“Machine Learning Surrogate Model for CEBAF Injector at 200 kV with K-Long Bunch Charge”

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KLF Collaboration Meeting

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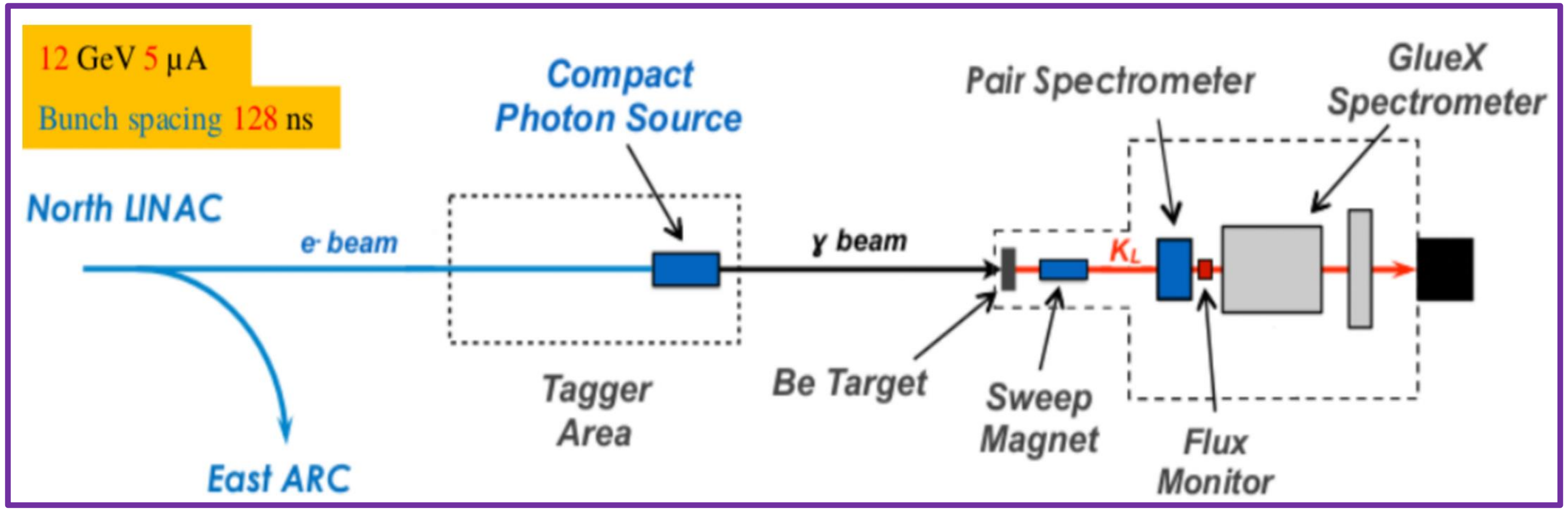
Outline

- Introduction/Motivation
- Challenges for K-Long Bunch charge
- CEBAF Injector for K-Long bunch charge at 130 kV/200 kV
- Beam dynamics/Optimizations at 200 kV (GPT)
- Machine Learning Surrogate Model
- Comparison between Physics (GPT) simulations and Neural Network
- Summary

CEBAF K-Long Beam

- The K-Long (beam of neutral kaons) experiment at JLab in Hall D, using the CEBAF with the GlueX experimental setup for strange hadron spectroscopy.



$$N(K_L)/s \approx 10^4, \quad \frac{N(K_L)_{JLab}}{N(K_L)_{SLAC}} \approx 10^3$$

M. Amaryan, et al. arXiv:2008.08215v3 [nucl-ex] 4 Mar 2021

Fig: Schematic view of Jefferson Lab Hall D beamline on the way e → γ → K_L.

- Measure differential cross section, polarizations of produced hyperons Λ, Σ, Ξ, Ω
- New and unique data can be obtained with intense K-Long beam aimed at LD2/LH2 Target.
- Deuteron target will provide the first-ever measurements with neutral kaons on neutrons.

CEBAF K-Long Beam Requirements

- Jefferson Lab K-Long experiment will run at CEBAF with much lower bunch repetition rates

CEBAF injector bunch currents and repetition rates for K-Long experiment.

Current (µA)	Repetition Rate (MHz)	Sub-harmonic of 499 MHz	Bunch Charge (pC)	Equivalent 249.5 MHz current (µA)
2.5	15.59	32nd	0.16	40
2.5	7.80	64th	0.32	80
5.0	15.59	32nd	0.32	80
5.0	7.80	64th	0.64	160
10.0	15.59	32nd	0.64	160

64 ns baseline
128 ns goal
128 ns 200 kV experiment

M. Amaryan, et al. arXiv:2008.08215v3 [nucl-ex] 4 Mar 2021

CEBAF with Low Frequency Beam

- Effect of Low Frequency Beam to Hall D on Measurement of a Lepton-Lepton Electroweak Reaction (MOLLER)
- KL Experiment:
  - 0.64 pC @ 7.8 MHz (128 ns, 5 µA average current) to Hall D
- MOLLER:
  - 0.26 pC @ 249.5 MHz (4 ns, 65 µA average current) at 11 GeV to Hall A
- Hall B:
  - 0.002 pC @ 249.5 MHz (4 ns, 50 nA average current)
- Hall C:
  - 0.12 pC @ 249.5 MHz (4 ns, 30 µA average current)

Space-Charge effect on low energy beam/high charge

- Space charge forces are the Coulomb repulsive forces inside a region of charge accumulation.

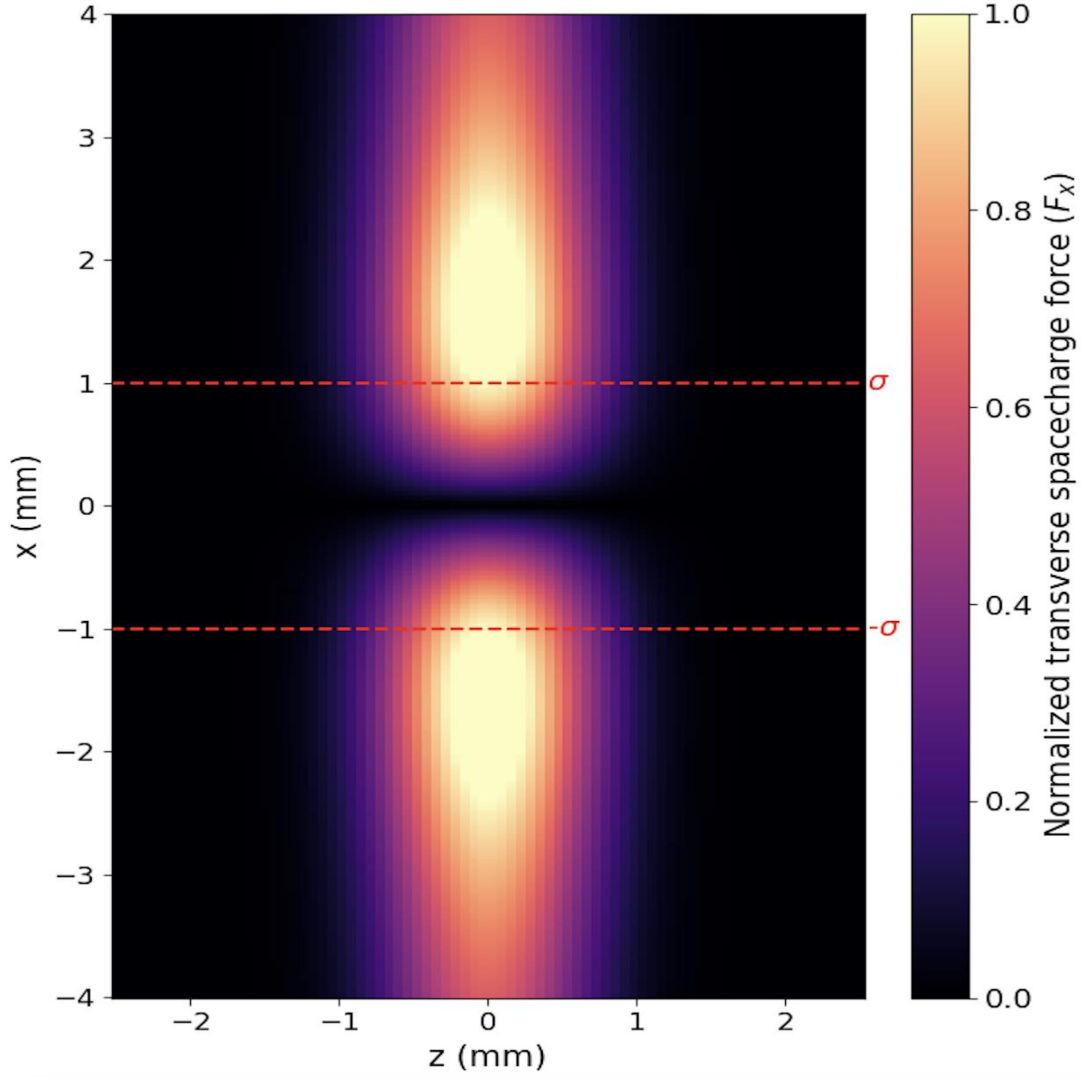
- Degrades beam quality and cause instabilities resulting in emittance growth, energy spread, increase in bunch length in linac, particle losses, can set up upper limit for beam current.

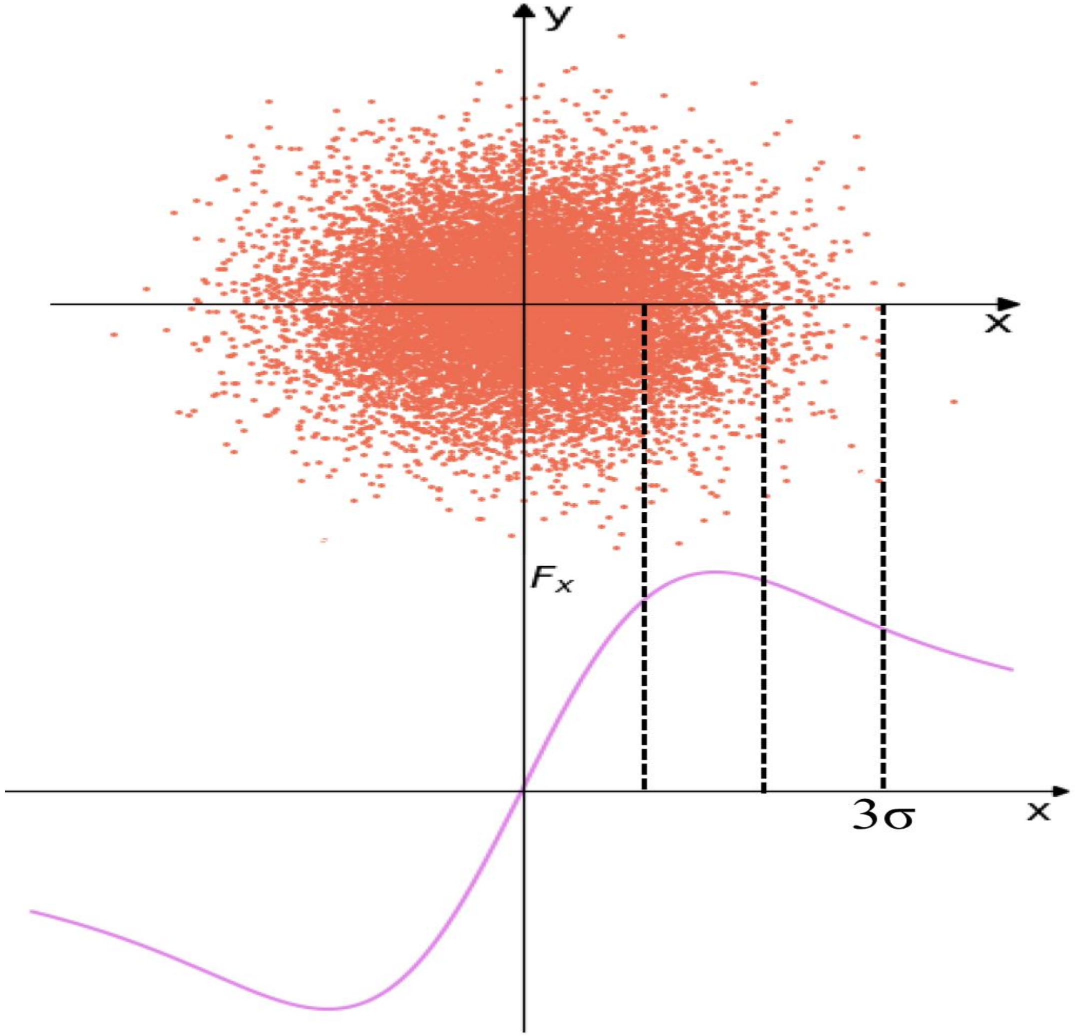
- For a Gaussian beam, direct space charge forces:

$$F_r = \frac{Q}{\sqrt{2\pi}\,\sigma_z} \frac{e}{4\pi\epsilon_0 \sigma_r^2 \gamma^2} \exp\left(-\frac{z^2}{2\sigma_z^2}\right) r$$

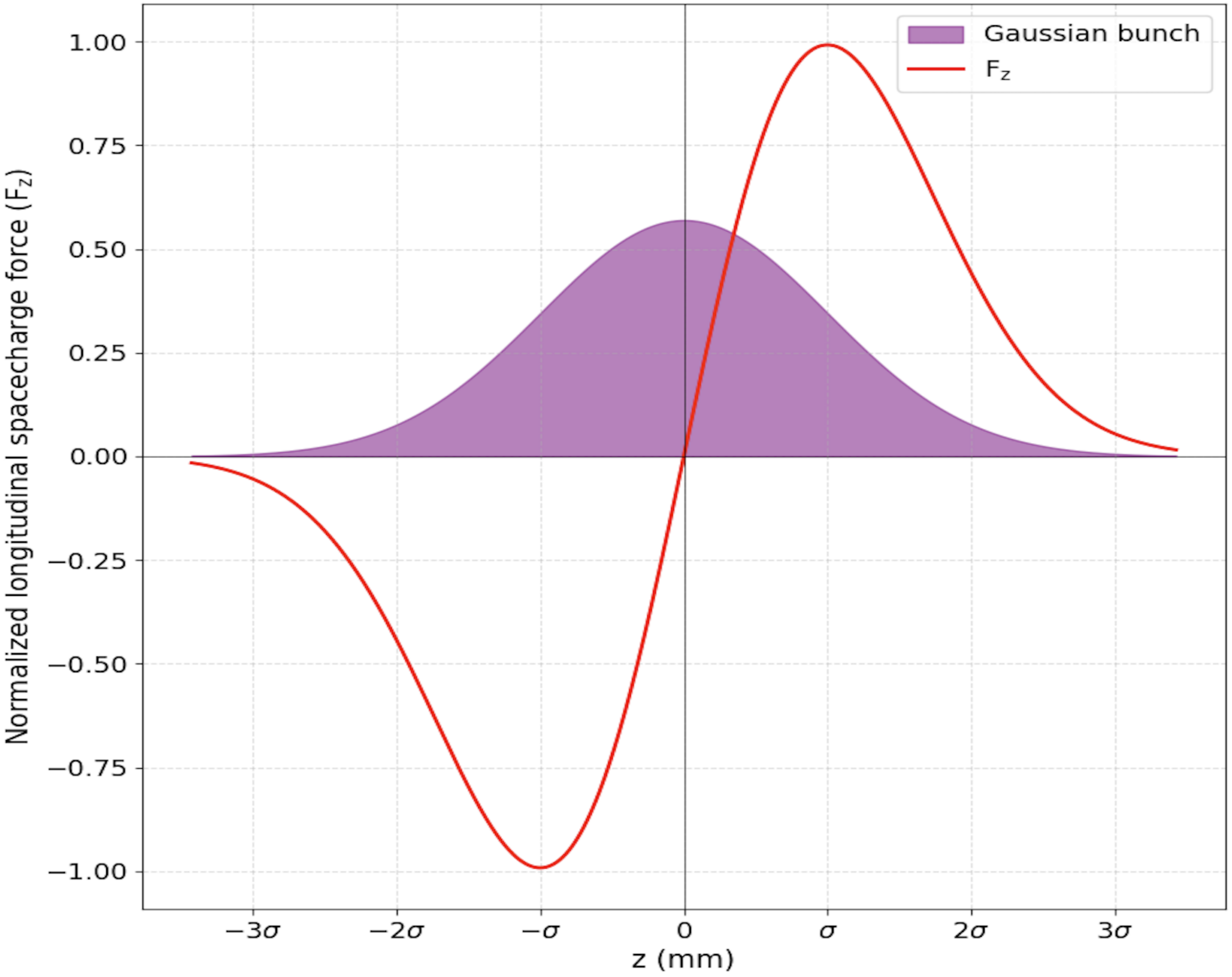
$$F_z = \frac{Q}{\sqrt{2\pi}} \frac{e}{4\pi\epsilon_0 \sigma_z^3 \gamma^2} z \left(1 + 2.\,log\,\frac{b}{a}\right)$$

Transverse Space-Charge force on low energy beam





Longitudinal Space-Charge Force on low energy beam



130/200 keV simulations

- Bunches with baseline K-Long beam parameters have been produced and measured in the CEBAF injector at 130 keV. Beam quality is good. Chopper scans of bunch length w/wo longitudinal bunching performed and agree with simulation expectations. Baseline beam (0.32 pC15.6 MHz) at 200 keV is expected to be acceptable.

- Simulations have been performed supporting operating at the injector upgraded energy of 200 keV. Simulations indicate good transmission and beam quality at twice baseline charge. At optimized settings for high charge, simultaneous operation with Halls A and C is indicated, with minor differences in the transverse beam optics.

https://wiki.jlab.org/klproject/images/7/72/K-Long_%282%29.pdf

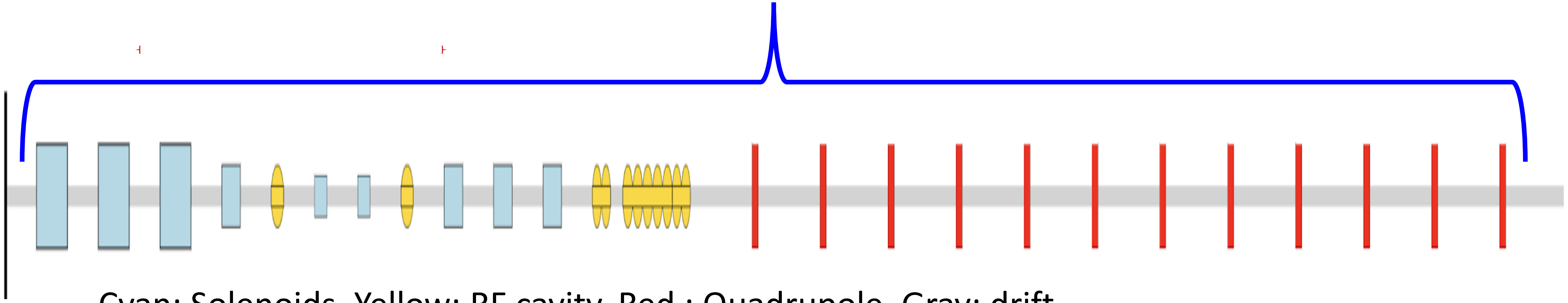
S. Pokharel et al.,
https://indico.jacow.org/event/41/contributions/2208/editing/paper

CEBAF Injector Optimization at 200 kV

- Performed using GDFMGO (non dominated sorting genetic algorithm (NSGA-II)) multi-objective global optimizer implemented in GPT.
- Optimizations were performed for K-long bunch charge (0.64 pC), at 320 µA beam current, laser frequency of 499 MHz for 200 keV beams. (it took almost 30 days with 8 CPU in Jlab ifarm) for 250 macroparticles. Simulations were performed at 10 k macroparticles.

Input Variables:
Solenoid Current/Magnetic field
Quadrupole Strength
RF Settings (Phase and amplitude) (more than 28 variables and more than 68 constraints)

