Optimization of rf manipulations

LIU-PS Beam Dynamics Working Group 21/03/2019

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Outline

Introduction

Optimization of the double splittings

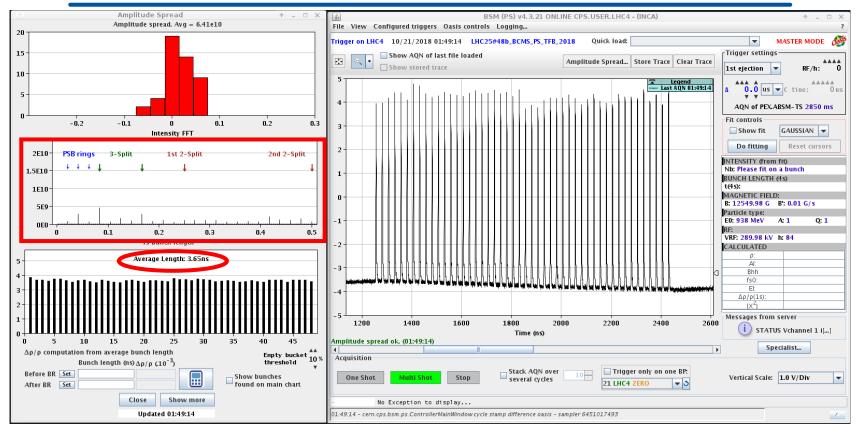
Optimization of the triple splitting

Conclusions

Introduction and motivation

- Aim at including more machine learning and optimization routines in RF operation, profiting from the progress made in OP
 - > Optimize the rf settings after early commissioning
 - Speed-up the setting up for LHC fills
 - Systematically reduce bunch-by-bunch variability
 - Minimize PS-SPS losses in view of operation with LIU beam parameters
- Settings are presently adjusted manually, some rf manipulations are good candidates for automatized optimization
 - Double splittings
 - > Triple splitting
- More complex rf manipulations could also benefit on a longer term
 - Bunch rotation
 - Controlled longitudinal emittance blow-up

Longitudinal beam quality from BSM



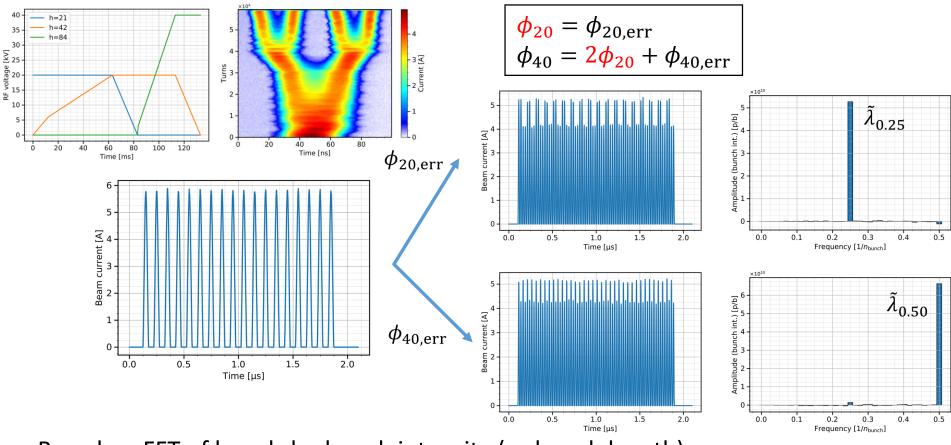
Adjustments can be done using analysis in BSM at extraction

S. Hancock R. Maillet

- Present performance: < ±10% variability in bunch intensity and bunch length at extraction
- Is this the beam quality sufficiently good? Are we reaching the limit imposed by beam loading?

