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Machine learning-based optimisation of plasma density ramps at CLARA FEBE

Jiaqi Zhang[1,2], Hossein Saberi[1,2], Guoxing Xia[1,2], Oznur Apsimon[1,2], Stewart Boogert[1,2], Thomas Pacey[3,2], Toby Overton[3,2]

[1]*Department of Physics and Astronomy, University of Manchester, Manchester, M13 9PL, United Kingdom*
[2]*Cockcroft Institute, Warrington, WA4 4AD, United Kingdom*
[3]*Accelerator Science and Technology Centre (ASTeC), STFC Daresbury Laboratory, Warrington, WA4 4AD, United Kingdom*

Email: jiaqi.zhang-11@postgrad.manchester.ac.uk
guoxing.xia@manchester.ac.uk

1. Introduction

➢ **Background:** Plasma wakefield acceleration (PWFA) has gained global attention for the achievable ultra-high accelerating gradients [1], which will drastically reduce the footprint, price, and carbon load of accelerators to be used for medical applications, free electron lasers (FELs), and future high-energy physics experiments [2].

➢ **Problem:** Gaussian profile of the plasma density is more practical than the linear plasma ramp [3,4]. No fitting model has been built so far for prediction of the optimal beam quality.

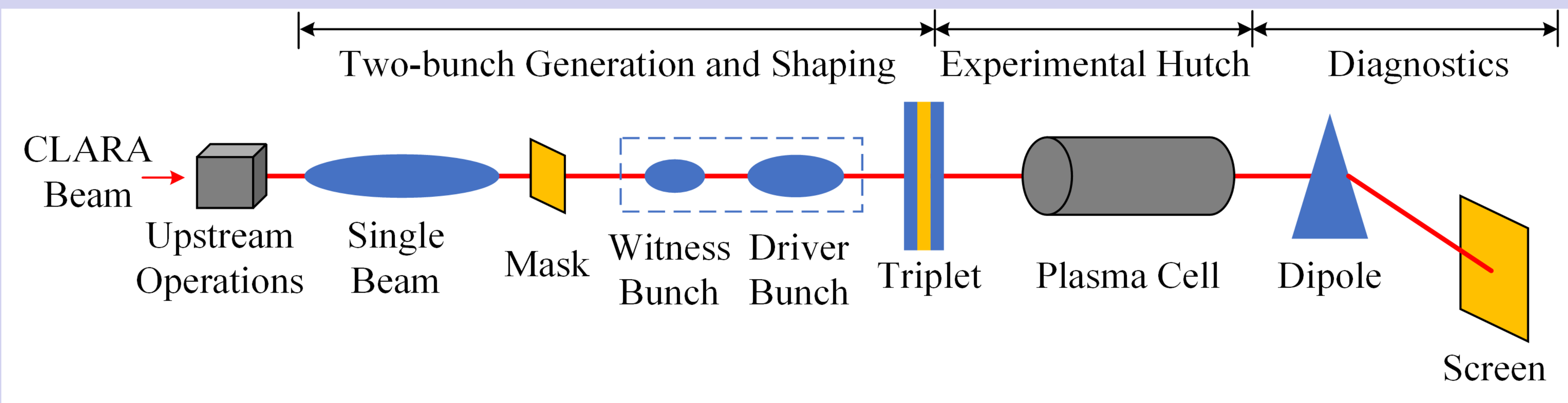
➢ **Facility:** The Compact Linear Accelerator for Research and Applications (CLARA) at the Daresbury Laboratory, capable of producing 250-MeV electron bunches. Recently, a new beamline attached to CLARA, the Full Energy Beam Exploitation (FEBE) facility, has been designed to provide ultra-short and low-emittance electron bunches [5].

➢ **Investigations:** Here we numerically investigated PWFA with a two-bunch configuration, i.e., the driver/witness bunch, at FEBE to double the energy of the witness bunch. The up-ramp plasma density profile was optimised based on machine learning. We trained the surrogate model for tolerance and sensitivity analyses.

