Electrostatic septum alignment studies at the CERN SPS



Work of the Automatic ZS Alignment Working Group (AZSAWG) [1]

M.A. Fraser[#], Y. Dutheil, B. Goddard, S. Hirlaender, V. Kain, K. Li, J. Prieto, M. Szakaly, L. Stoel, F. Velotti, CERN & M. Kagan, SLAC



2nd ICFA Workshop on Machine Learning for Charged Particle Accelerators

400 GeV slow extraction system



Electrostatic septum (ZS)

ZS is composed of 5 independent tanks mounted on a single girder, which spans almost 20 m along the extraction straight:





10x anode positions: UP and DO 12 mechanical degrees of freedom, motion H plane only

Simulation tool

pyTrack: a simplified tracking model written fully in Python [2]:

- Linear machine + thin sextupole kicks + scattering modelled in pycollimate [3]
- Source term at septa upstream is generated in MAD-X and resampled every time
- Only the last 3 turns before extraction are simulated: huge speed up
- Custom or off-the-shelf optimisers can be easily plugged into the library. Collaborations welcome!

Septa geometry:

- More detailed than MAD-X: independent tanks with field
- Less detailed than FLUKA: "ribbon" anodes instead of individual wires

Simulation results

Error studies:

- 1. Position girder at minimum losses
- 2. Randomly misalign all tanks except ZS1 upstream, yielding 9 DOF
- 3. Simulate alignment procedure over a few hundred shots
- 4. Repeat for many different initial misalignment seeds N(0, σ =500 µm)

Comparison of algorithms:

Current (operational) vs. gradient descent:



Alignment procedures/algorithms

Current (operational) alignment procedure:

- 1. Scan girder and fix at location of minimum loss
- 2. Scan every anode motor sequentially from upstream to downstream, fixing at minimum of loss each time
- 3. Repeat until no further benefit

Pros: simple; Cons: time-consuming, poor worst-case convergence

Gradient descent:

- 1. Scan girder and fix at location of minimum loss
- 2. Estimate gradient:
 - Probe each degree of freedom, left and right: 2 shots * 9 degrees of freedom = 18 shots
- 3. Move all anodes together in direction of decreasing gradient with exponentially decreasing step size.

Bayesian Optimisation [4]: maximise a target function f: $X \rightarrow Y$

1. Define a probability measured over a suitable function space with a Gaussian process (infinite-dimensional generalisation of a multivariate Gaussian), $f(x) \sim \mathcal{GP}(\mu(x), k(x, x'))$



#Mail to: mfraser@cern.ch

- 2. Probe point x^{*} maximising expected improvement w.r.t. that $\mathbf{x}^* = \operatorname{argmax} \mathbb{E}[f(\mathbf{x}) \mid \mu(\mathbf{x}), \mathbf{k}(\mathbf{x}, \mathbf{x}')]$ probability measure,
- 3. Update the probability with each function evaluation.
- 4. Repeat and stop after given number of steps.

References

[1] AZSAWG: <u>https://indico.cern.ch/category/9695/</u> [2] J. Prieto, https://gitlab.cern.ch/jprietop/pyTrack CERN's Gitlab. [3] F.M. Velotti, PyCollimate: <u>francesco.maria.velotti@cern.ch</u> [4] Bayesian Optimization, https://github.com/fmfn/BayesianOptimization Bayesian optimisation vs. gradient descent:

