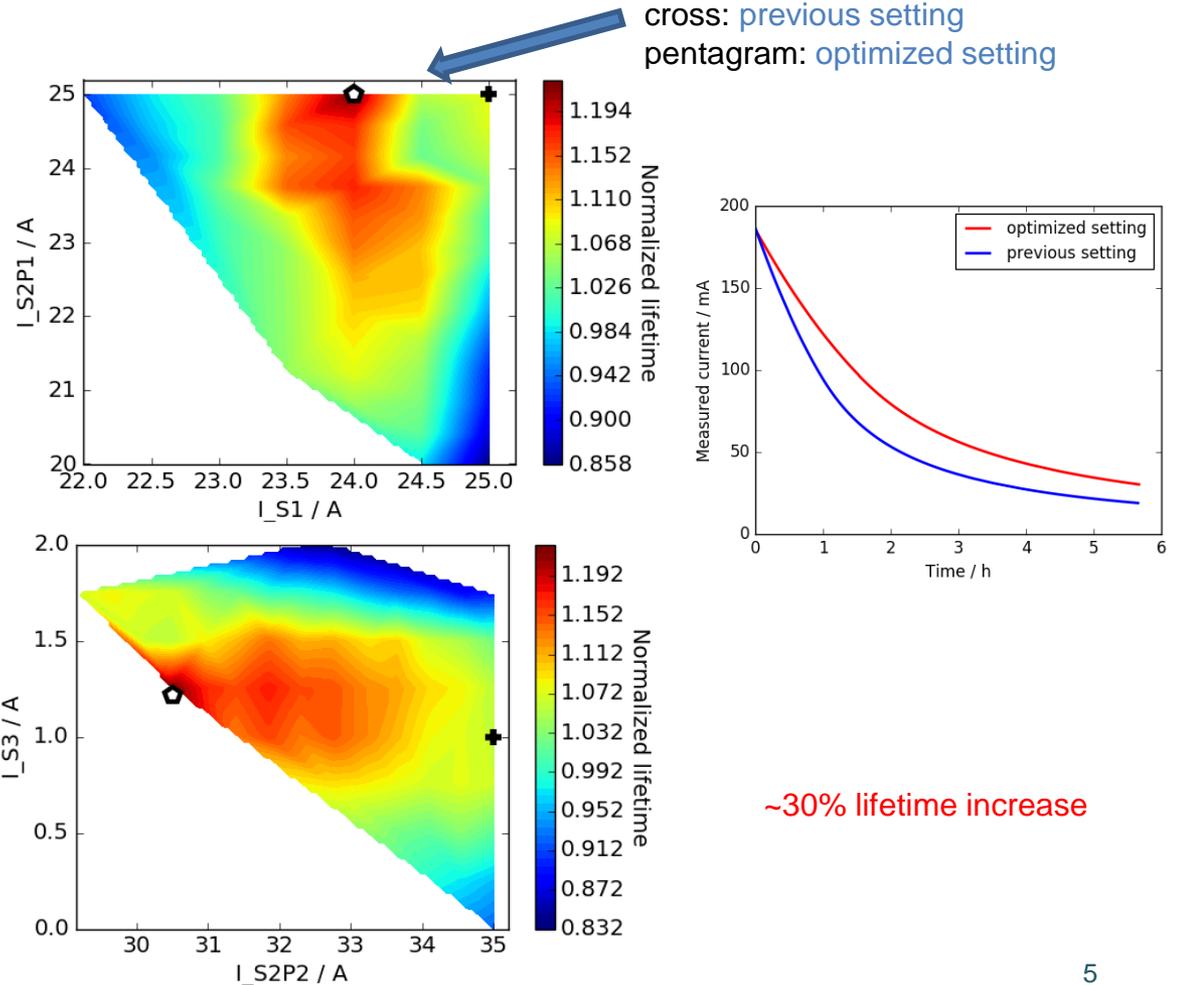
$$\frac{1}{\tau} = \frac{1}{\tau_{\text{touschek}}} + \frac{1}{\tau_{\text{gas}}}$$

- Why beam-based?:
 - Models hardly agree with machines
- Requirement:
 - Fast, robust, easy to implement



- Manual tuning
 - Local information, requiring skills and deep knowledge of machine
- Global scan: make grids in the N-dimensional space, scan all possible solutions in the grids
 - Suitable: knobs < 4 , slow
 - Overall information: Map
 - MLS : 4 sextupole families (details in slide 12)

Name	S	Setpoint	Readback	Mem	C
S1P1RP	●	23.000000	23.003	20.496300	[S] [R]
S1P2RP	●	23.000000	23.006	20.496300	[S] [R]
S2P1RP	●	25.000000	25.006	23.961800	[S] [R]
S2P2KRP	●	27.000000	26.988	34.000000	[S] [R]
S2P2LRP	●	27.000000	27.018	34.000000	[S] [R]
S3P1RP	●	0.000000	0.005	0.000000	[S] [R]
S3P2RP	●	0.000000	-0.001	0.000000	[S] [R]



How to deal with higher-dimensional problems?

- Numerical optimization methods for functions:
 - Noise
 - Efficiency: many iterations
- Robust Conjugate Direction Search(RCDS):
 - Conjugate direction search+Line optimizer
 - X^N problem to $X * N$ problem
 - Noise consideration and outlier deletion
 - Efficient if the initial conjugate direction set is prepared
- Metaheuristic algorithms: genetic algorithm (GA),
particle swarm optimization(PSO)