➢ **Research goals:**
- Obtain the optimal beam quality.
- Review beam quality stability around the optimal parameter point.

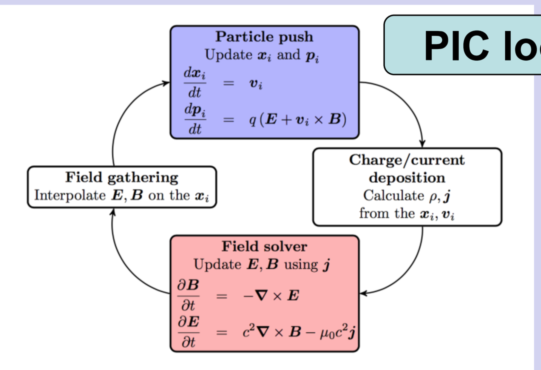
2. Schematic of PWFA Experiments at CLARA FEBE

- ➢ Driver/witness configuration is generated by the mask technology.
- ➢ The discharge method is planned to form the ramp plasma density profile.
- ➢ Diagnostics include the energy spectrometer, quadrupole scanner, and so on.



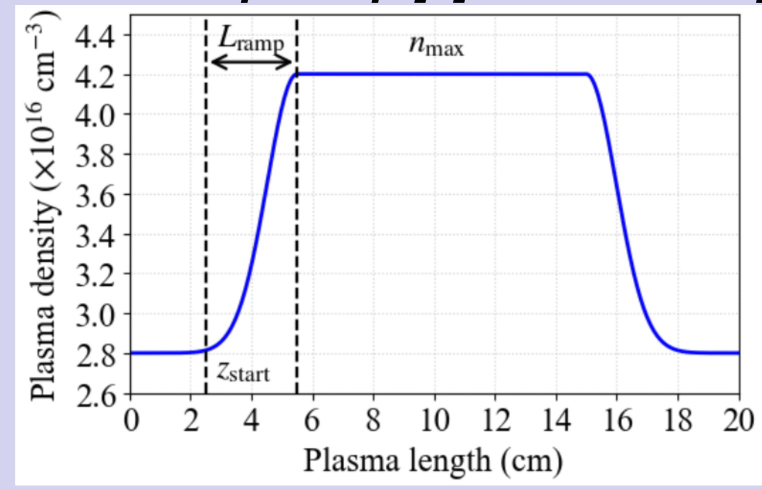
3. Particle-in-cell Code

***Fourier-Bessel particle-in-cell (FBPIC)* [6]**
- ➢ Quasi-3D cylindrical coordinate
- ➢ Maxwell's equation solver in the spectral space
- ➢ GPU-based code running in the STFC SCARF cluster
- ➢ Avoid spurious numerical dispersion



4. Simulation Parameter Settings

Gaussian up-ramp [3] & down-ramp profiles coupled:

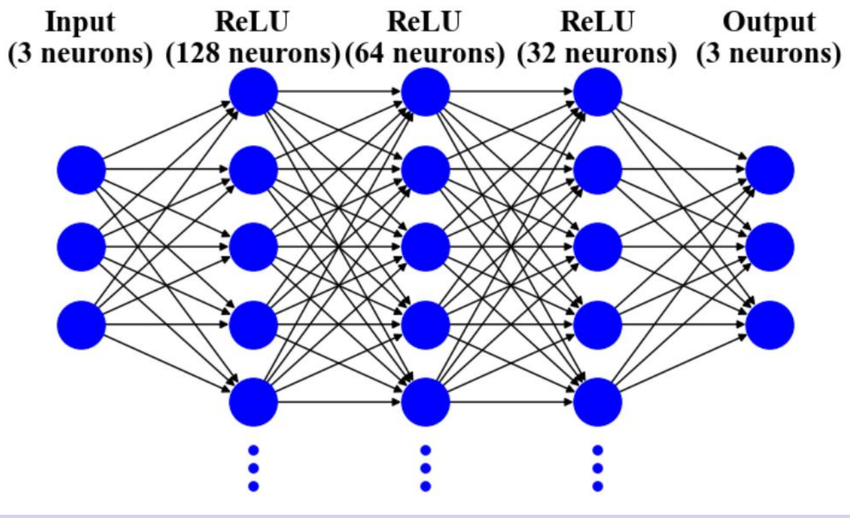


Parameters	Driver	10 pC witness
Beam density (cm^{-3})	1.19×10^{15}	1.98×10^{15}
Charge (pC)	150	10
Energy (MeV)	250	250
Bunch length (μm)	10	10
Transverse size (μm)	50	10
Energy spread (%)	1	1
Emittance (mm mrad)	5	5

$$n_p(z) = n_{low} + (n_{max} - n_{low}) \exp\left(-\left(z - z_{start} - L_{ramp}\right)^2 / 2\sigma^2\right), \text{ where } \sigma = L_{ramp} \Big/ \sqrt{2\ln(1/\varepsilon)}$$

5. Structure of the Neural Network

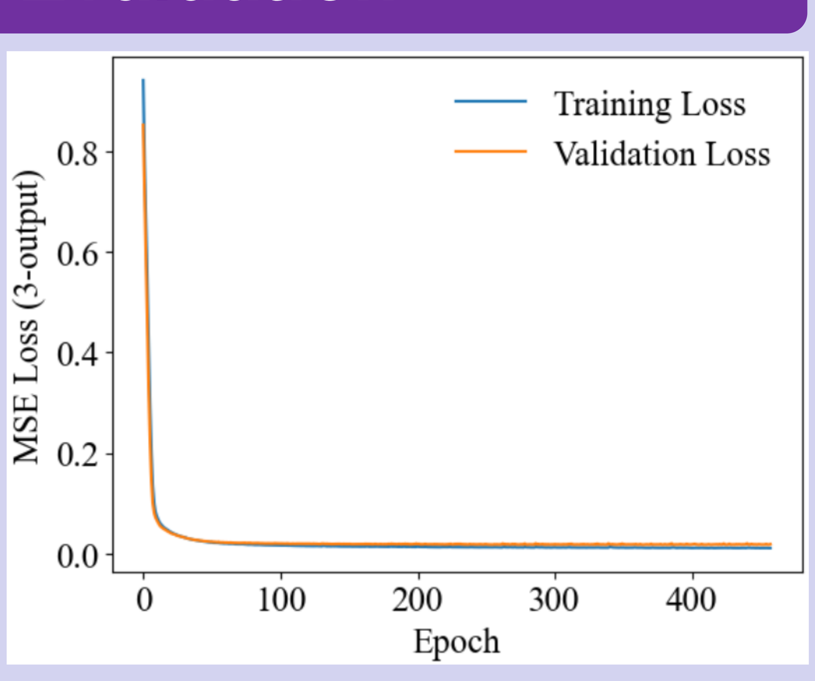
Layer (Type)	Output Shape	Param #
Input Layer (Dense)	(None, 3)	0
Hidden Layer 1 (Dense)	(None, 128)	512
ReLU Activation 1 (ReLU)	(None, 128)	0
Hidden Layer 2 (Dense)	(None, 64)	8256
ReLU Activation 2 (ReLU)	(None, 64)	0
Hidden Layer 3 (Dense)	(None, 32)	2080
ReLU Activation 3 (ReLU)	(None, 32)	0
Output Layer (Dense)	(None, 3)	99