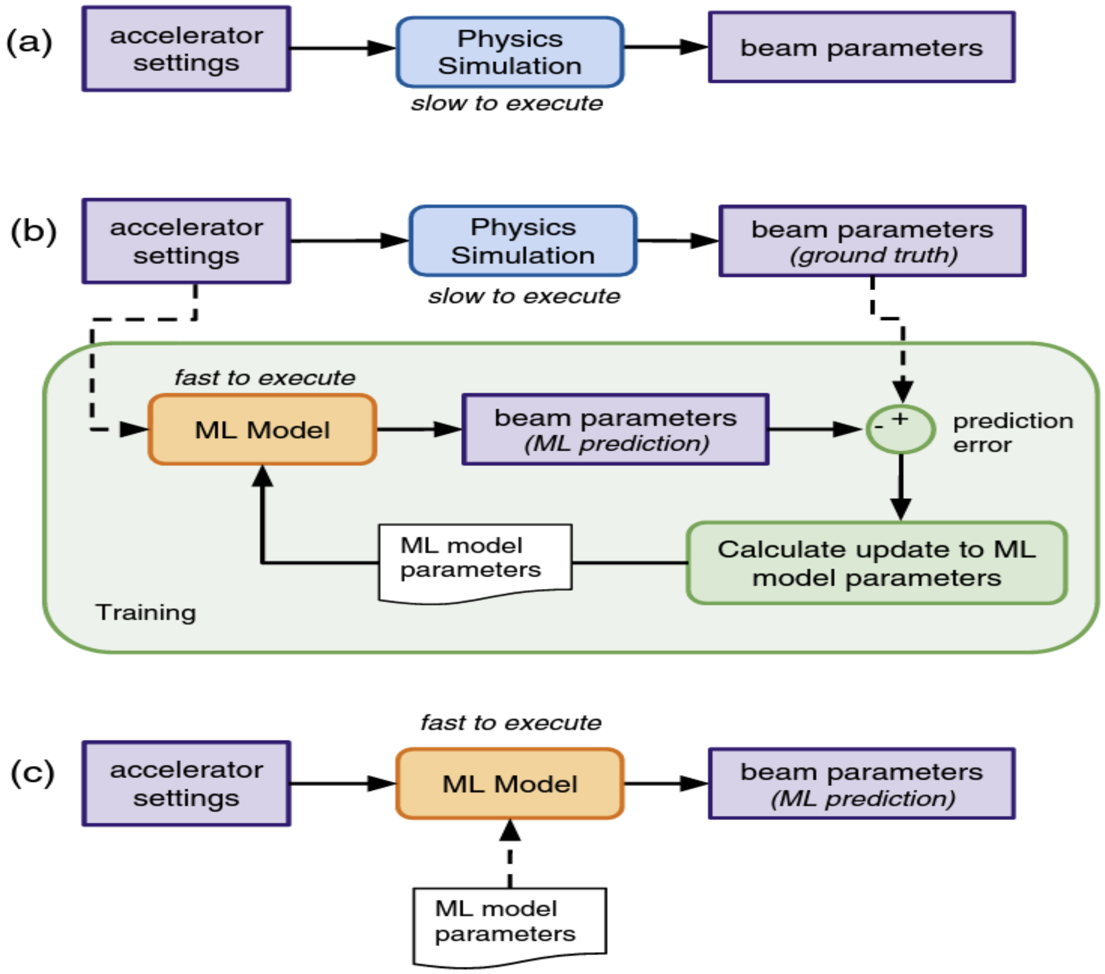
Output Beam Parameters:
Beam Transmission
$\epsilon_{n,x,y}\sigma_{x,y}, \sigma_t \ \sigma\_E_k$



Cyan: Solenoids, Yellow: RF cavity, Red : Quadrupole, Gray: drift

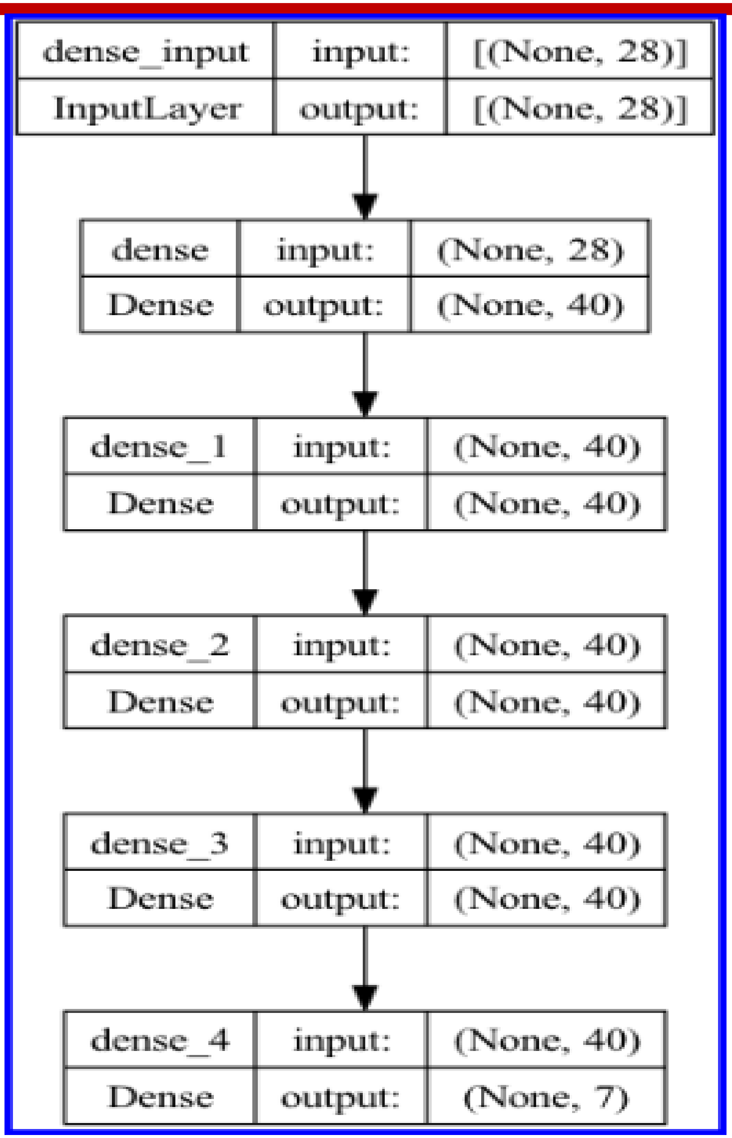
A Neural Network Surrogate Model

- Machine learning model that is trained to approximate the behavior of a more complex, computationally expensive, or time-consuming model or process.
- The goal is to provide a faster and less resource-intensive way to make predictions or perform simulations.



A. Edelene et al, PRAB 23, 044601 (2020)

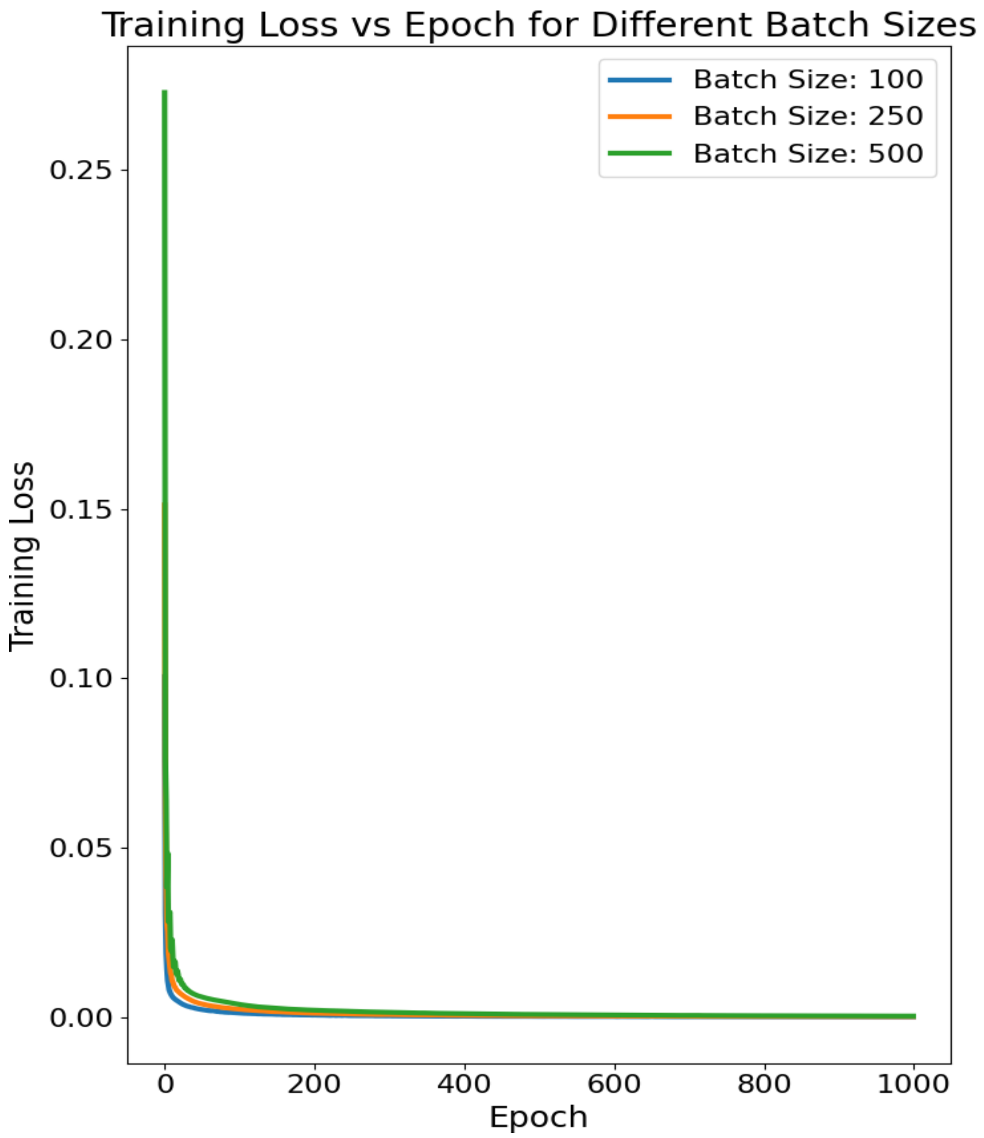
Machine Learning Model

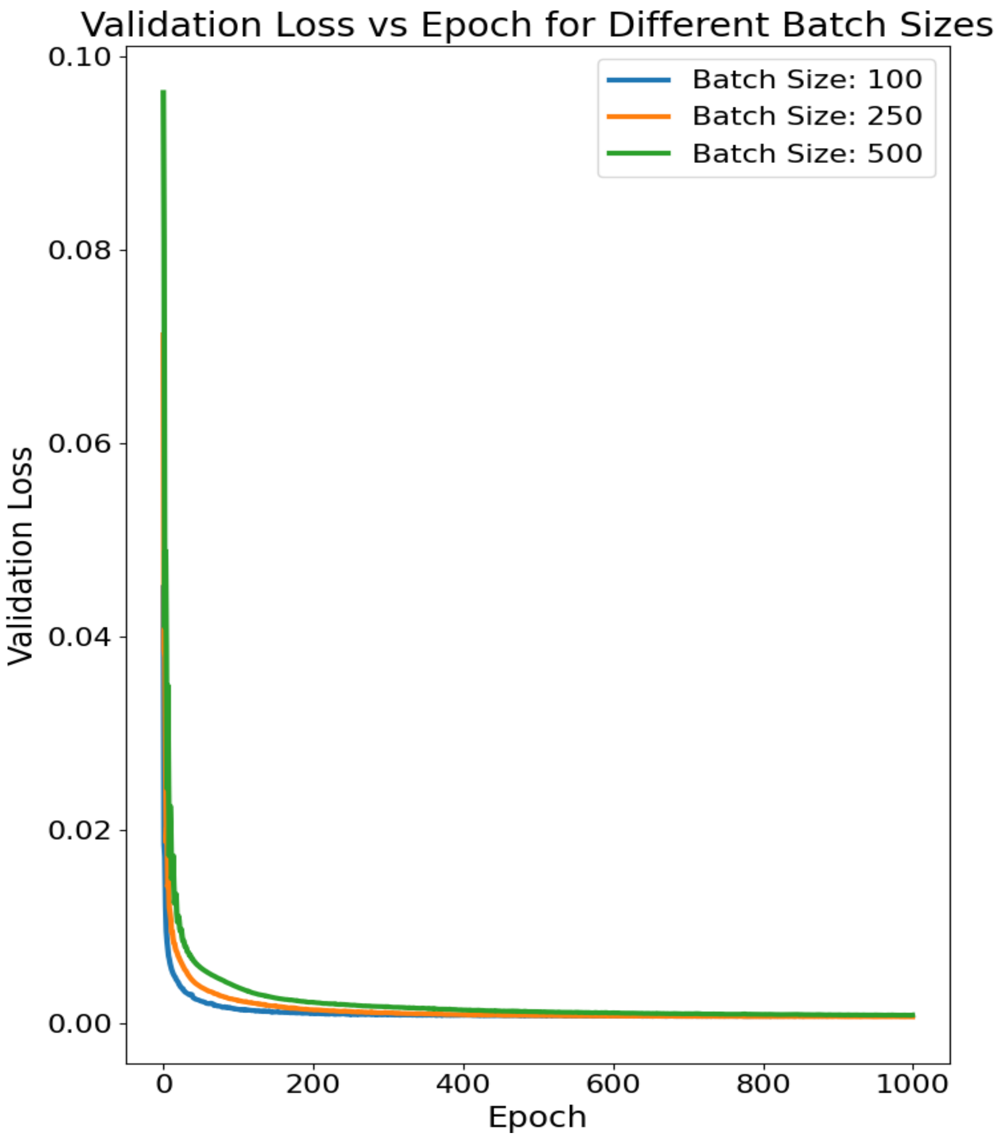


- The NNs were implemented in KERAS, with TensorFlow in python.
- Fully connected, feed-forward NN with four hidden layers, each with 40 nodes and hyperbolic tangent activation functions
- Trained for 1k epochs with a batch sizes of 100, 250 and 500 points.
- Used Adam optimization algorithm for training, with an initial learning rate 0.001 and hyperparameters β1= 0.9,and β2= 0.999.
- For training, the random sample data was randomly split into training(75%),validation(25%).
- Data taken from GPT simulations.