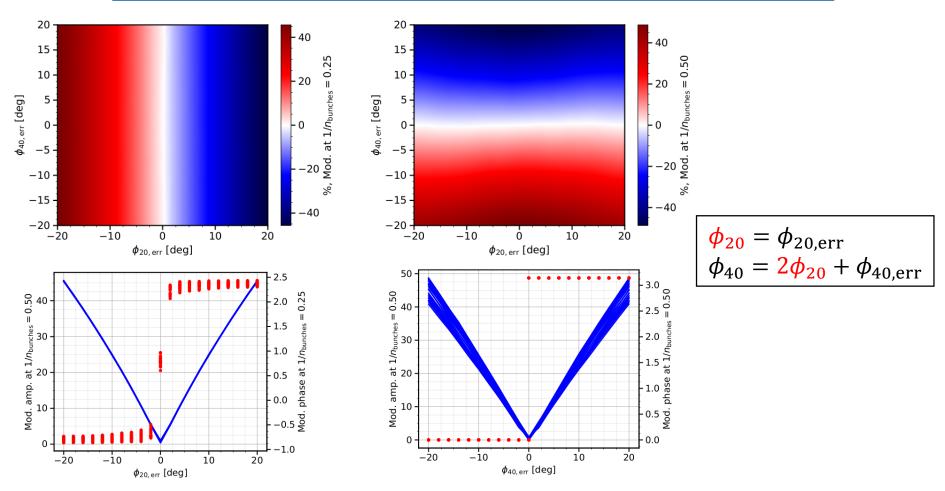
Phase error in the double splittings

LHC Beams in the PS: Reliability and Reproducibility issues, S. Hancock, LHC Performance Workshop, Chamonix (2003)



- Based on FFT of bunch-by-bunch intensity (or bunch length)
- The amplitude of each harmonic gives the pattern, the phase gives the orientation
- For double splittings: peaks at 1/2 and (1/2)/2=1/4

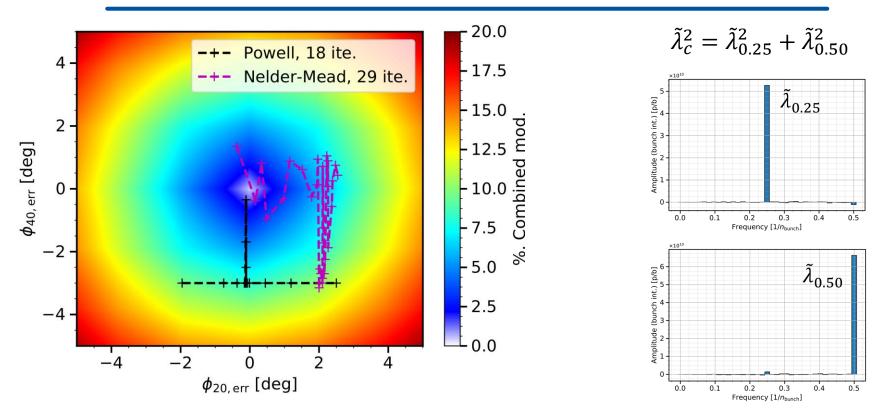
Phase error in the double splittings



Both steps of the splitting are independent and can be treated separately

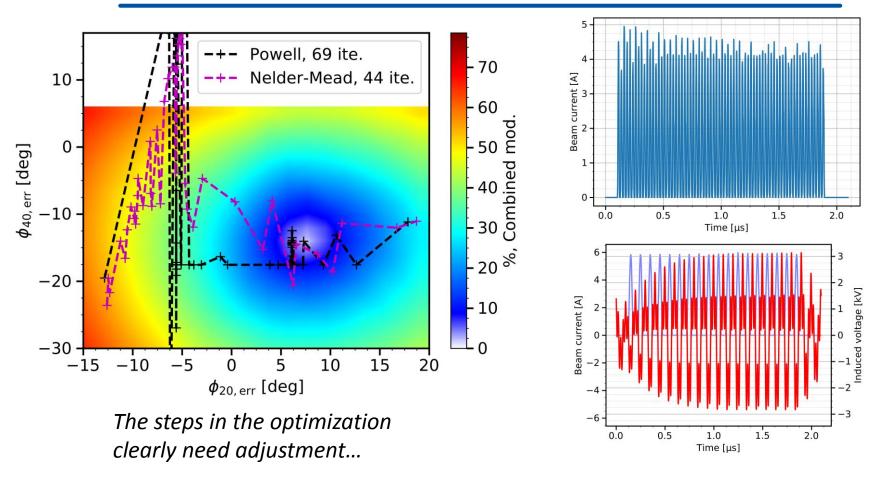
 A machine model based on linear regression of measured data should be sufficient as a mean to optimize double splittings

