Multiobjective Optimization of the LCLS-II Photoinjector

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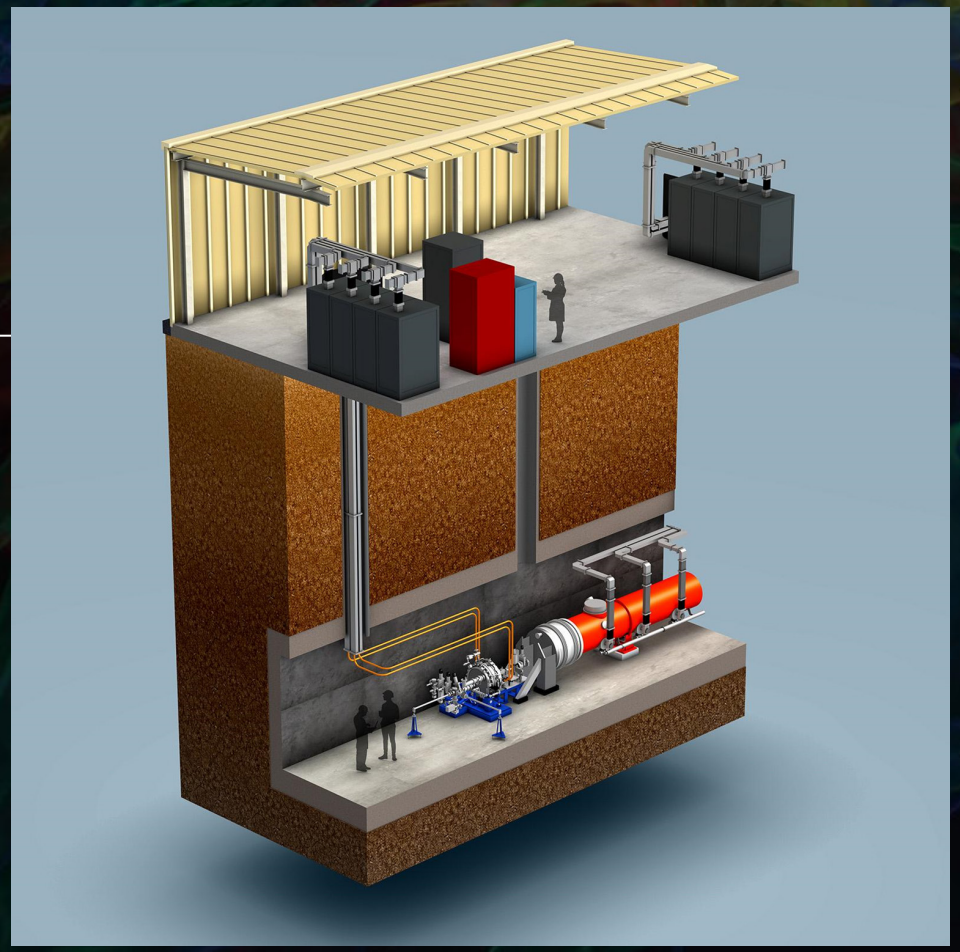
Stanford University | U.S. DEPARTMENT OF ENERGY

Overview

- Motivation
- Sampling methods
- Optimization methods
- Results



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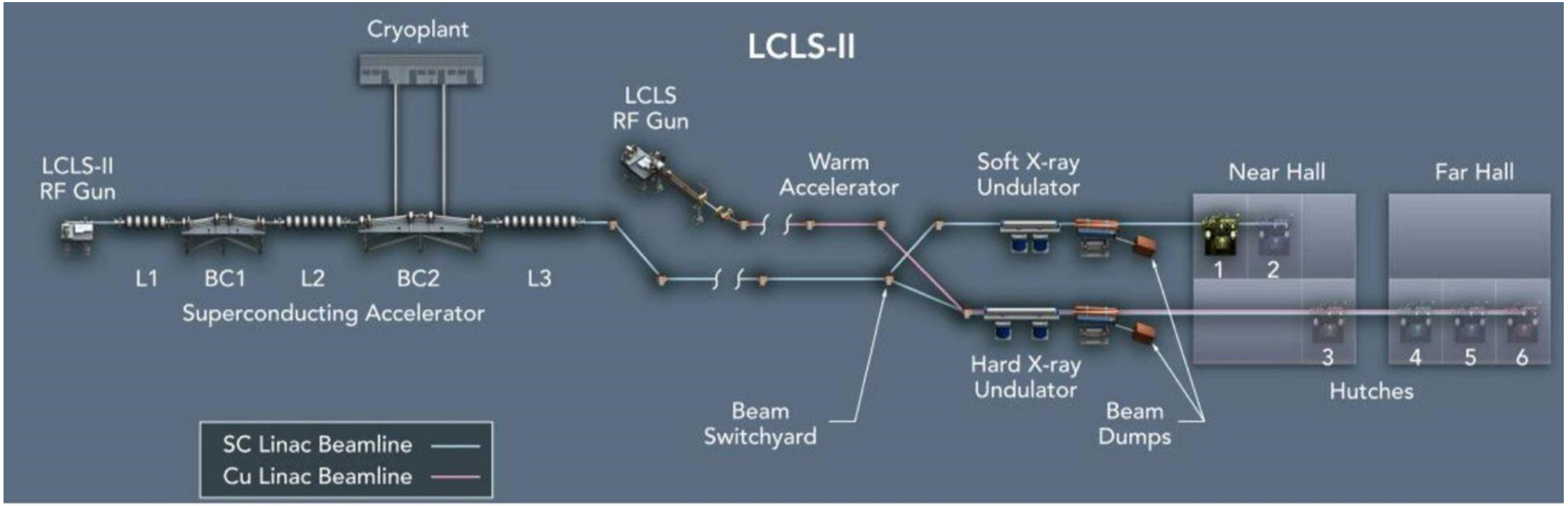
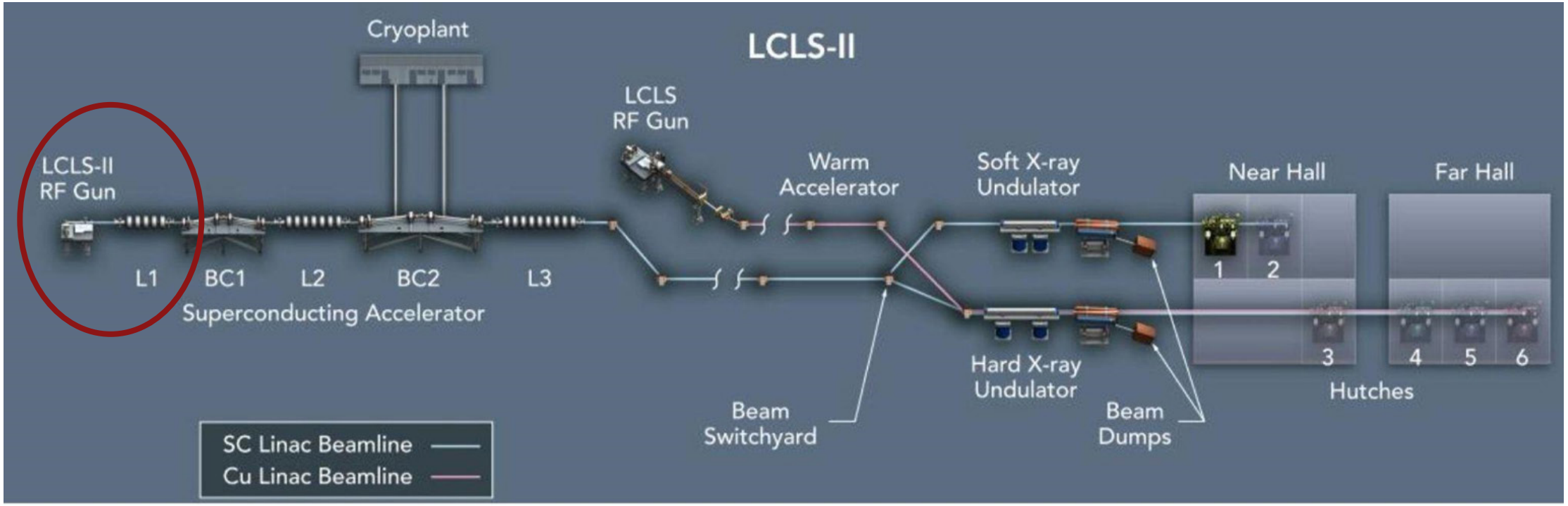
Motivation