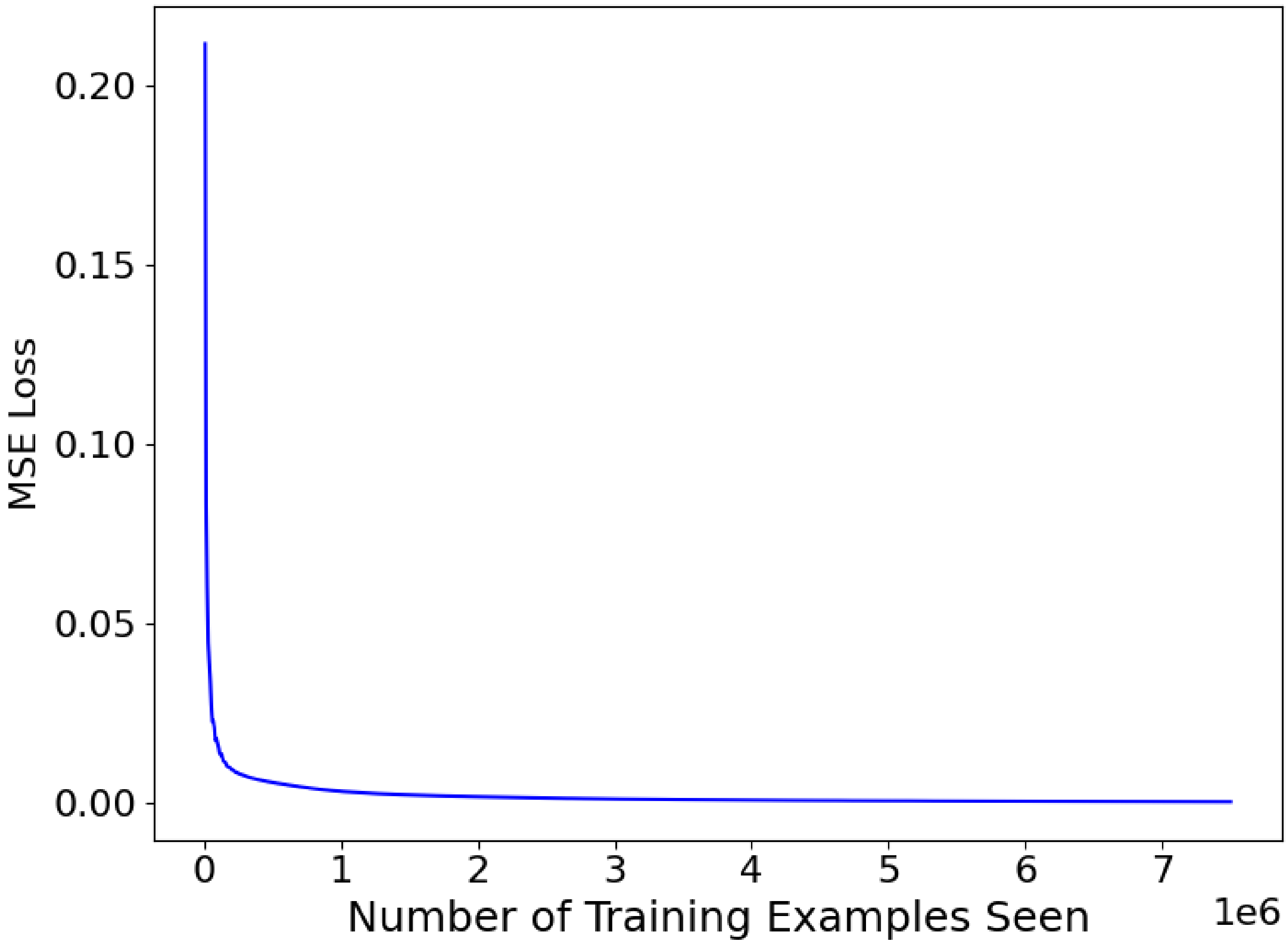
Fully connected Feed-forward NN Surrogate model with four layers, 28 inputs, 7 outputs.