Optimization of double splittings



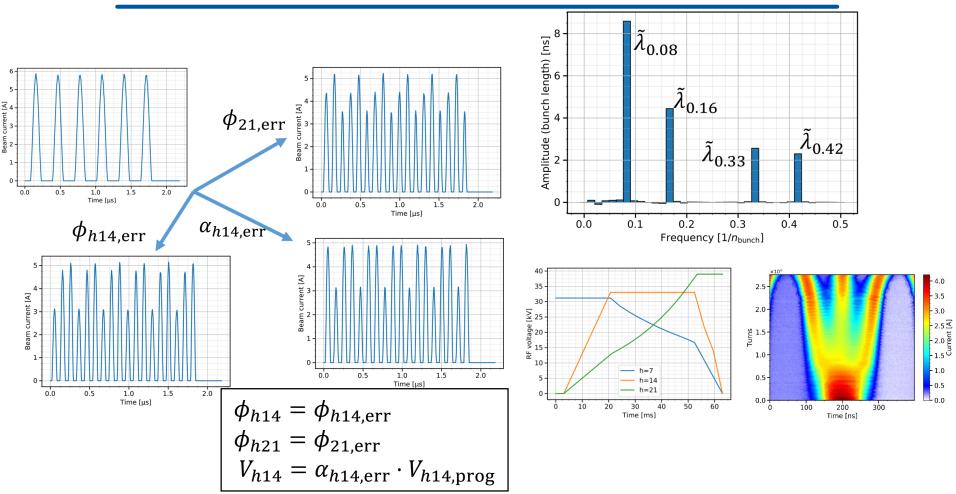
- Optimization using Powell or Nelder-Mead downhill simplex methods were tested
- Each function call would correspond in operation to one cycle (or super-cycle)
- Even with fine tuning, the optimization will still require a certain number of iterations, cannot be used in daily operation (~10-30 min in practice for that test...)
- Reinforcement learning should help to minimize the number of iterations

Effect of beam loading on double splittings

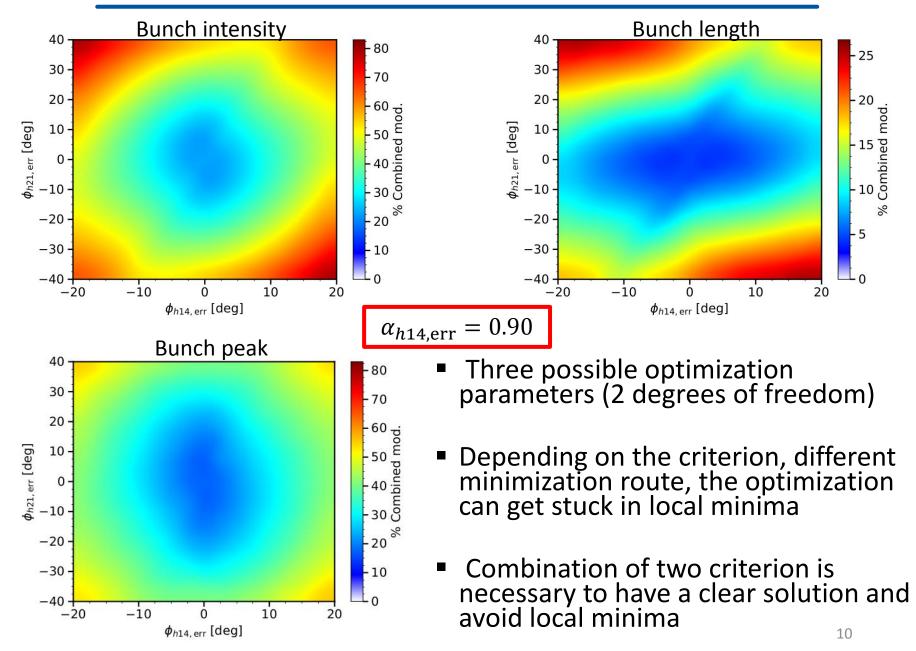


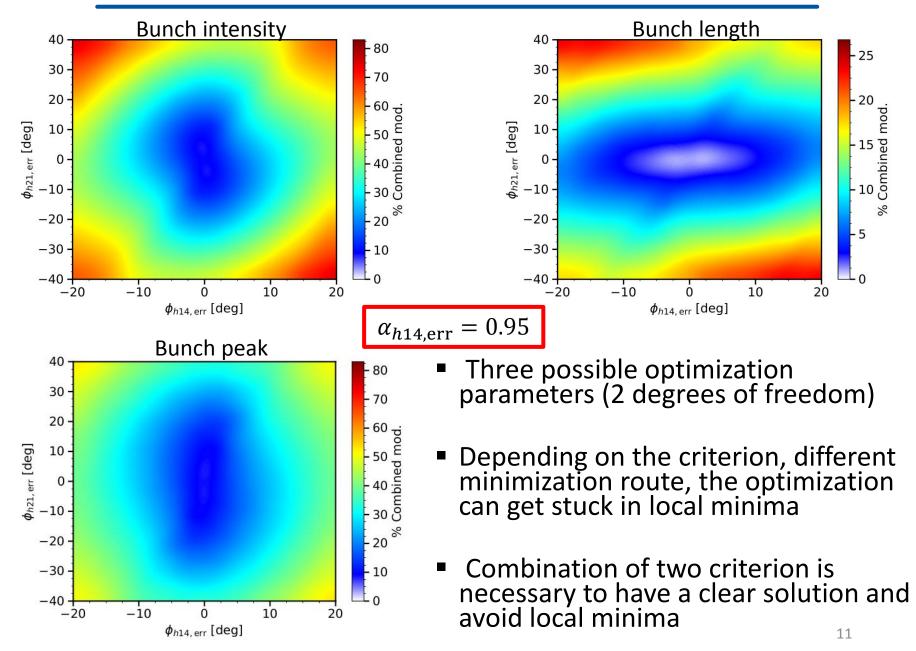
- Beam loading is a limitation to the best achievable bunch-by-bunch variability (variation of effective rf amplitude and phase along the batch because the machine is not full)
- The optimum point is shifted in phase, and the optimization in simulations manages to reach the optimum