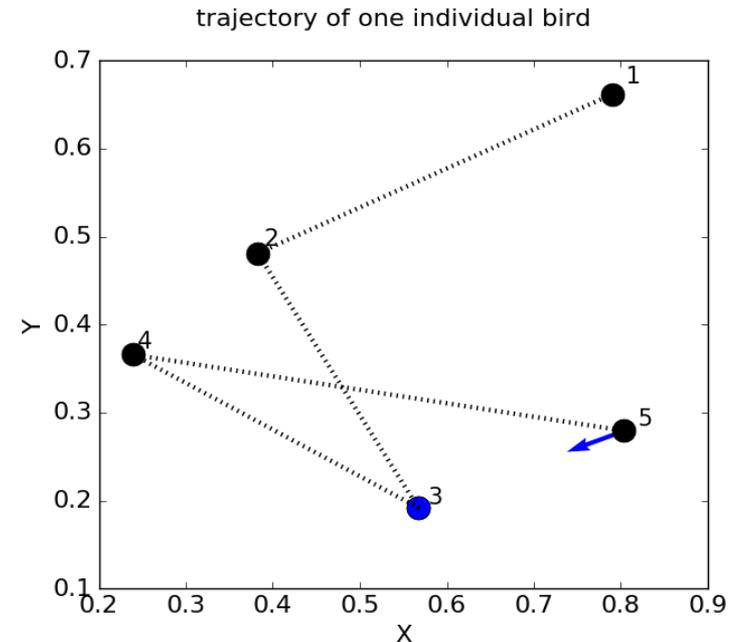
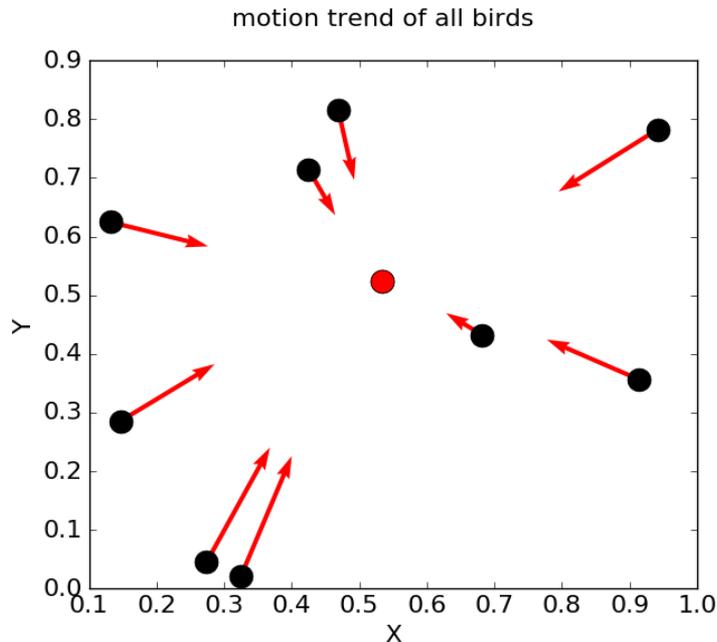
Name	S	Setpoint	Readback	Mem	C
S1PR	●	88.6272	88.578	88.6272	
S2PDR	●	72.6533	72.640	72.6533	
S2PTR	●	72.6533	72.639	72.6533	
S3PDR	●	39.9495	39.911	39.9495	
S3PTR	●	39.9495	39.934	39.9495	
S4PDR	●	31.1680	31.121	31.1680	
S4PTR	●	31.1680	31.119	31.1680	
S3PD1R	●	39.9495	40.13	39.9495	
S4PD1R	●	31.1680	31.45	31.1680	
S3P1T6R	●	39.9495	40.20	39.9495	
S3P2T6R	●	39.9495	39.97	39.9495	
S4P1T6R	●	31.1680	31.30	31.1680	
S4P2T6R	●	31.1680	31.24	31.1680	

- **Particle Swarm Optimization** is a population-based optimization method, like GA
 - Initialized with a population of random solutions in the search space
 - Searching for optima by updating population iteratively
- Easy to understand and implement
- Fast convergence*:
 - The program will find a better solution very quickly
- Not sensitive to population size*:
 - Experimental time matters a lot

* Yuhui Shi, Russell Eberhart. Empirical study of particle swarm optimization. Proc. IEEE Congr. Evol. Comput., 1999



- Developed by Dr. Eberhart and Dr. Kennedy in 1995
 - To simulate the behavior of bird flocking
- Scenario:
 - A group of flying **black** birds searching the only one piece of food in certain space
 - Every bird does not know where the food is
 - The bird closest to the food turns **red** and can be recognized and replaced by others(**gbest**)
 - The birds have memory, every bird marks the best position in its flightpath with **blue** color(**pbest**)
 - **All other birds following the red bird** and **influenced by the blue positions** until the food is found



- How the particles move in the algorithm:
 - Each particle is the bird in the swarm
 - Velocity directing the flight of the particles (where to go and how far)
 - Velocity and position update through Eq. a and Eq. b iteratively

velocity update

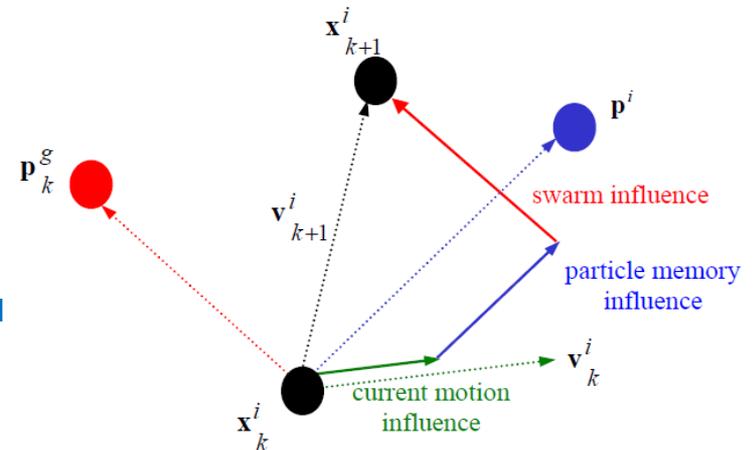
$$v(k+1) = w * v(k) + c1 * rand() * (pbest - x(k)) + c2 * rand() * (gbest - x(k)) \quad (a)$$

position update

$$x(k+1) = x(k) + v(k+1) \quad (b)$$

w : inertia factor, how much to follow the previous motion
c1 : cognitive factor, leaning from its personal best fitness (**pbest**) in the memory
c2 : social learning factor, leaning from global best fitness (**gbest**) in the swarm

w, c1 and c2 should be properly chosen to balance fast convergence and the ability to cover more space in the search



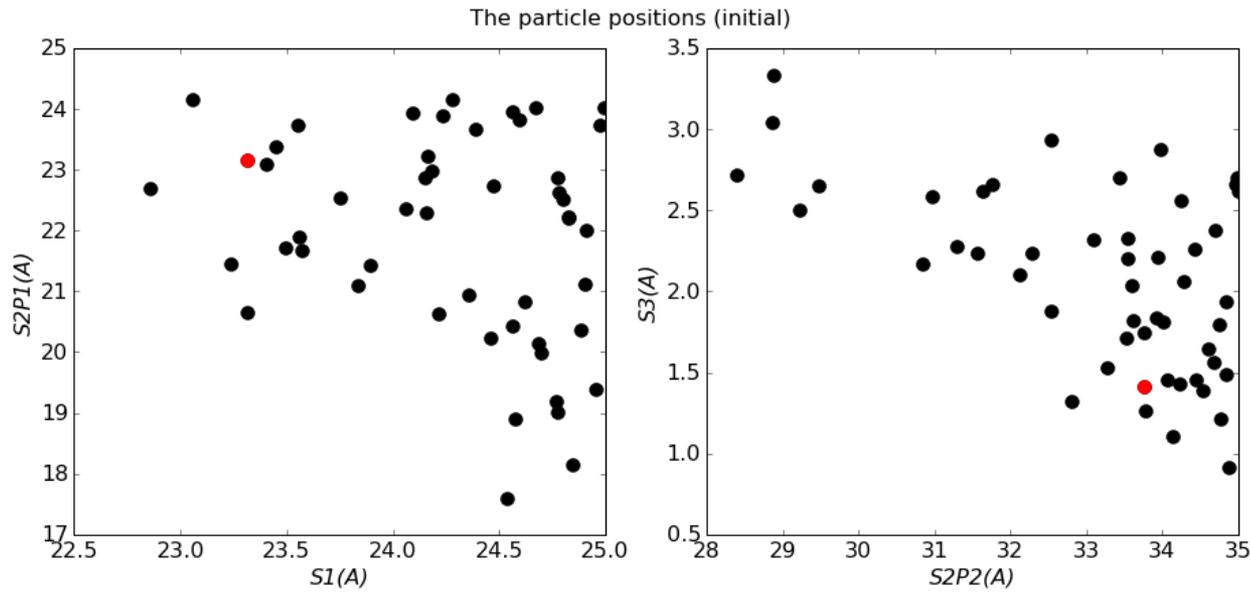
Hassan etc . "A Comparison of Particle Swarm Optimization and the Genetic Algorithm." *American Institute of Aeronautics and Astronautics* (2005)

```
For each particle
  Initialize particle's position, velocity randomly in the search space
  Position: sextupole setting
END

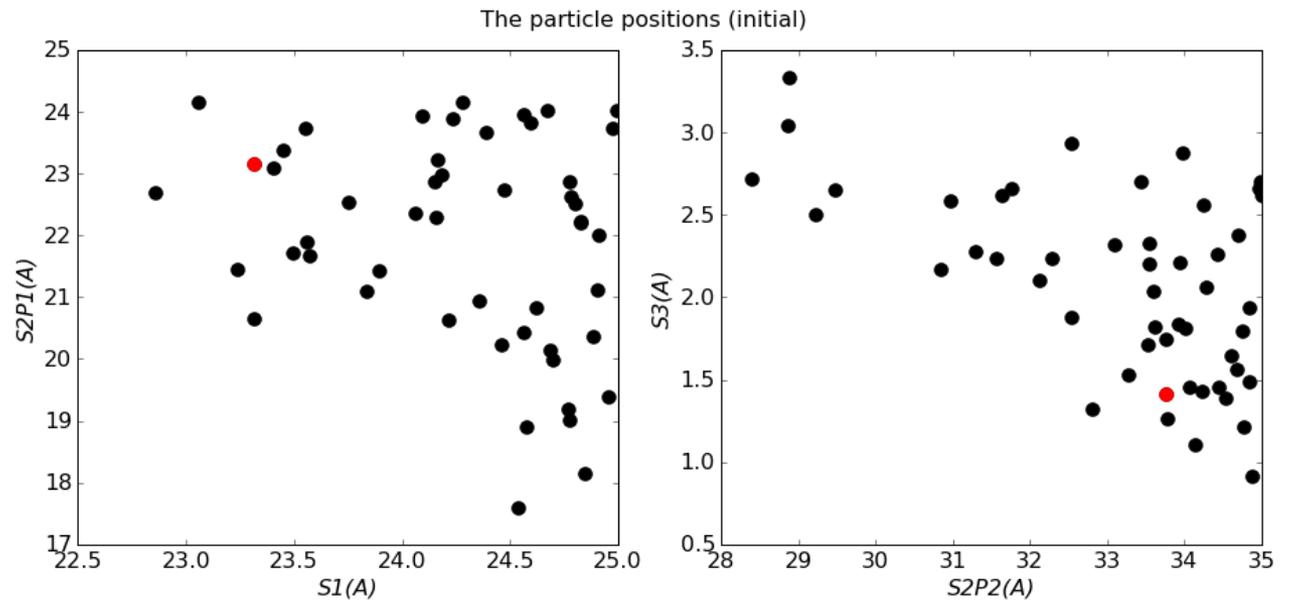
Do
  For each particle
    Calculate fitness value: Lifetime
    If the fitness value is better than its personal best
      set current value as the new pbest
  End

  Choose the particle with the best fitness value of all as gbest

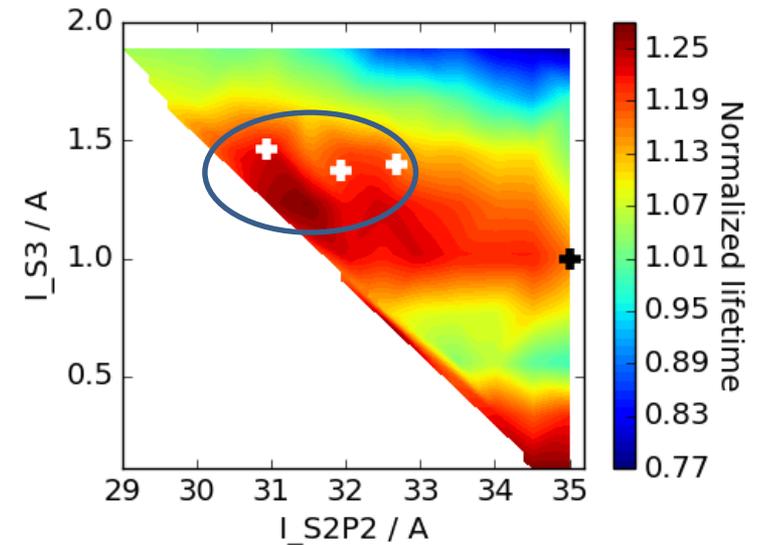
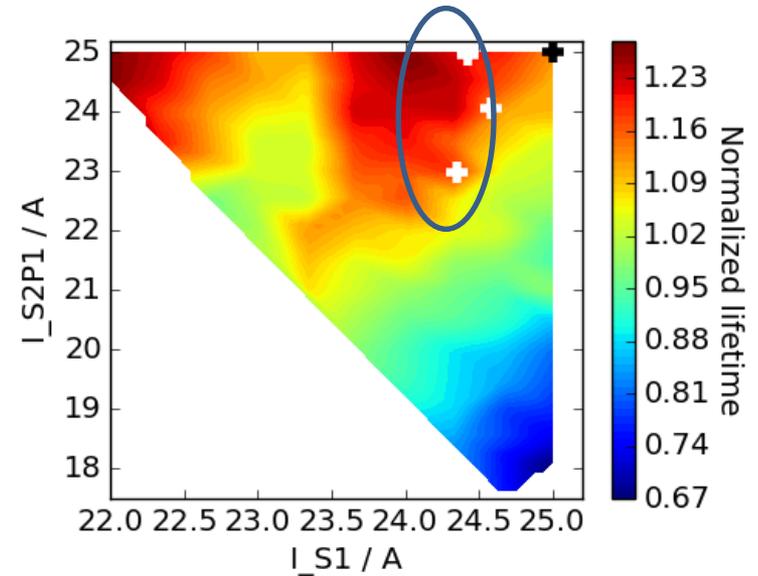
  For each particle
    Calculate particle velocity according equation (a)
    Update particle position according equation (b)
      to get new sextupole setting
  End
While maximum iterations or minimum error criteria is not attained
```