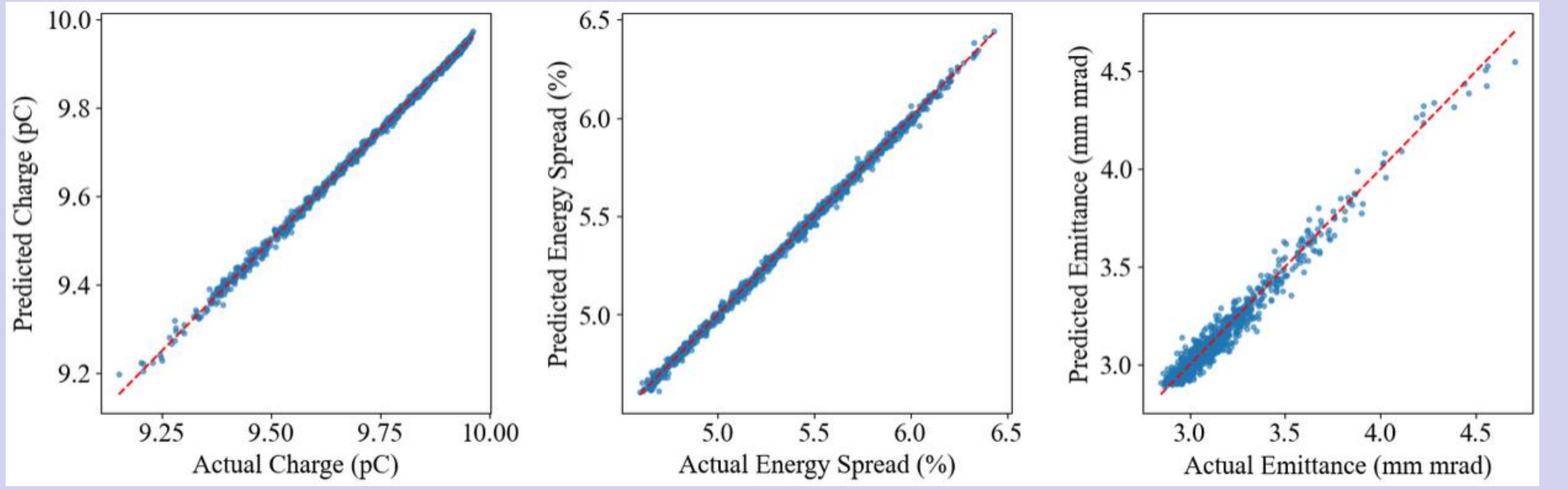


Total parameters: 32843

6. Model Training and Evaluation

- ➢ A total of 1000 simulations were performed, with 20% reserved for validation.
- ➢ The training loss decreases rapidly within the first 10 epochs.
- ➢ The training curve remains smooth and stable throughout.
- ➢ The validation curve closely follows the training curve, with no signs of significant overfitting.



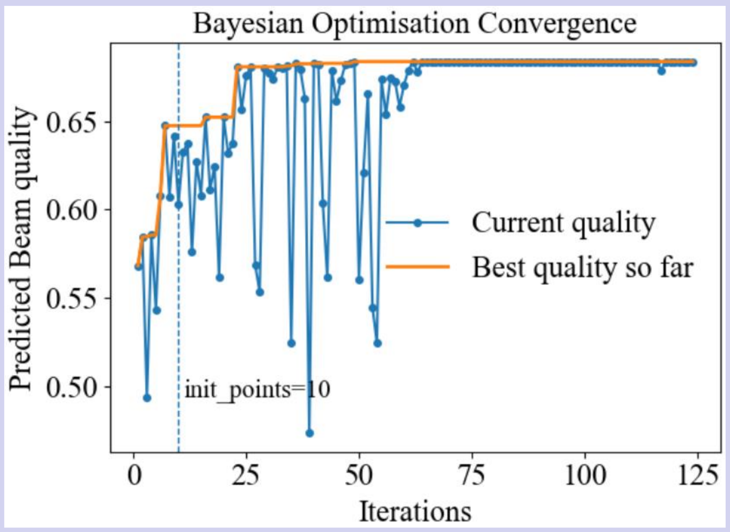


Mean Absolute Error (MAE):
0.006 pC (0.063%), 0.015% (0.290%), 0.043 mm mrad (1.366%)