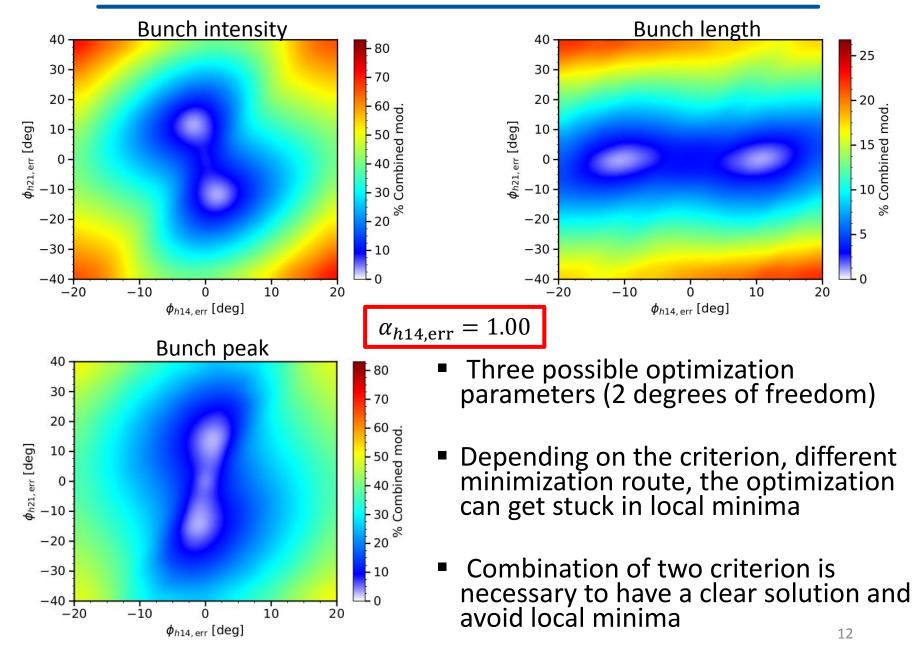
Phase and amplitude error in triple splitting

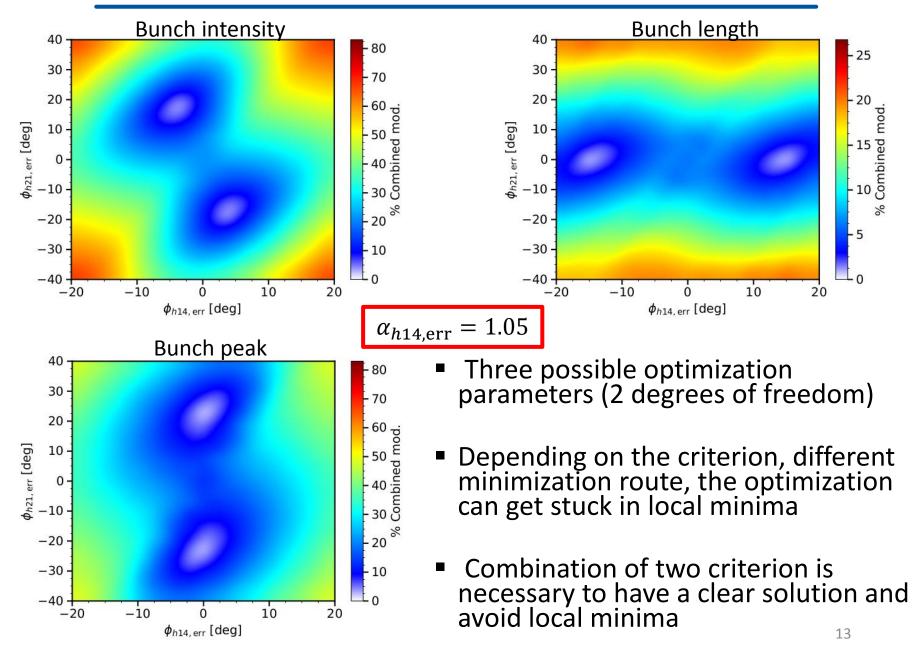


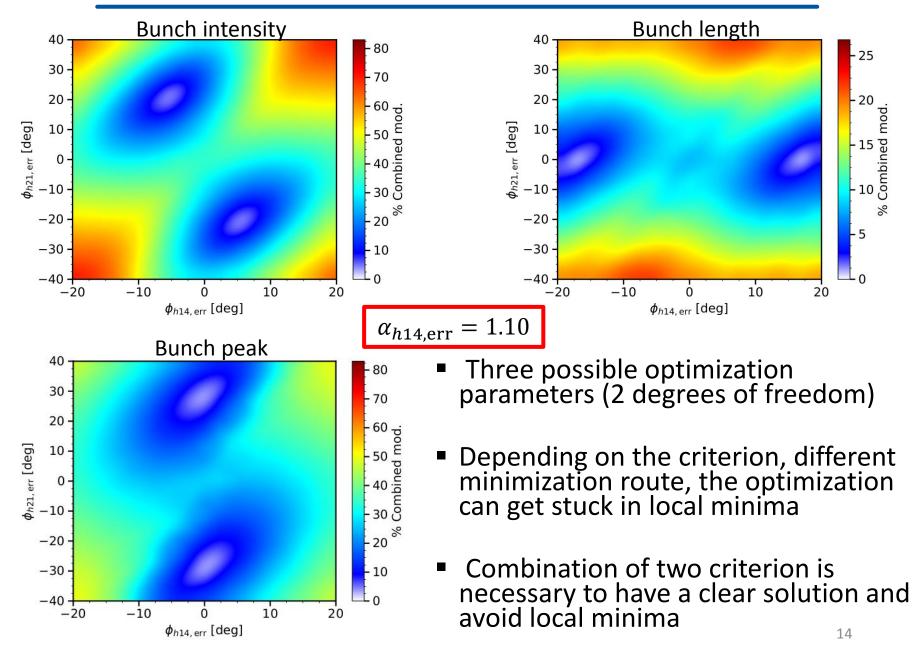
- Using the same method as for double splittings, using FFT on the beam at extraction (accounting double splittings)
- For triple splitting, the peaks are at (1/3)/4=1/12, (2/3)/4=2/12, (4/3)/4=4/12, (5/3)/4=5/12