A simulation example

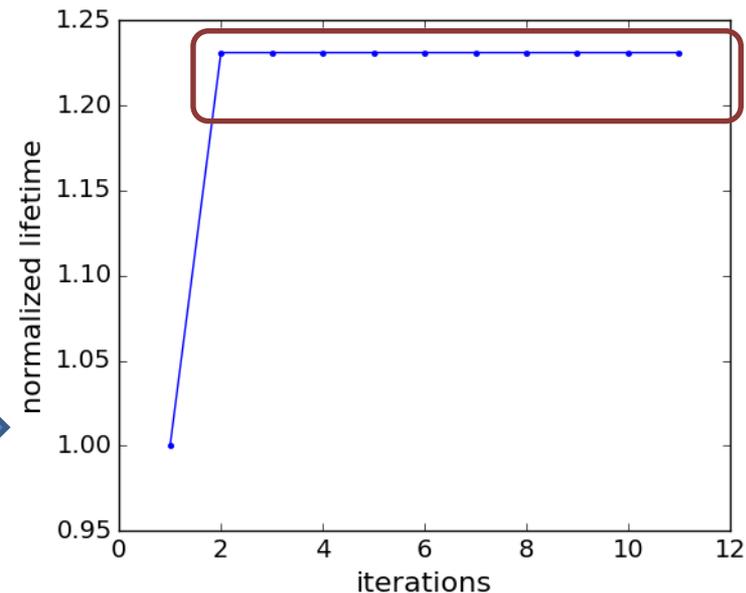
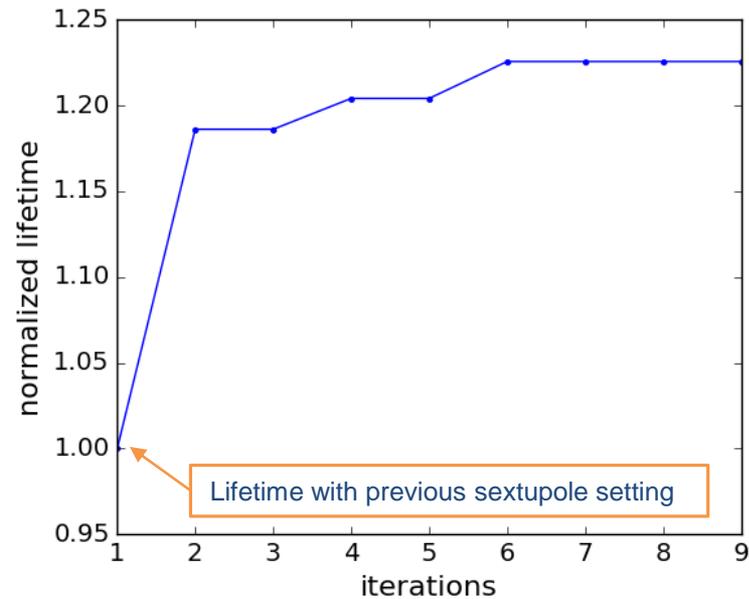
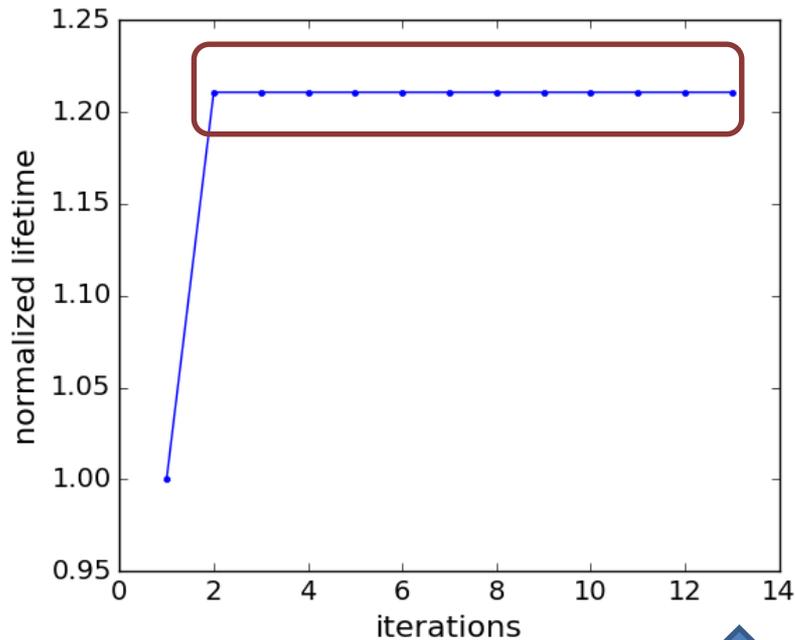


- Variables, fitness and constraint
 - S1, S2P1, S2P2, S3 to vary
 - Single bunch: focus on the Touschek effect
 - Fitness value: normalized 1% lifetime
 - Chromaticity : $\xi_{i_X} > 0.15, \xi_{i_X} > 0.15$
- Global scan: 4D
 - stepsize= 0.3 A, 440 solutions in total
 - ~2.5 h scan time: current, step size relevant
 - Black cross: previous setting
- PSO:
 - 15 particles
 - 0.5 h run time for 10-14 iterations
 - White crosses: PSO optimized settings
- Comparison:
 - Global scan provides overall information
 - PSO is faster, but not unique
 - Beam size stable in the optimization