Machine Learning: Result

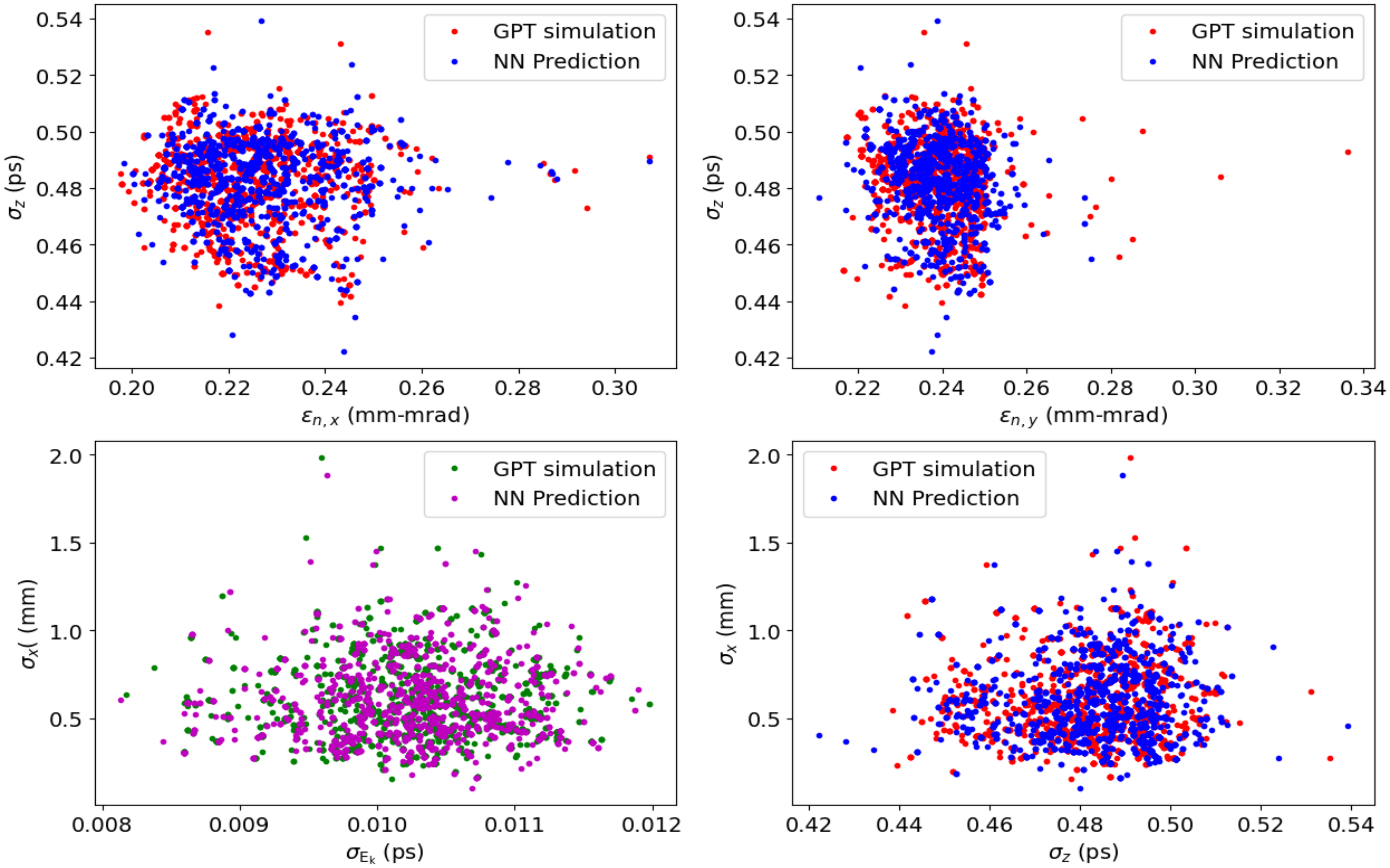




Machine Learning: Result

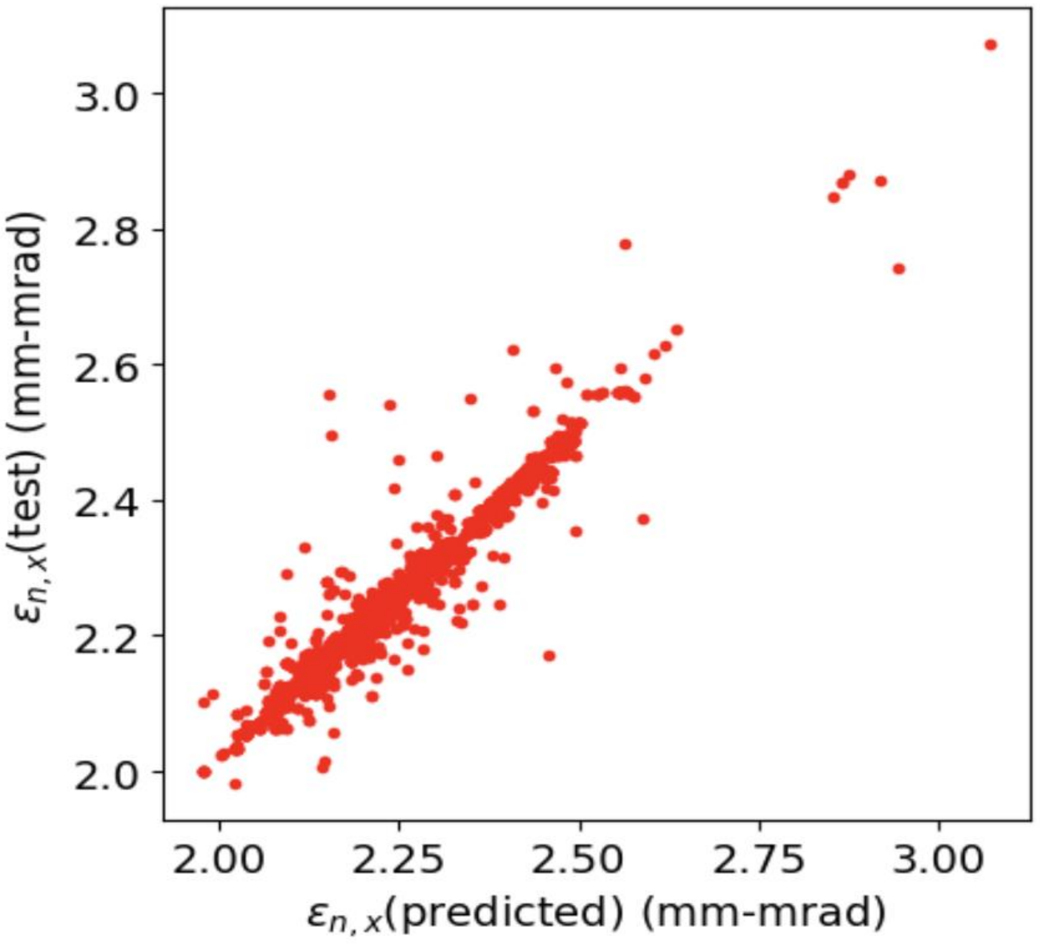


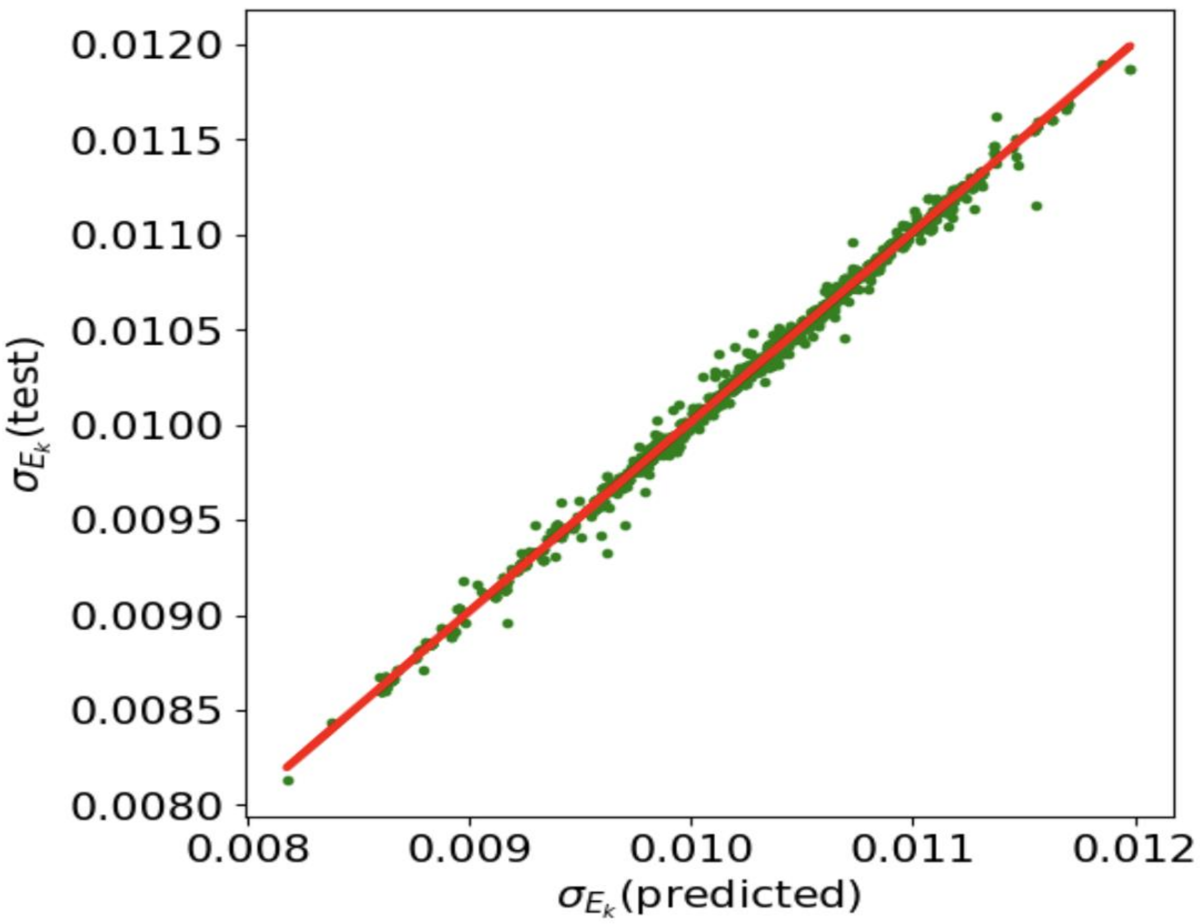
Machine Learning: Result



Point predictions from the NN surrogate model and the corresponding points from the physics (GPT) simulation.

Machine Learning: Result





Point predictions from the NN surrogate model and the corresponding points from the physics (GPT) simulation.

Machine Learning: Plan

- NSGA-II using DEAP in python
- Obtain the optimized setting for magnetic elements and RF settings
- Using Machine learning, compare the results with GPT optimizations
- After getting the optimized settings for 200 kV K-long bunch charge from ML,
  - Perform beam simulation with Parity Quality Beam (for simultaneous operations of MOLLER and K-Long experiment)
  - For 0.64 pC, 0.32 pC, and 0.26 pC
  - With spin flip: flip-left, flip-right