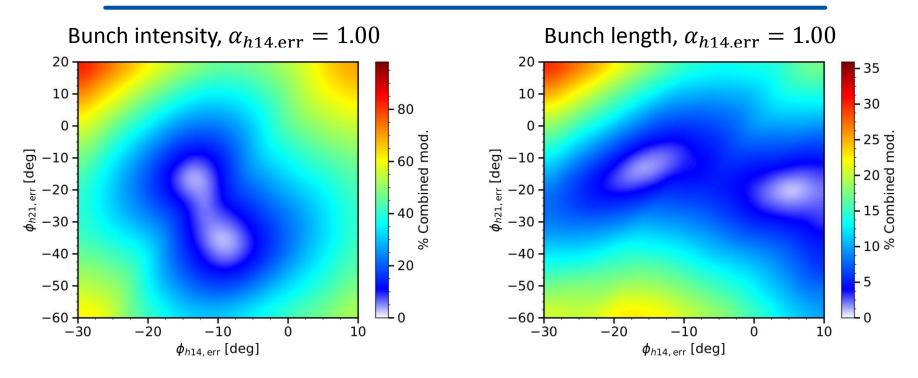






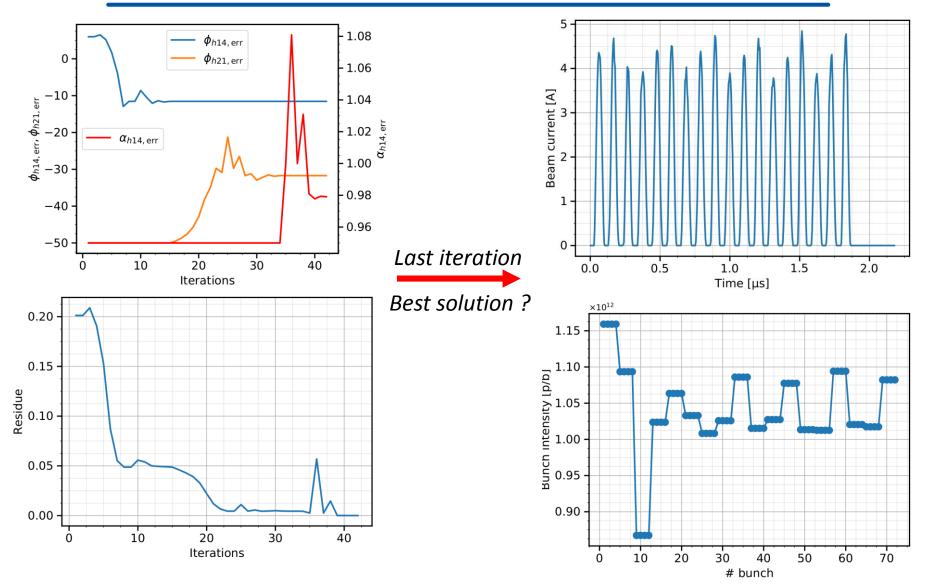


Effect of beam loading on triple splitting



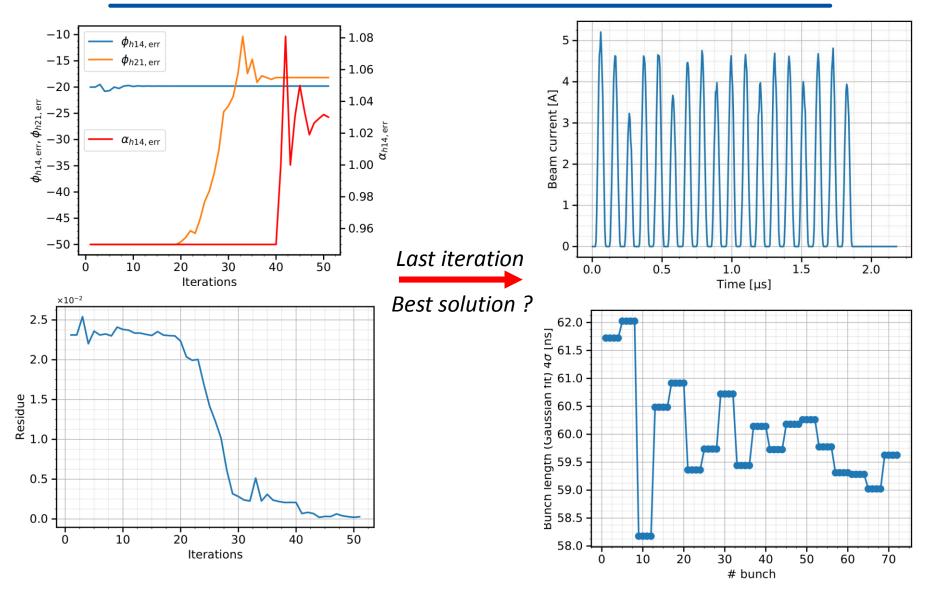
- Beam loading also affects the triple splitting, the optimum point is shifted in phase and in amplitude of the step at h=14
- The optimum point differs for optimization on the bunch intensity or the bunch length
- NB: one-turn delay feedback is not included in the simulations, impedance reduction is essential to improve the lowest achievable bunch-by-bunch variability

Optimization of triple splitting (intensity)



Using Powell optimizer to minimize bunch-by-bunch intensity variability

Optimization of triple splitting (length)



Using Powell optimizer to minimize bunch-by-bunch length variability

17

Conclusions and next steps

- Optimization routines were tested in simulations on the double and triple splittings, without and with intensity effects, and will be used as a basis for more complex developments.
- The optimization routines could be fine tuned to reduce the number of iterations. In order to have an operational optimizer for the splittings, machine learning methods could be applied to minimize the number of required iterations.
- Machine learning can also help establishing the dependence of bunch-by-bunch variability as a function of the feedback efficiency in simulations, by building a surrogate model.
- Which machine learning methods could be applied for which rf manipulation?
 Linear regression (double splittings)
 - Neural networks (triple splitting, bunch rotation, controlled emittance blowup...)
 - > Bayesian optimization (statistical fluctuations in measurements)
 - Multi objective optimization (triple splitting)
 - Reinforcement learning (using measured data along the run)
 etc...