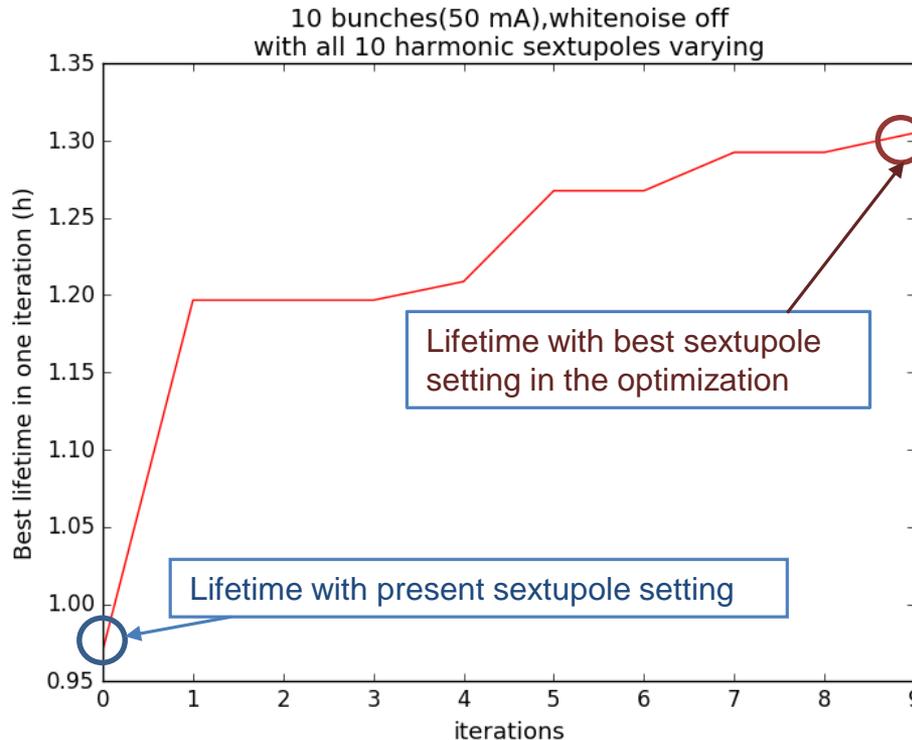
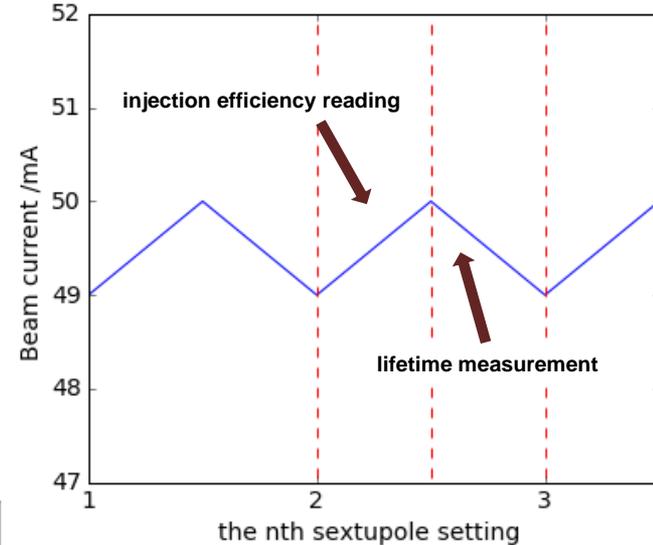
Three runs:

- Maximum 15 iterations:
- >20% lifetime increase achieved



Inertia component plays the major role, C1 and C2 should be tuned !!