LCLS-II
Cryoplant
LCLS
RF Gun
LCLS-II
RF Gun
Warm
Accelerator
Soft X-ray
Undulator
Near Hall
Far Hall
L1
BC1
L2
BC2
L3
Superconducting Accelerator
1
2
3
4
5
6
Hutches
Hard X-ray
Undulator
Beam
Switchyard
Beam
Dumps
SC Linac Beamline
Cu Linac Beamline

Motivation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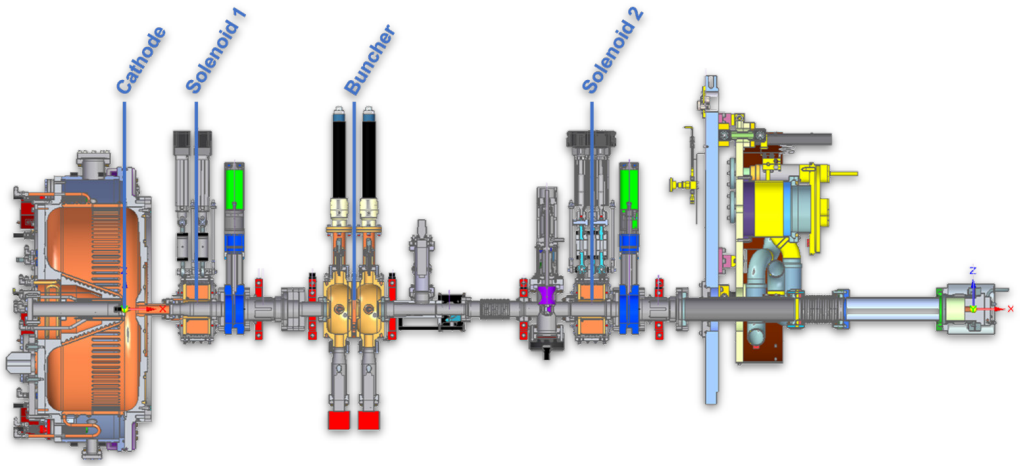
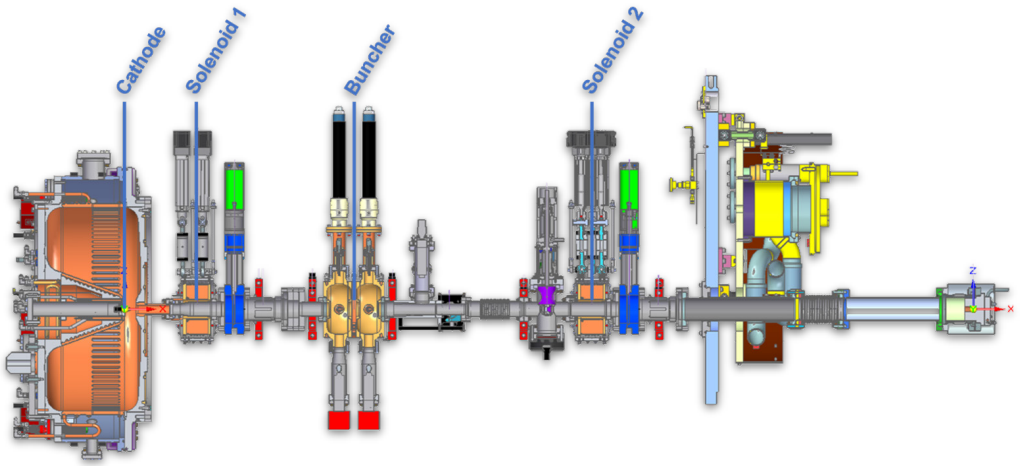
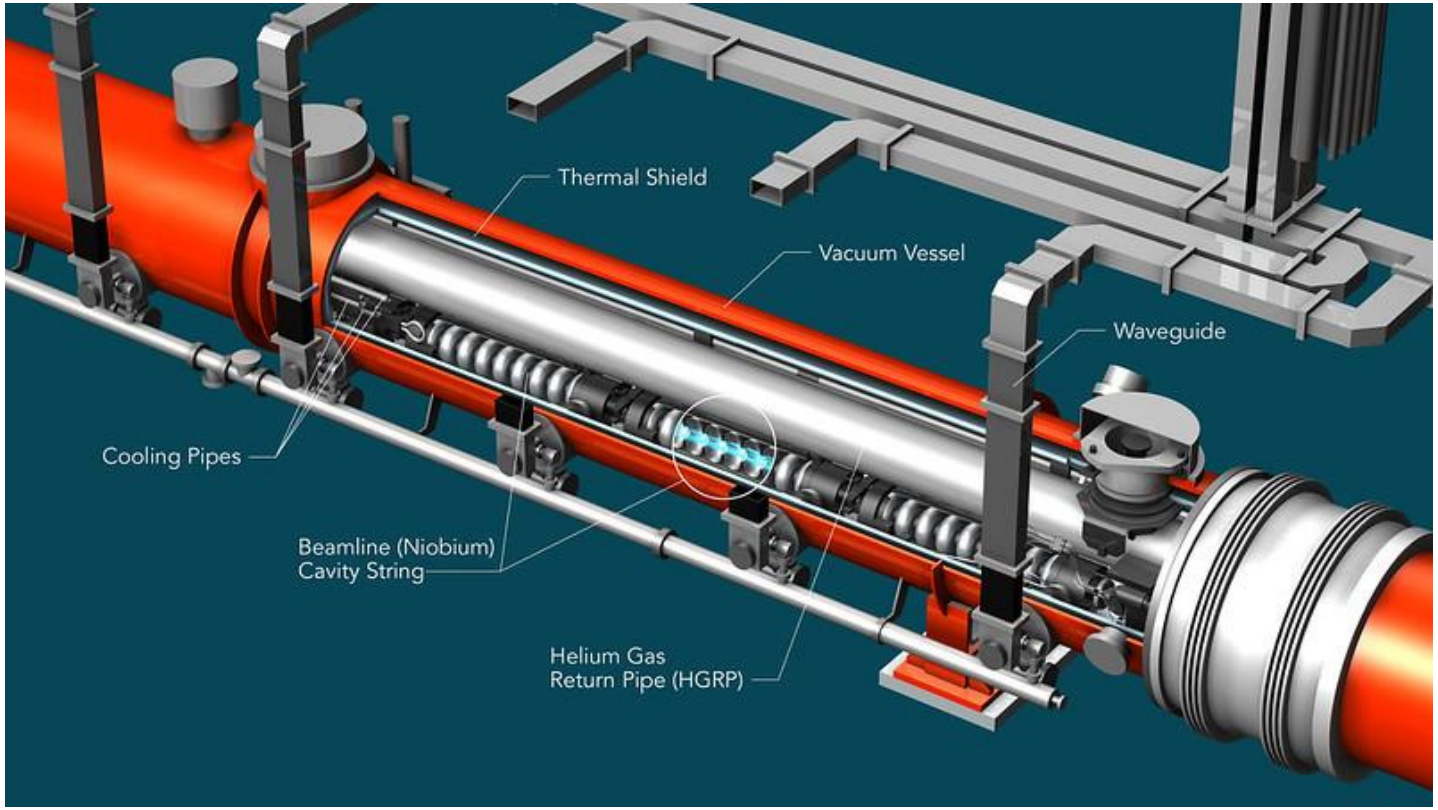
Motivation