7. Bayesian optimisation and Final Quality

Beam quality definition [7]:

$$Quality = \frac{Q[\mathrm{pC}]}{\sigma_{E,RMS}[\%]\,\varepsilon_N[\mathrm{mm\ mrad}]}$$



Optimal parameters (predictions):

z_{start} = 2.49 cm, Q = 9.52 pC (9.54)
n_{max} = 4.24×10^{16} /cm^3, σ_E = 4.75% (4.74)
L_{ramp} = 1.19 cm, ε_N = 3.06 mm mrad (2.95)
Quality = 0.655 (0.682)

Final quality for energy doubling:

Non-ML: Q = 8.60 pC, σ_E = 5.77%, ε_N = 6.50 mm mrad, *Quality* = 0.229
ML: Q = 9.54 pC, σ_E = 5.84%, ε_N = 2.74 mm mrad, *Quality* = 0.596 (160% higher)

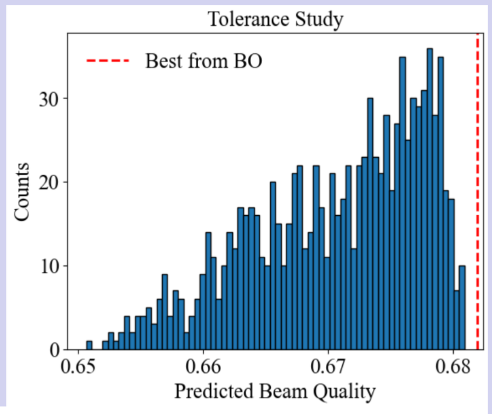
8. Robustness and Parameter Sensitivity

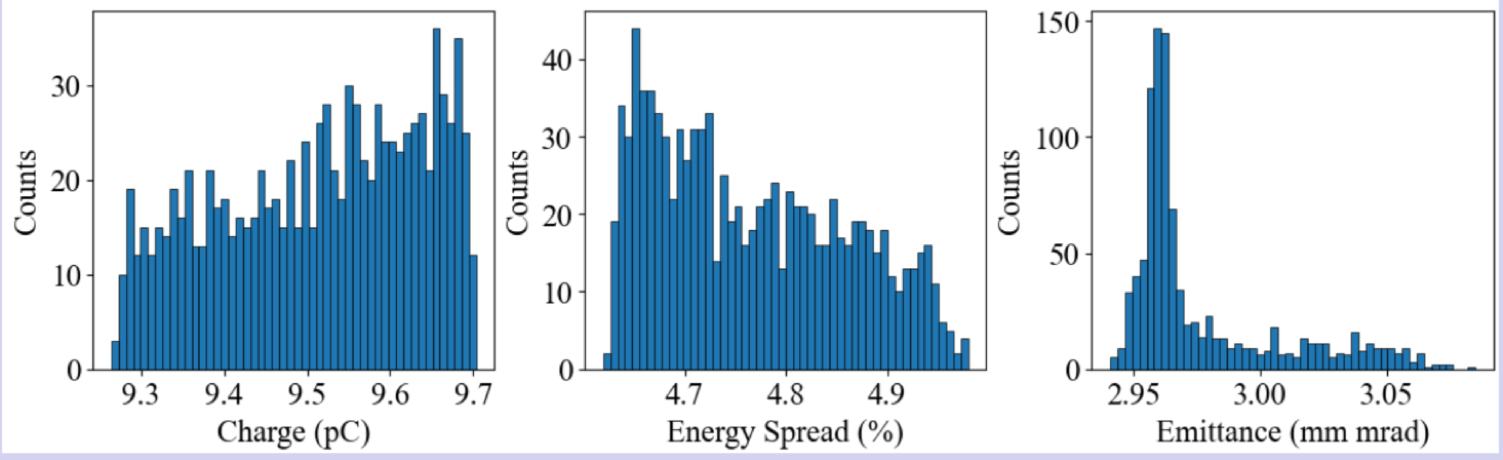
Parameter Variation:

z_{start} = 2.24 – 2.74 cm (±10%), n_{max} = 4.03 – 4.45×10^{16} /cm^3 (±5%)
L_{ramp} = 1.09 – 1.33 cm (±10%)