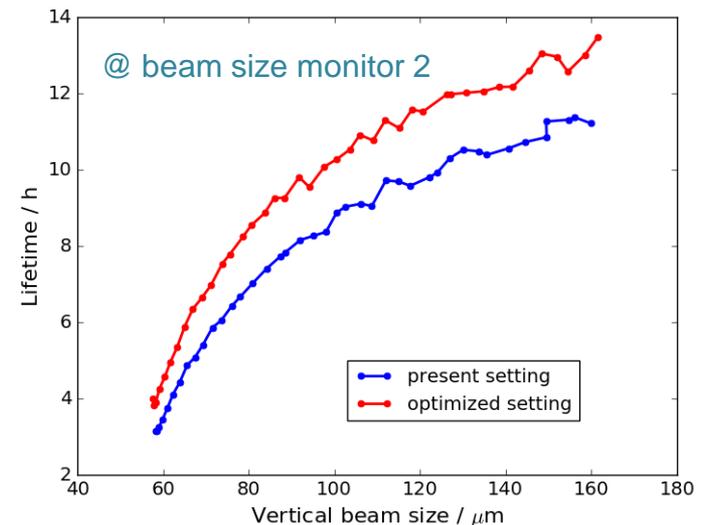
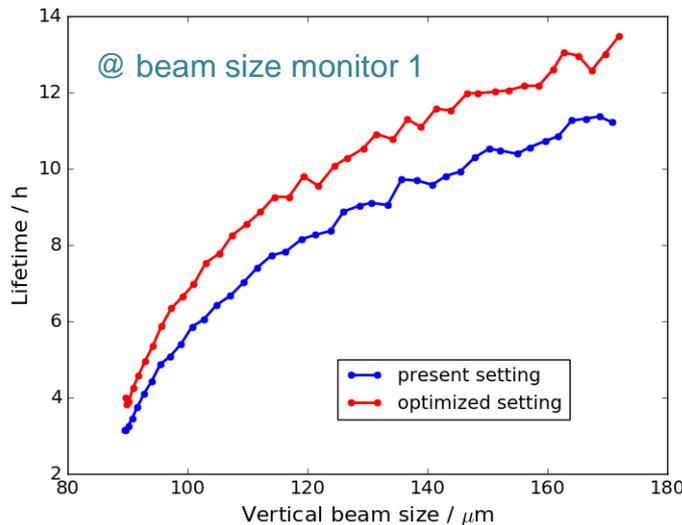
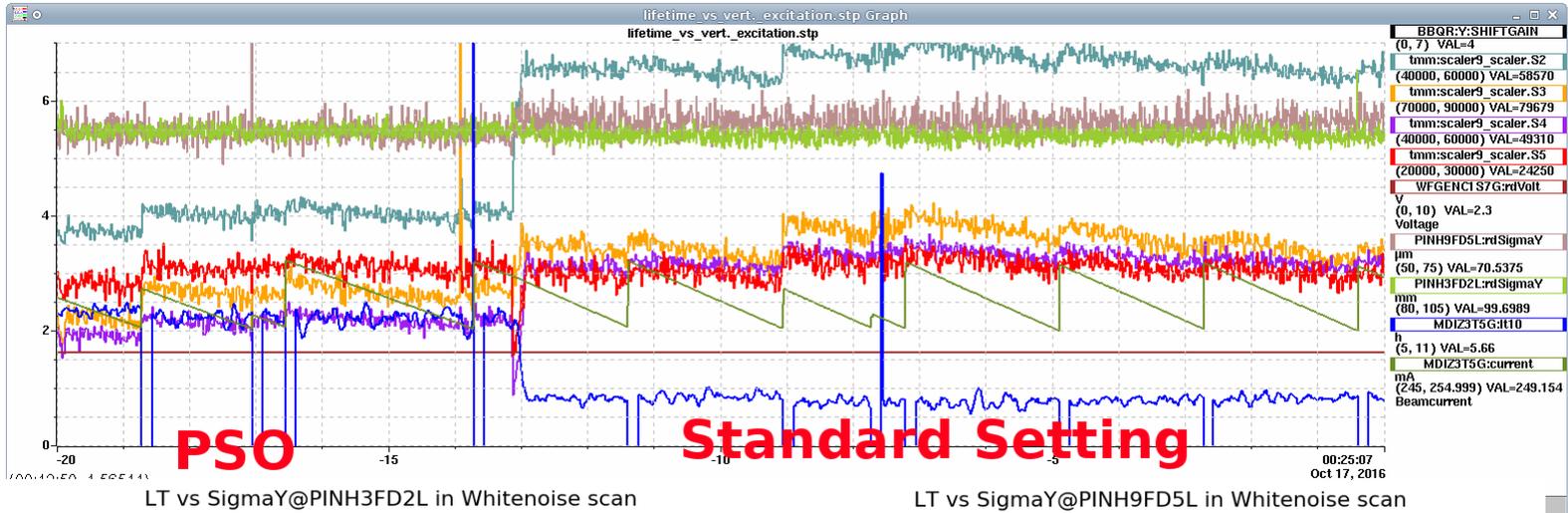
- All 10 harmonic sextupoles: for EMIL optics
 - 10 bunches, 50 mA, vertical excitation off
 - Injection efficiency as the constraint: > 90%
 - 49mA to 50mA: injection efficiency average
 - 50mA decaying to 49mA: lifetime measurement
 - 35 particles, **315 settings** tried in **9 iterations**: ~8h



New sextupole setting uploaded in standard user operation

- Lt increase: 21%
- Touschek LT increase: 25%

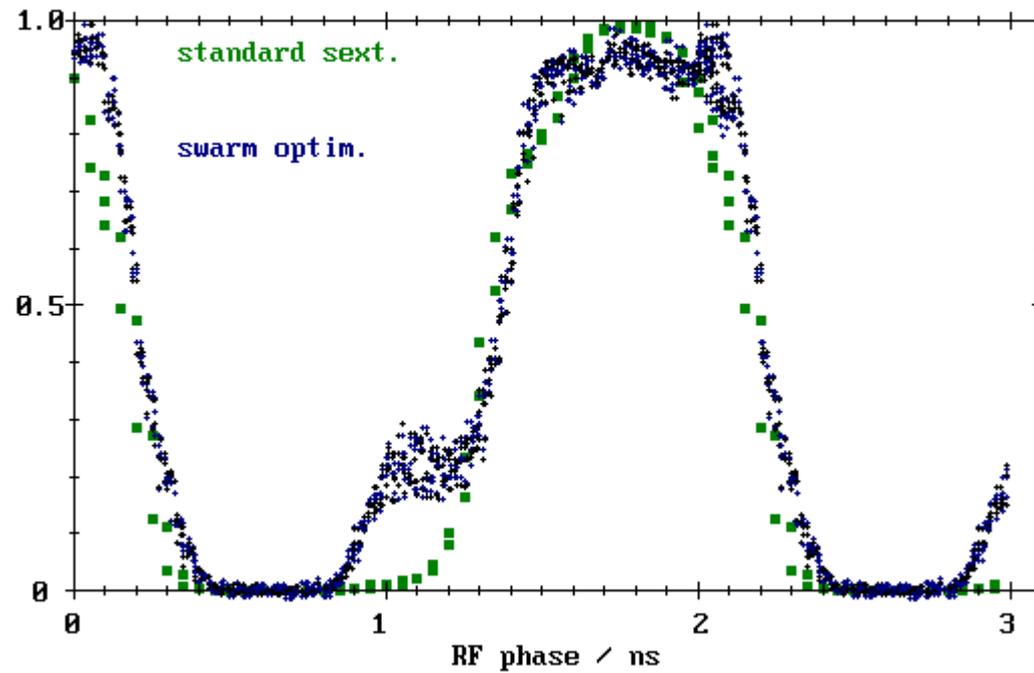
	LT/h	Touschek LT/h	PINH3 σ_y	PINH9 σ_y
PSO	6.9	4.67	99.5 μm	69.5 μm
Present	5.7	3.74	99.3 μm	69.9 μm



norm005.BMP

optSext1.txt

injection efficiency vs. RF-phase difference
between synchrotron and storage ring



An large outlier in fitness value may lead the particles to wrong direction.

