Problem

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Each configuration takes a few minutes to simulate.

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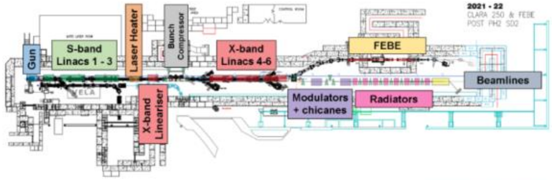
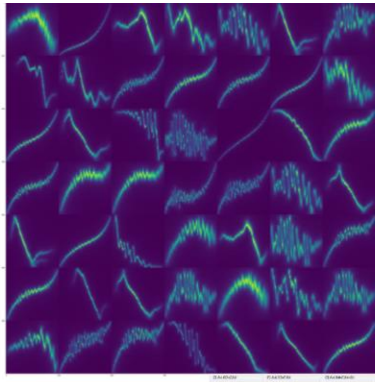
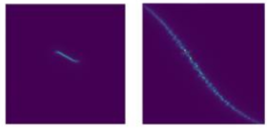






17 Parameters
- 7 RF cavities with configurable phase and field amplitude.
- Relative Momentum Scatter imparted by the laser heater.
- Dechirper Factor.
- Bunch Compressor Angle.

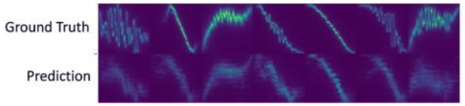
2 Outputs
- Region of Interest – scaled image of the LPS graph focused on the point of interest.
- Fixed Extent – The whole of the LPS graph.

Solution

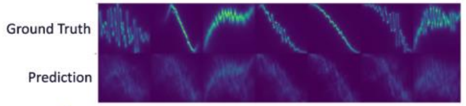
Using machine learning, we create a surrogate model of the simulation that runs in linear time.

Simpler models as used in previous works lack the predictive power for fine structure details critical for FEL performance

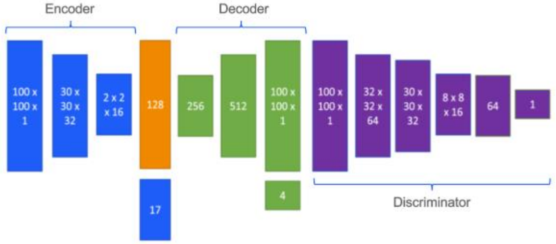
Simple CNN based model produces low quality fine structure details



DNN autoencoder model produces better images, but blurred



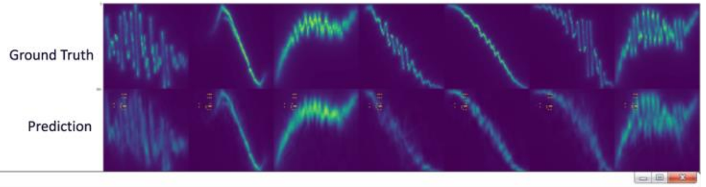
Combining a conditional variational autoencoder with a generative adversarial network to build a CVAE-GAN by affixing a discriminator to a CVAE model and training the model adversarially.

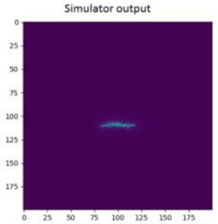


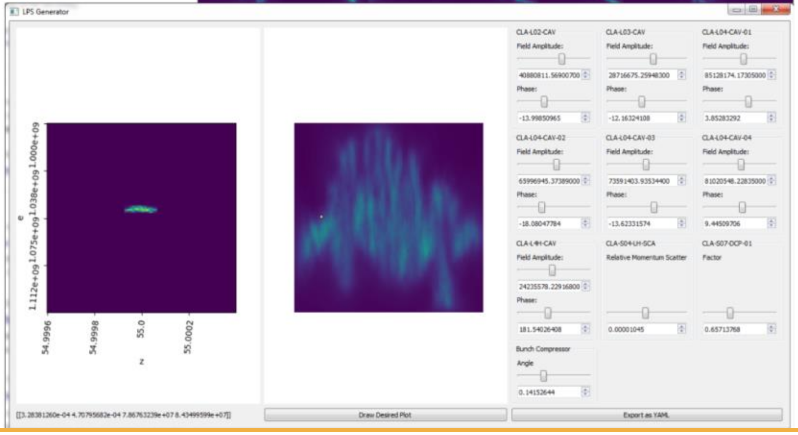
Adversarial training leads to the generation of images which are almost indistinguishable from simulation.

Results

Real time generation of LPS graphs matching simulation. Milliseconds instead of minutes!

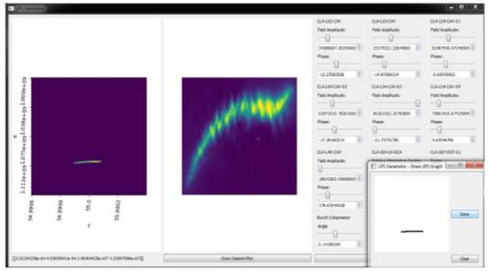






Rapid Search

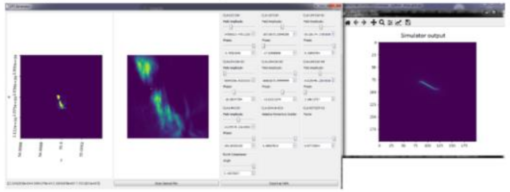
Operators can draw their desired graph and get the parameters which closely match it within seconds.