Summary

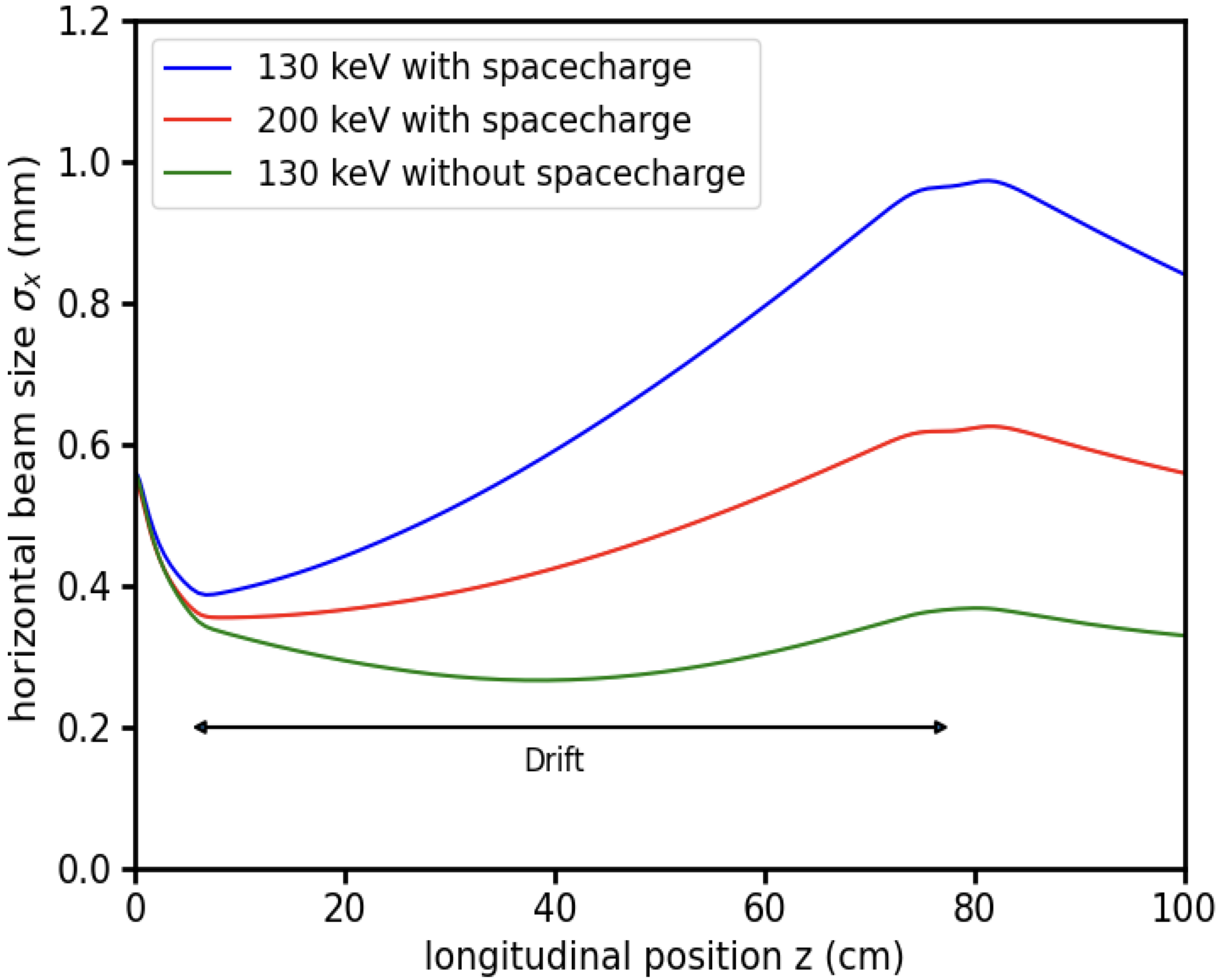
- Conclusion:
  - Optimizations and simulations performed at 200 kV for K-Long bunch charge.
  - Further optimization of CEBAF Injector is in progress (Using GPT and ML) with parity quality beam
  - Beam dynamics studies were carried out and understood properly.
  - Waiting for 200 kV beam measurement for K-Long and Chopper Phase scanning at 200 kV

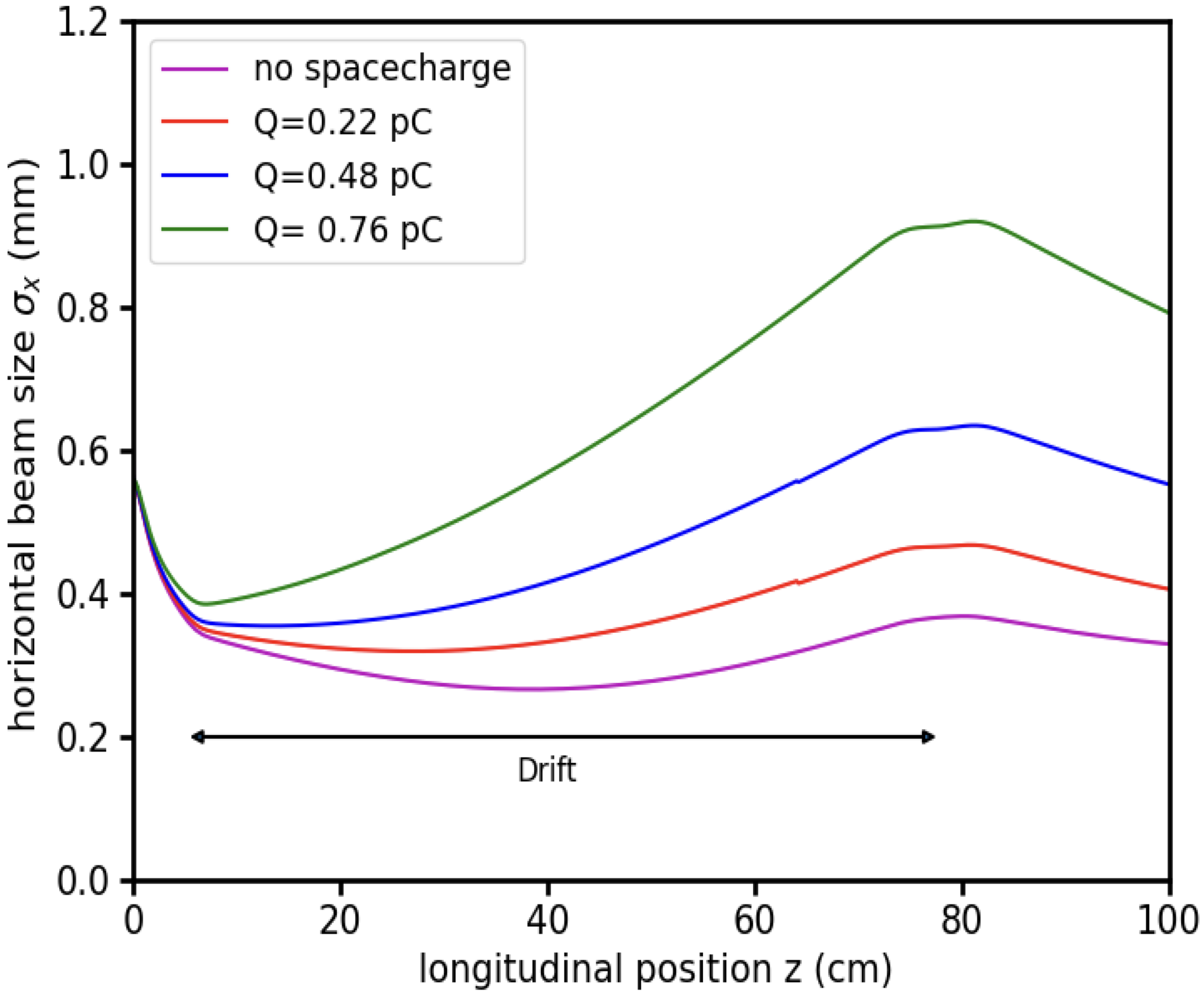
Thank you!

Namaste

Back up Slides

Transverse beam size variation due to space charge





Bunch length variation due to space charge