- MLS:
 - statistic error in the measurement: **pbest** or **gbest** only update when they are larger than the old value at least 3σ , σ :statistic error
 - Error may be introduced in the lifetime normalization
 - Do the measurement in the high current case, larger signal-to-noise ratio
- BESSY:
 - Errors in the injection efficiency reading: good setting maybe filtered
 - 50mA decaying to 49mA makes the statistic error ignorable

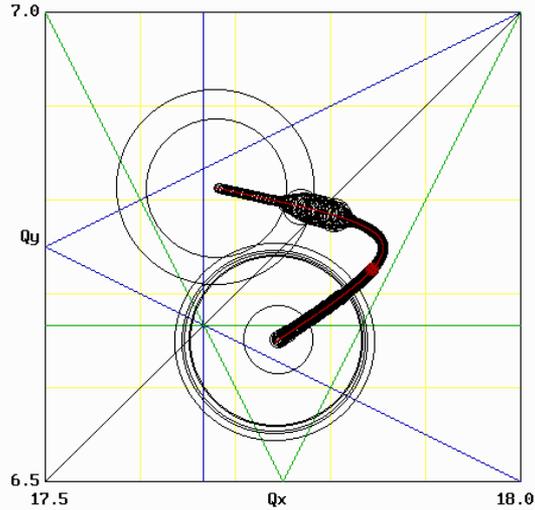
- PSO is a useful tool:
 - Fast
 - Not unique results, absolute optima may not be found in only a few iterations
- More investigations:
 - To study why lifetime is better: resonance driving terms?
 - Improve the PSO efficiency by tuning inertia factor, cognitive factor and social learning factor
- Potential uses:
 - Transfer line (steers, quadrupoles) optimization for injection rate at MLS
 - Decoupling (skews) at BESSY II

Thanks for your attention!

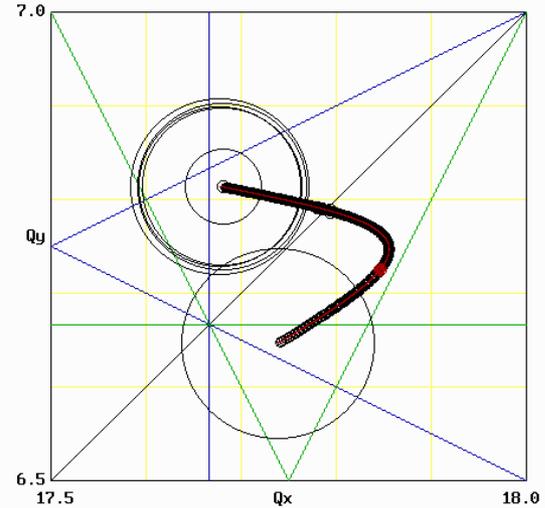
Comparison of present and optimized setupole settings:

Sextupoles	present	PSO optimized
S3PDR	77	87.36
S3PTR	79.6	75.40
S4PDR	68.4	70.95
S4PTR	100	130
S3PD1R	72	78.36
S4PD1R	48.4	61.29
S3P1T6R	79.6	32.50
S3P2T6R	79.6	30.19
S4P1T6R	75	58.33
S4P2T6R	75	69.33