Motivation


Cathode
Solenoid 1
Buncher
Solenoid 2

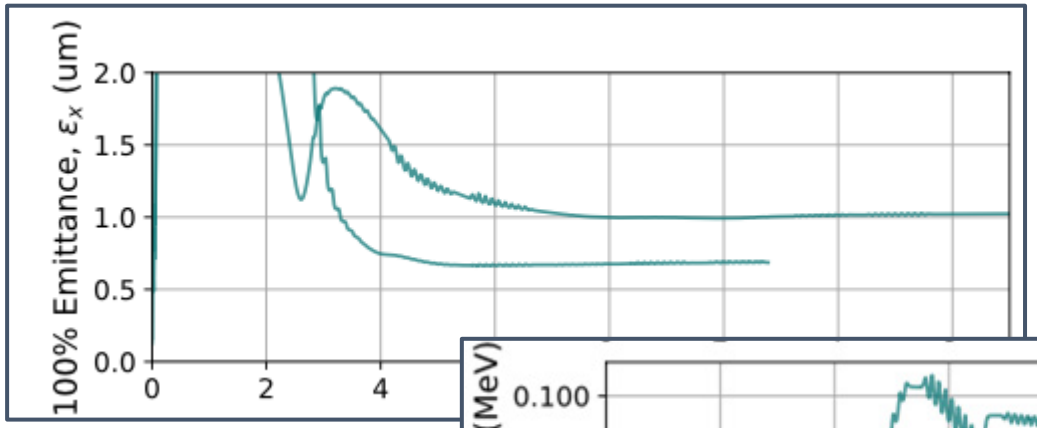

Thermal Shield
Vacuum Vessel
Waveguide
Cooling Pipes
Beamline (Niobium)
Cavity String
Helium Gas
Return Pipe (HGRP)

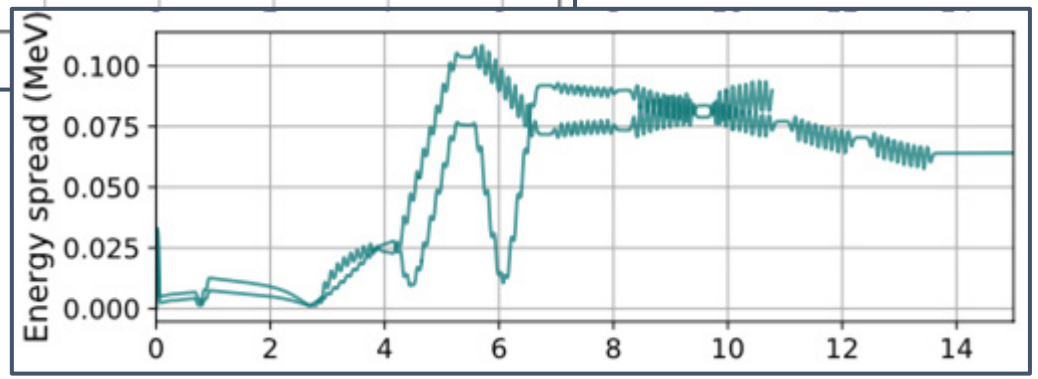
Motivation

General injector optimization:

In the case of Free Electron Lasers (FEL) we care about:

- emittance
- bunch length
- energy spread

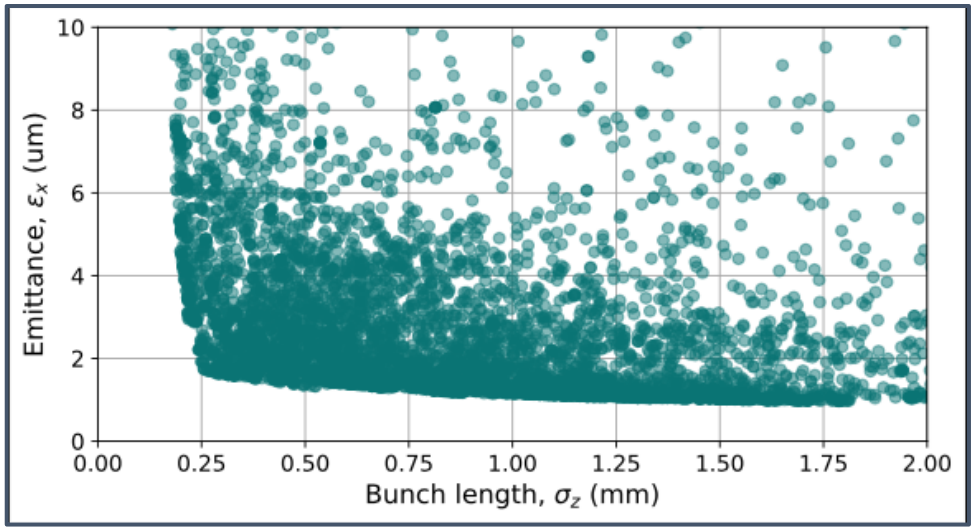




Questions we aim to answer:

Does the initial sample impact the optimization results?

Does the optimization method impact the number of evaluations needed to reach the Pareto front?



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Optimization bounds and penalties:

Only included knobs with the largest impact on results:

- Based on previous optimization and simulation results
- Buncher phase and first cavity in the cryomodule impact emittance heavily
- Cavities at the end of the cryomodule only serve to add energy and adjust dE if needed
- Emittance is typically frozen by cavity 5
- Large emittance values are penalized in optimization

Variable	Minimum	Maximum	Unit	Scale
Solenoid strength(s)	0.02	0.07	T/m	10^{-3}
Buncher gradient	1.0	1.8	MV/m	1.0
Buncher phase	-100	-10.0	Degrees	1.0
Cavity gradient 1-4	0.0	32.0	MV/m	1.0
Cavity phase 1-4	-40.0	40.0	Degrees	1.0

$$P_e = \begin{cases} \epsilon_{x_i} - 0.3, & \text{if } \epsilon_{x_i} > 0.3 \\ 0, & \text{otherwise,} \end{cases}$$

Emittance penalty

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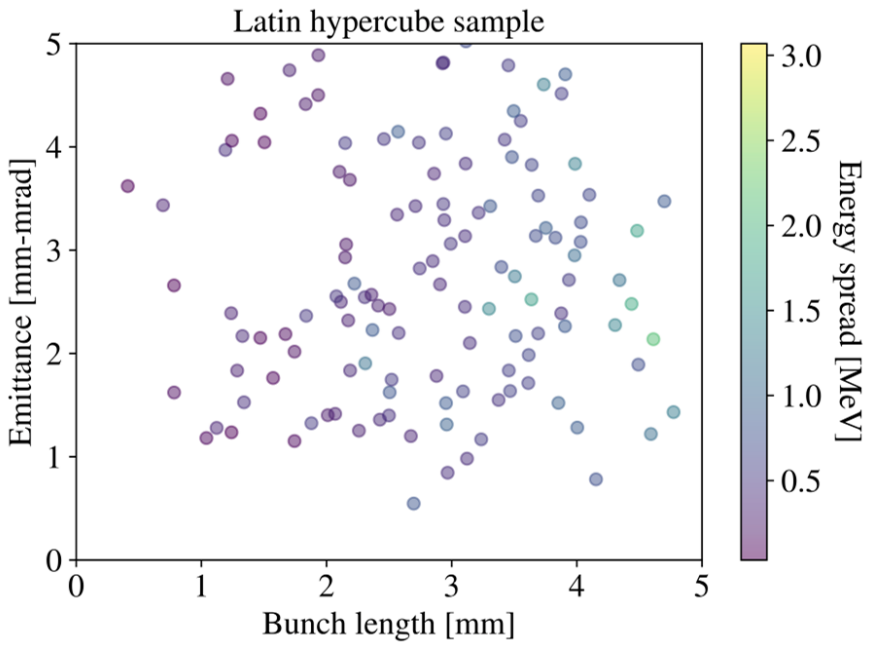
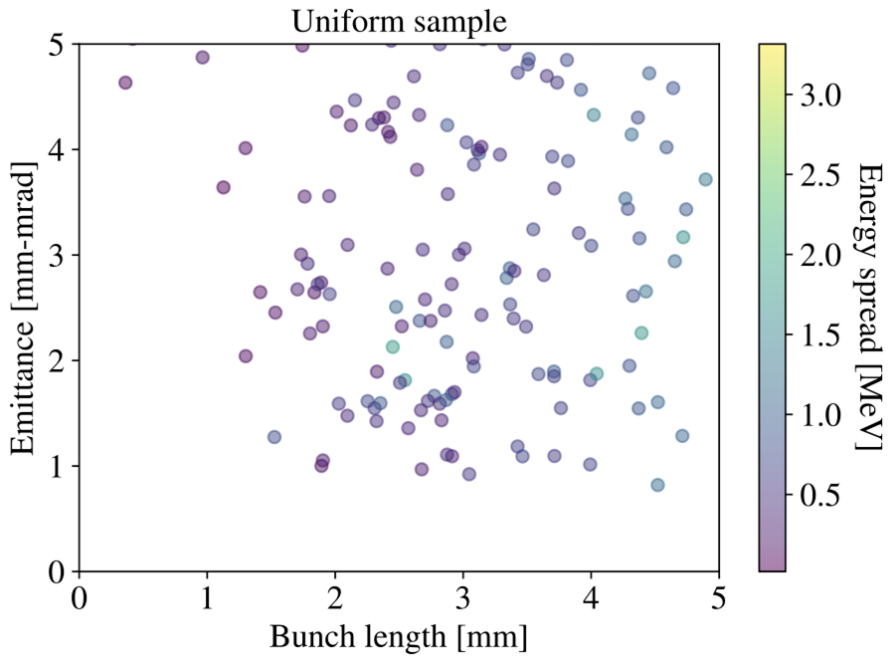
Sampling Methods:





Latin Hypercube

Sample in each row and column when looking at the input space as a grid in N-dimensional space.

Uniform Random Sample

No guarantees on distribution in input space.

Five samples of each type (LHS and uniform), were done to make sure statistical noise would not affect the optimization results.

Optimization Methods:

Genetic Algorithm

- Based on natural selection
- Current favorite of the accelerator phys. community
- Widely used in codes and several papers (easy to use?)
- Requires large computational resources or long compute times

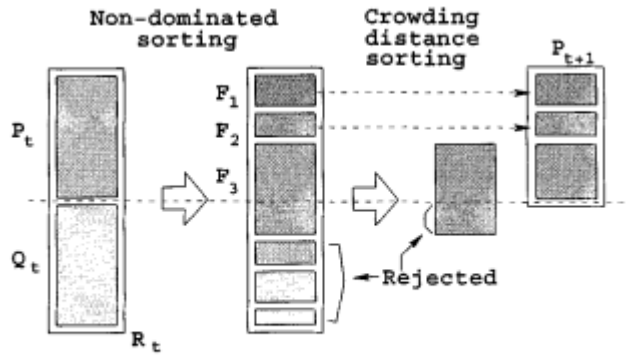
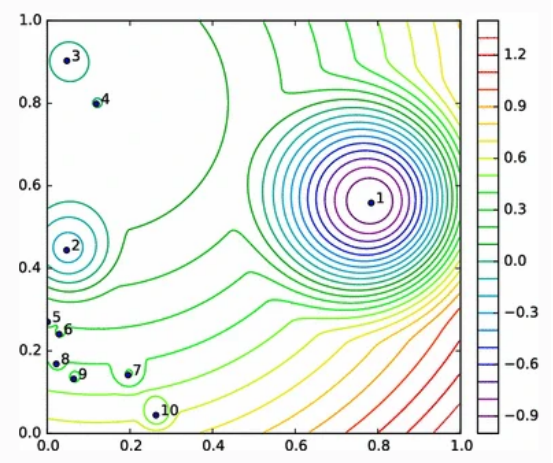


Fig. 2. NSGA-II procedure.

K. Deb, et. al, A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II, 2002

APOSMM

- Developed to parallelize and avoid local minima when using local optimization methods
- Keeps and uses all previous results to inform next optimization step
- Requires scalarization set up



J. Larson and S. Wild, Asynchronously parallel optimization solver for finding multiple minima, 2018

VTMOP

- Develops surrogate models of the objective space
- Multiobjective method like NSGA-II
- Keeps and uses all previous results to inform next steps
- *a posteriori* approach

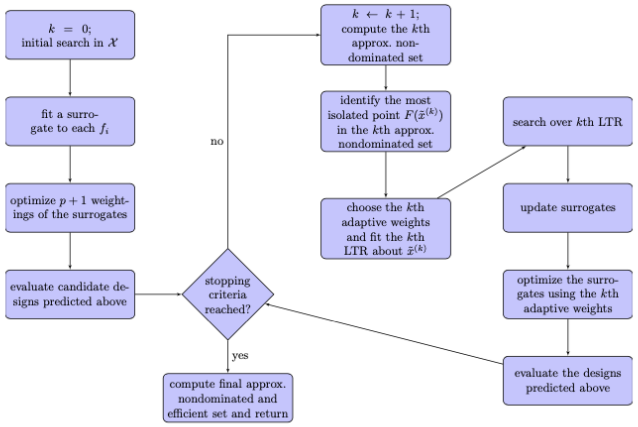
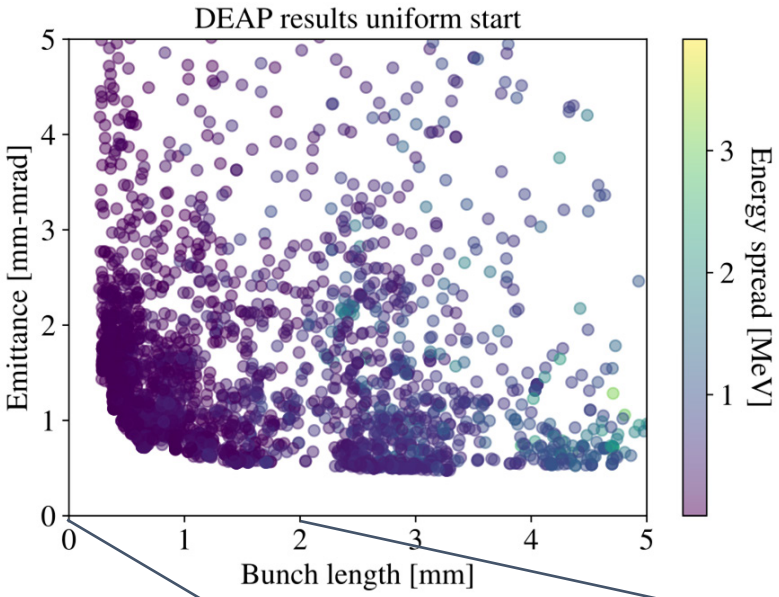


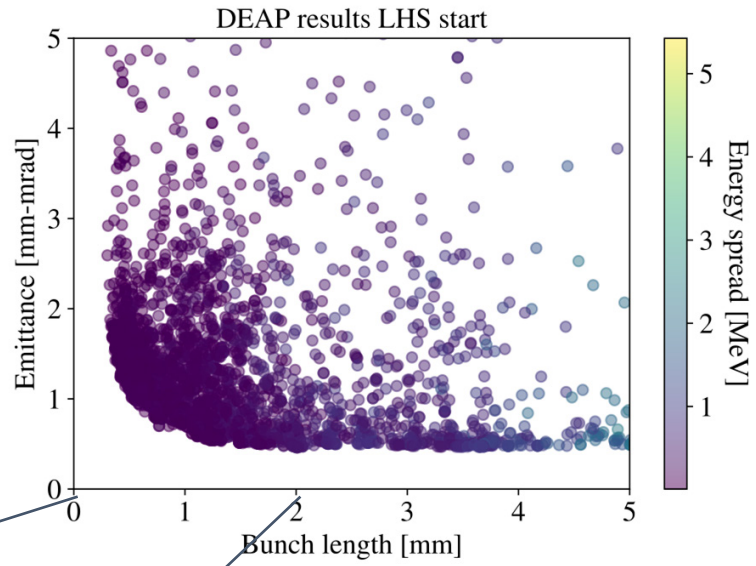
Fig. 1. Algorithm flowchart for VTMOP. For further details on each of these steps, see Sections 3.1–3.4

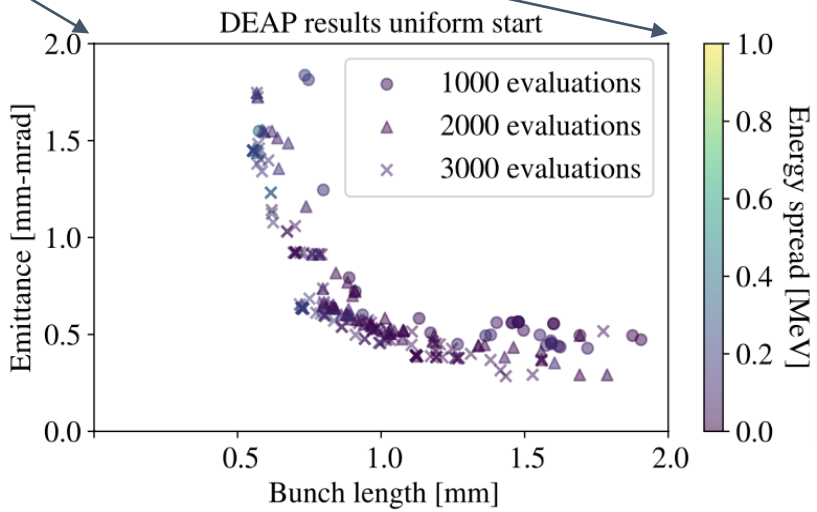
T. Chang, et al. Algorithm XXXX: VTMOP: Solver for Blackbox Multiobjective Optimization Problems, 2022

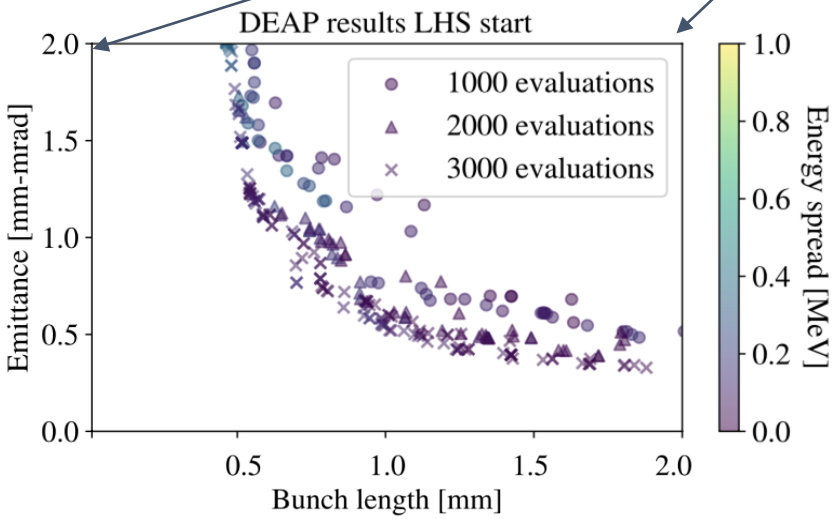
Optimization results: Genetic Algorithm (NSGA-II)



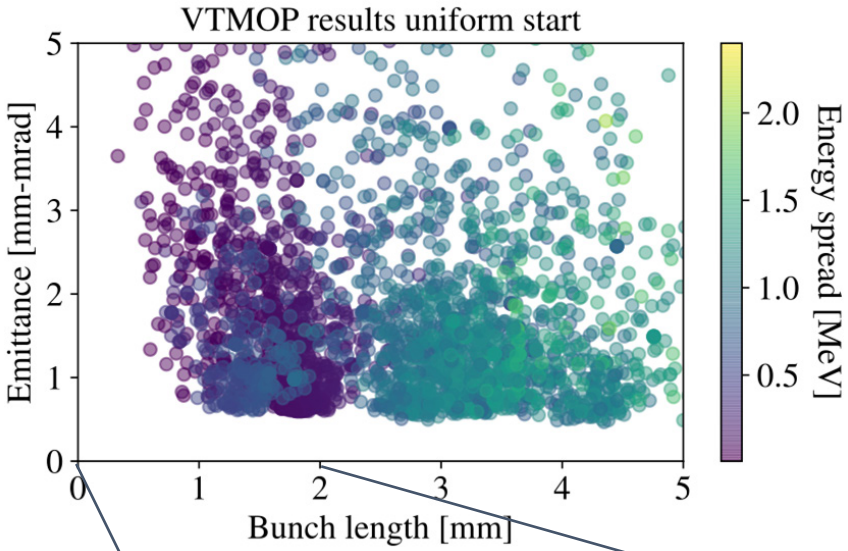
- LHS+NSGA-II performs slightly better w.r.t distribution of results
- No appreciable difference in Pareto fronts



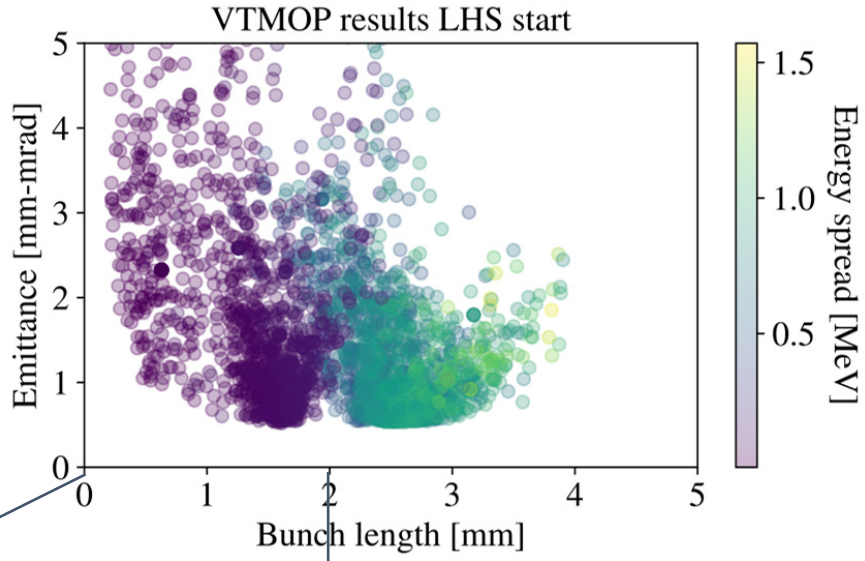


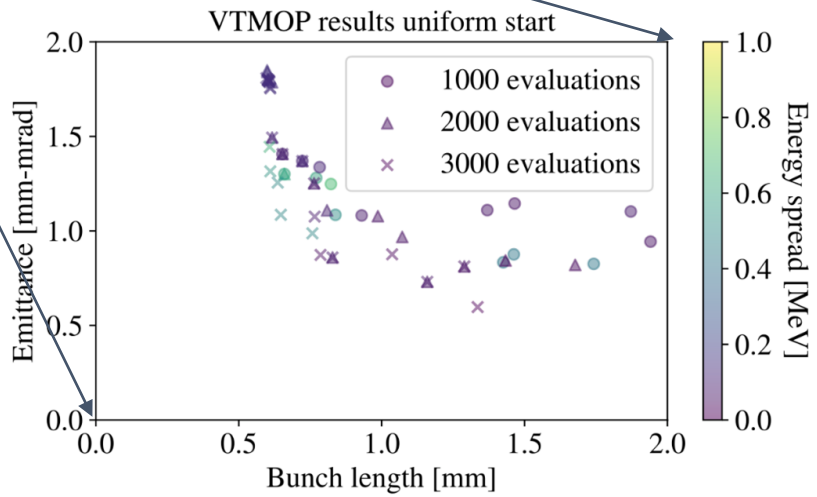


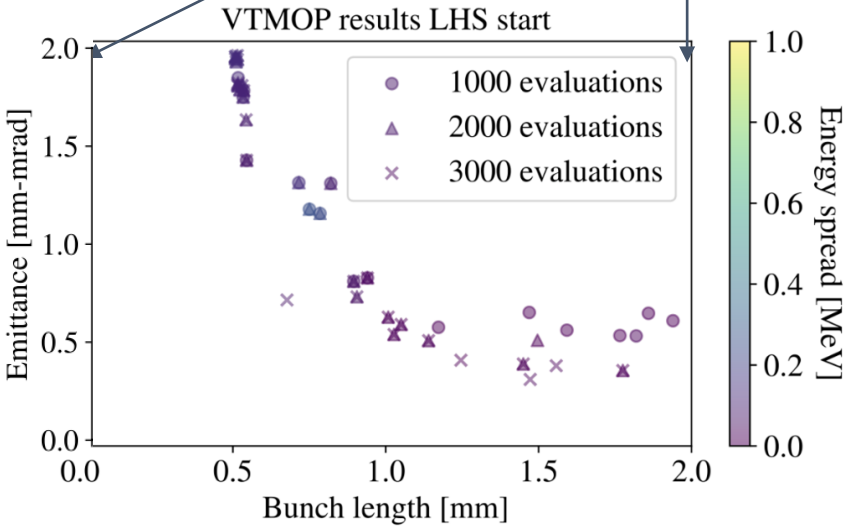
Optimization results: Surrogate models (VTMOP)



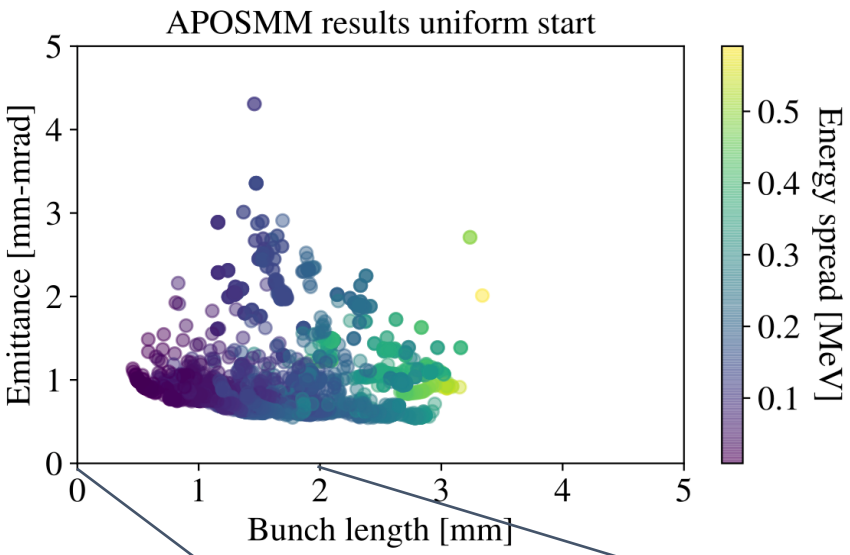
- LHS+VTMOP performs significantly better w.r.t distribution of results
- Less time is spent on long bunch length areas
- Results in different Pareto front per sample type



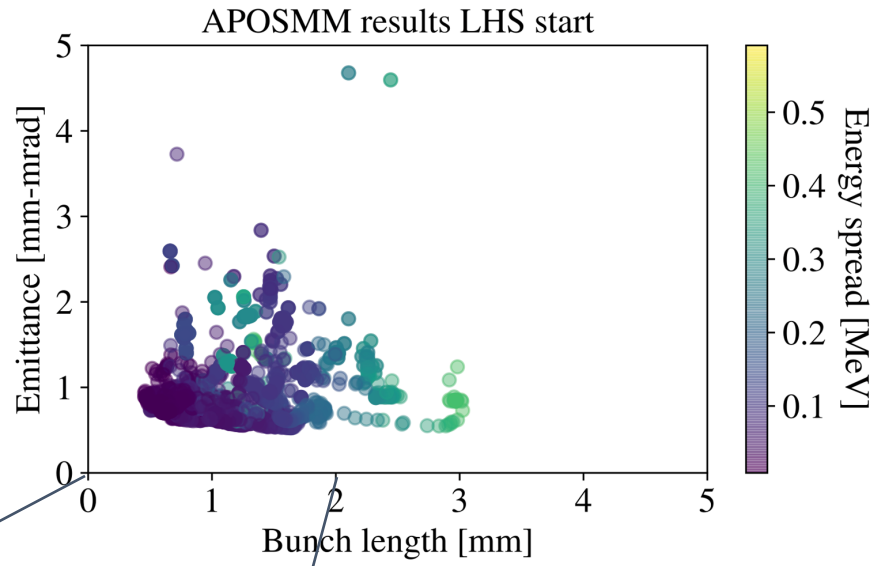


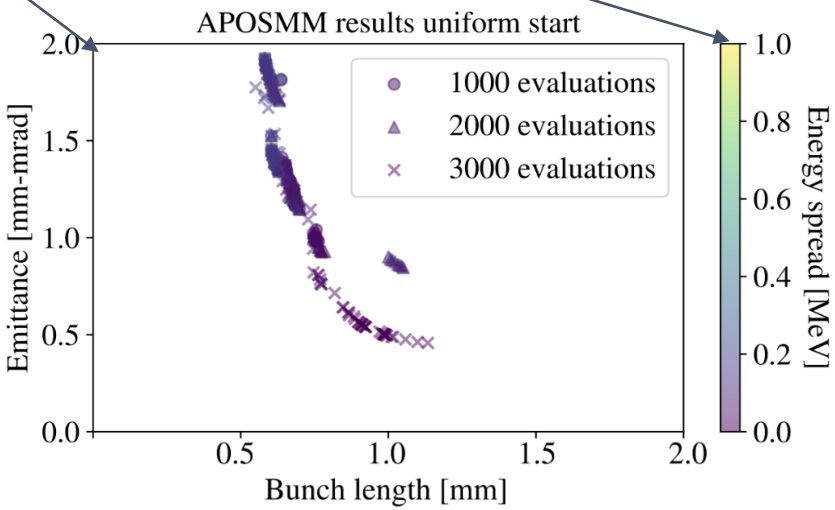


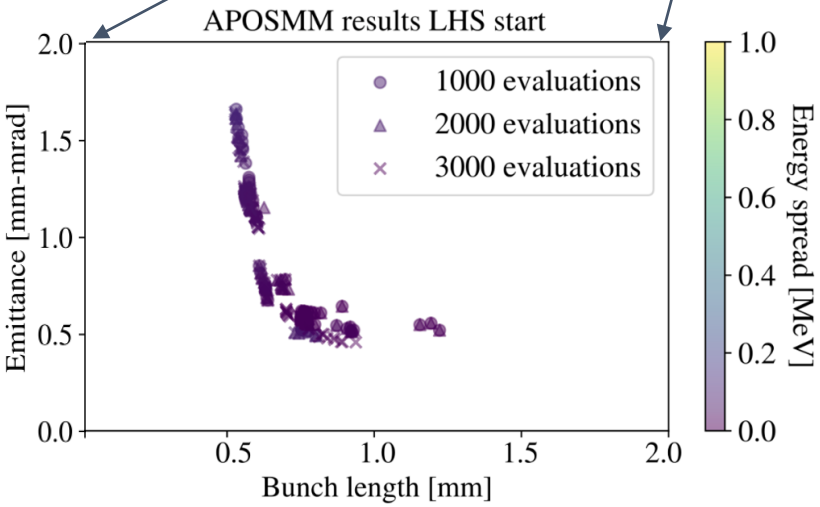
Optimization results: Gradient based multistart (APOSMM)



- LHS+APOSMM performs better w.r.t low objective values
  - Fewer evaluations needed to reach Pareto front
- Pareto front is identical but requires more evaluations for the uniform case.







Conclusions:

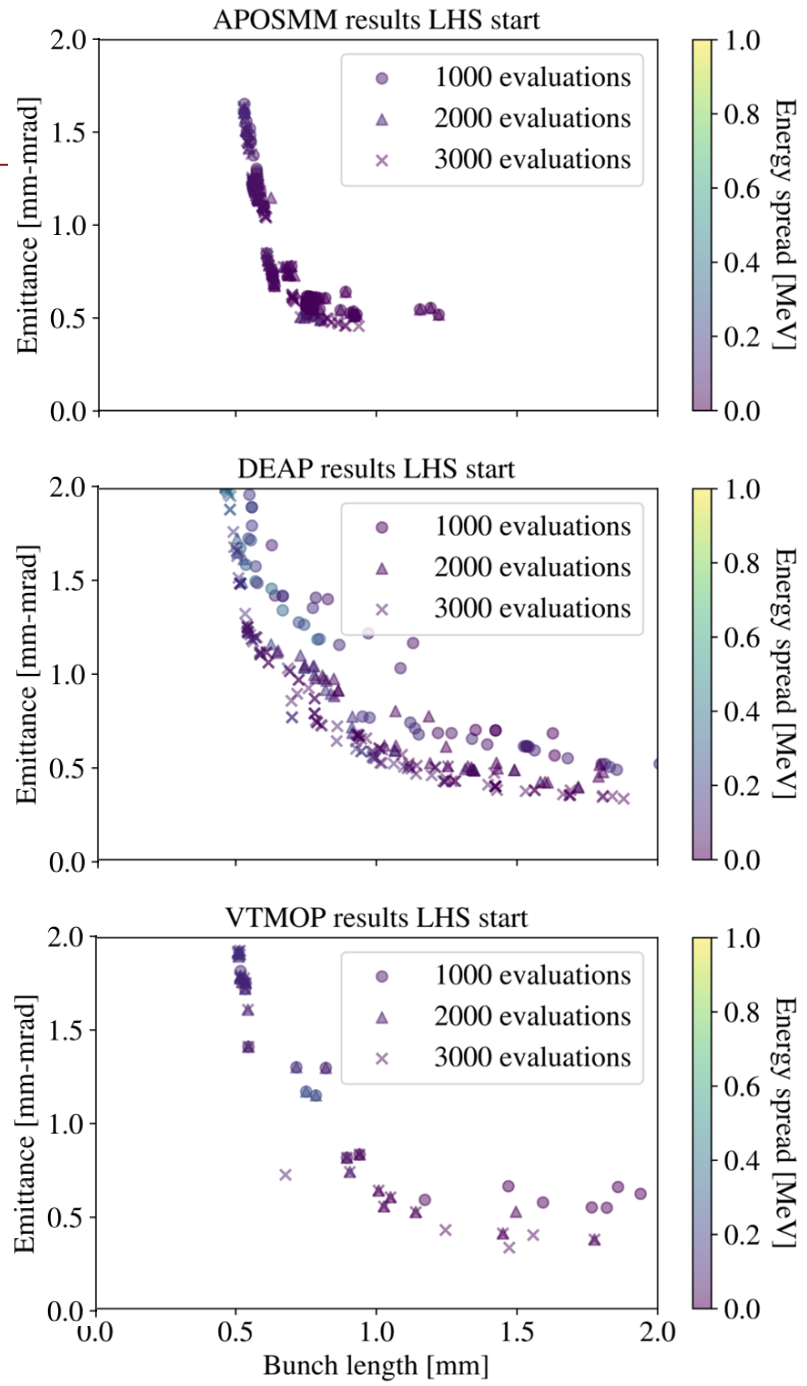
Use what you know to save time!

Does the initial sample impact the optimization results?

- Using a LHS could reduce number of points needed for optimization depending on the algorithm
  - Pareto front is reached in fewer evaluations when using methods that do not depend heavily on randomization/heuristics

Does the optimization method impact the number of evaluations needed to reach the Pareto front?

- All three methods are able to reach similar Pareto fronts given enough evaluations
- NSGA-II and VTMOP work well for objective space exploration
- APOSMM needs fewer evaluations than NSGA-II or VTMOP, given some prior knowledge of the objective space



Paper under review:
https://arxiv.org/abs/2206.03882

Thank you!

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