Tolerance analysis (1000 LHS samples):

Q : mean = 9.514 (-0.27%), σ = 0.122 (1.28%)
σ_E : mean = 4.765 (0.53%), σ = 0.095 (1.99%)
ε_N : mean = 2.977 (0.91%),, σ = 0.031 (1.04%)



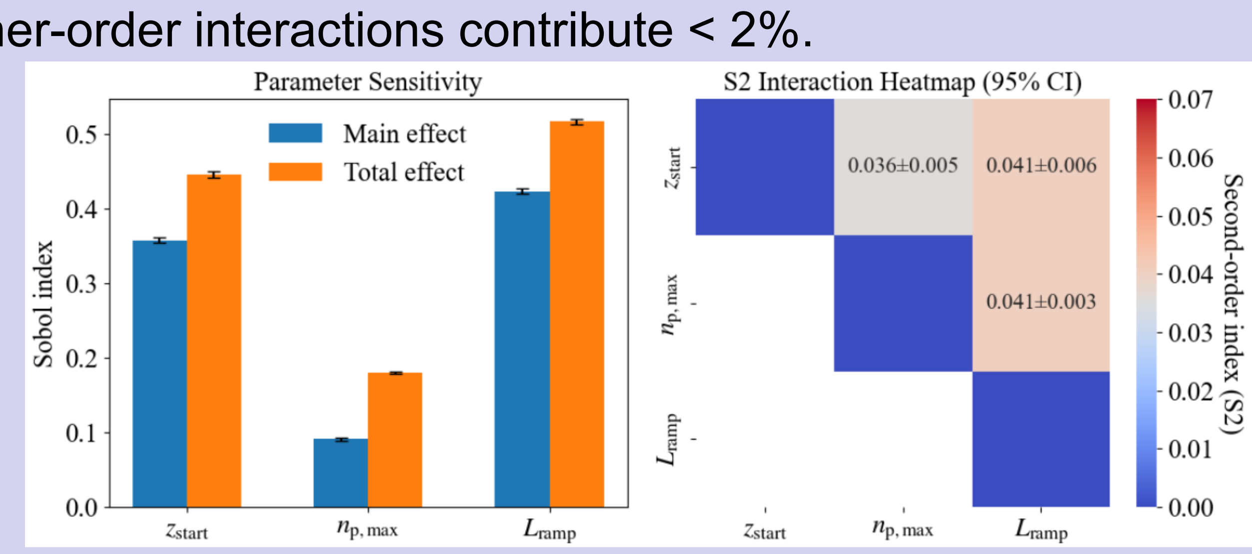


Parameter Variation:

z_{start} = 2.0 – 5.0 cm, n_{max} = 3.5 – 4.5×10^{16} /cm^3, L_{ramp} = 0.5 – 5.0 cm

Sobol sensitivity analysis (2^{18} LHS samples):

- ➢ Main effects dominate, explaining 87% of the variance:
- ➢ Sensitivity ranking: $L_{ramp} > z_{start} > n_{max}$.
- ➢ Pairwise interactions account for ~12% (~91% of total interaction effects).
- ➢ Higher-order interactions contribute < 2%.



Summary

We performed machine learning–based optimisation of PWFA for the energy-doubling scheme at CLARA FEBE. The surrogate model achieved mean absolute percentage errors below 2%. Using Bayesian optimisation, we identified the optimal parameters and obtained a final-energy beam quality of 0.596, representing a 160% improvement compared with the non-ML baseline. Tolerance analysis confirmed that the mean beam quality remains within 1%, with deviations below 2%. Sensitivity studies further revealed that the main effects dominate the variance, with the sensitivity ranking following $L_{ramp} > z_{start} > n_{max}$.

Acknowledgements

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➢ Computing resources are provided by STFC Scientific Computing Department's SCARF cluster.

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