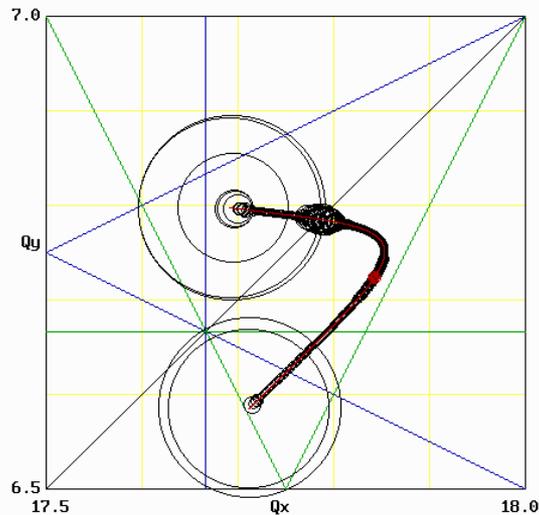
16111300.txt before optimization



16111301.txt skew Q-optimized

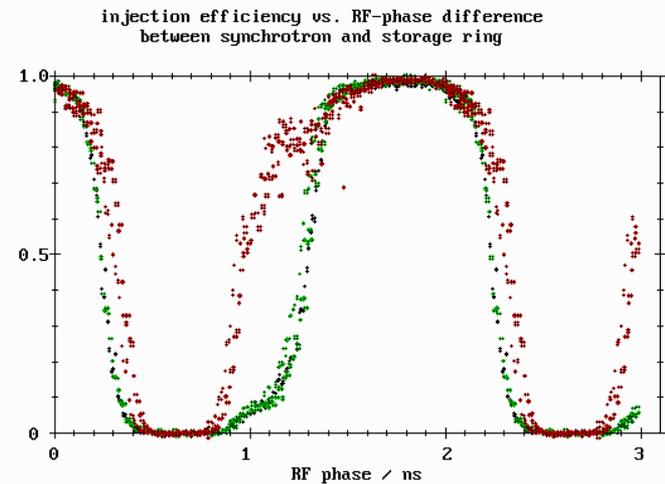


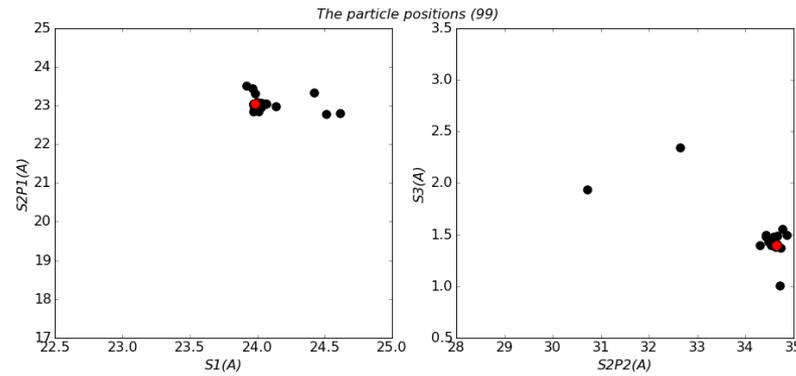
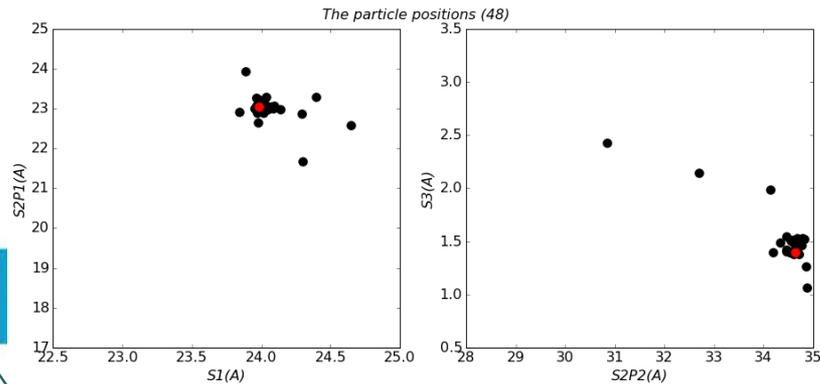
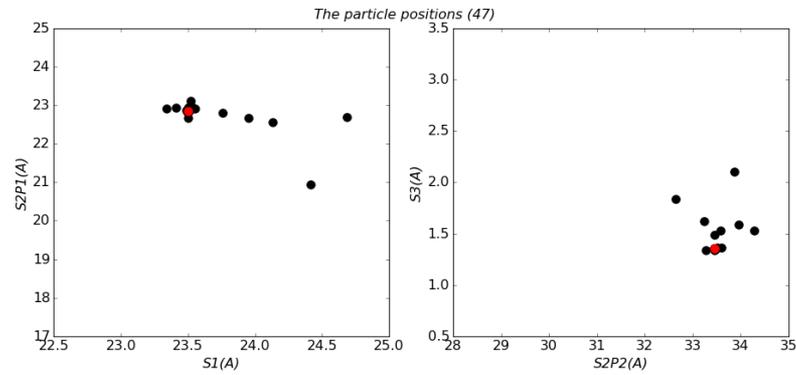
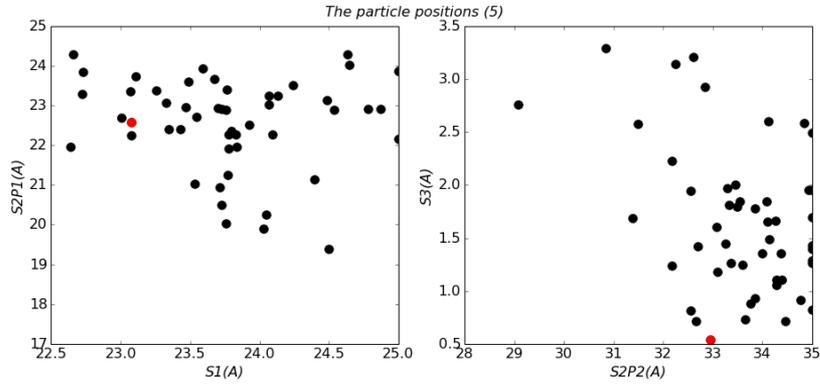
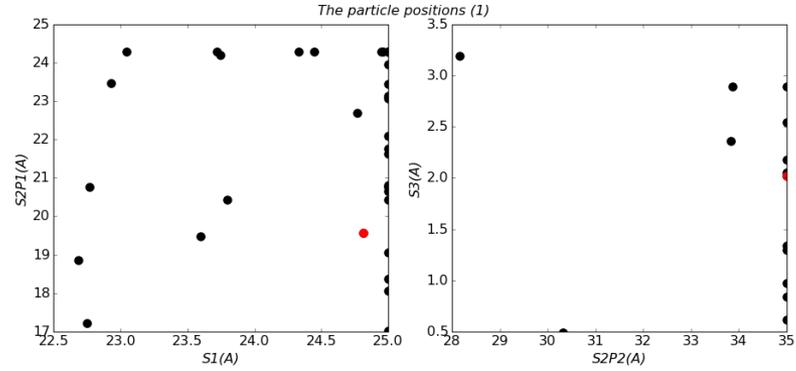
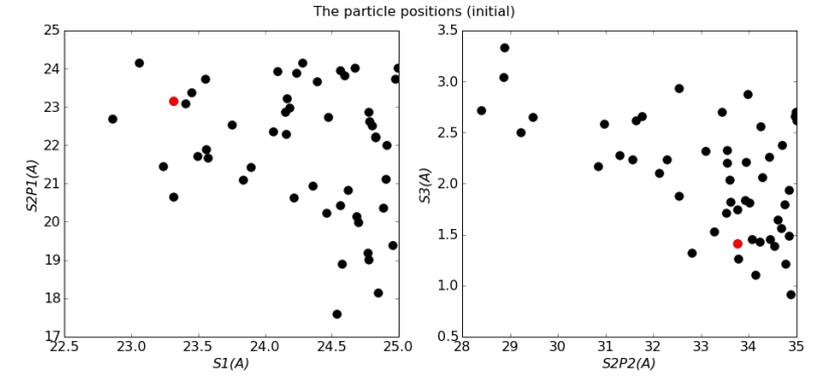
16111302.txt skew Q- and sextupoles optimized



13Nov000.BMP

phscan3.txt



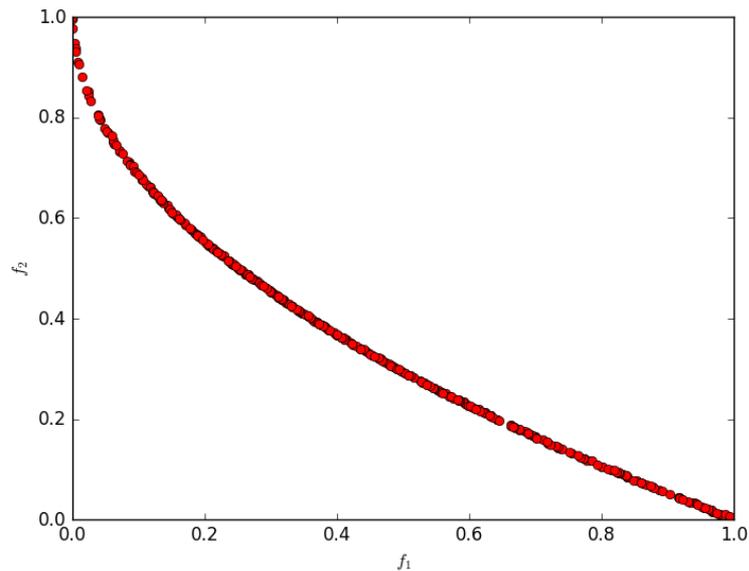


A solution x_1 is said to dominate another x_2 , if the conditions are true:

1. The solution x_1 is no worse than x_2 in all objectives
2. The solution x_1 is strictly better than x_2 in at least one objective

If any of the above conditions is violated the solution x_1 does not dominate the solution x_2

If any solution in the set does not dominate x_2 , then x_2 is non-dominated solution



Begin

Initialize swarm

Initialize leaders in an external archive

Sorting(leaders)

it= 0

While it < maxit

For each particle

 Select leader(gbest)

 Update Position (Flight)

 Mutation

 Evaluation

 Update pbest

EndFor

 Update leaders in the external archive

 Sorting(leaders)

 it++

EndWhile

Report results in the external archive

End