Future Work

We intend to generate multiple screens at once from multiple locations along the beamline, as well as perform comparisons to real-world data using a transverse deflecting cavity, potentially applying transfer learning using a small quantity of TDC data to augment a larger quantity of simulation data.

Currently the network breaks down at extreme regions, we believe as a result of imbalanced sampling. A new dataset has been generated which contains many more samples from a wider range of parameters.



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WEPV020 - Learning to Lase: Machine Learning Prediction of FEL Beam Properties

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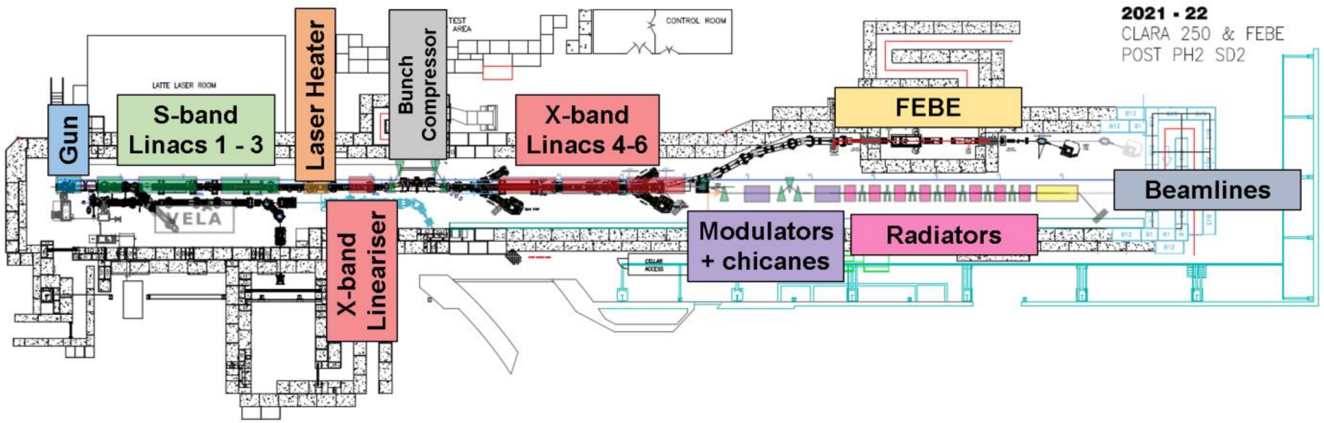

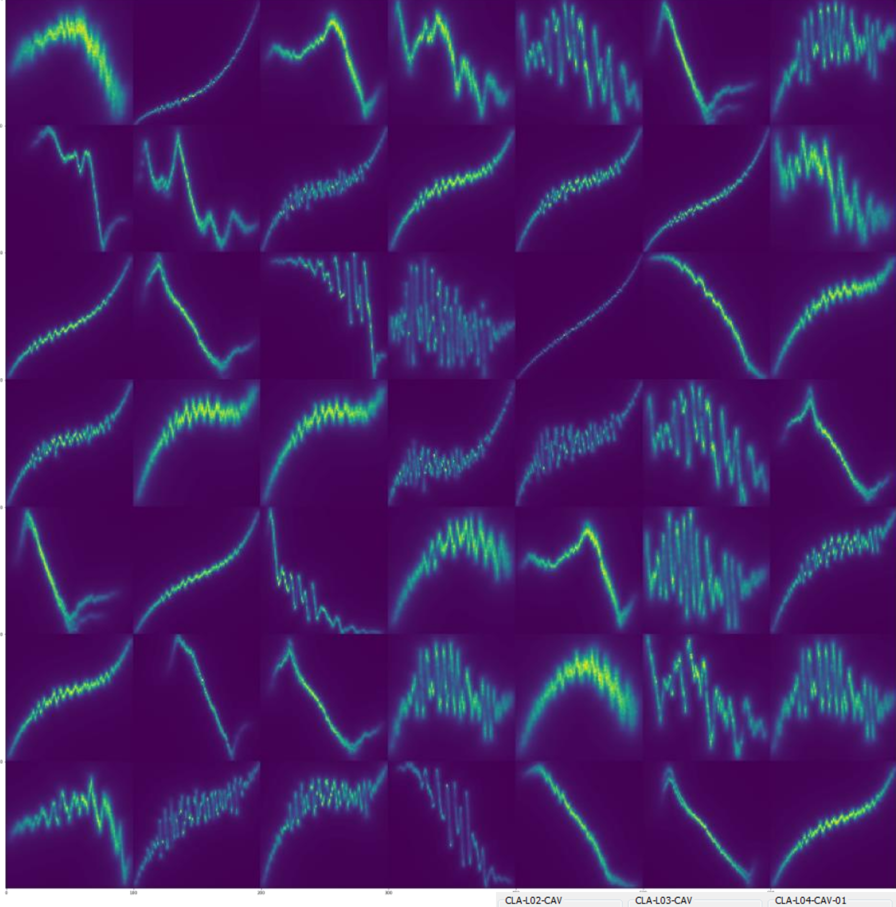

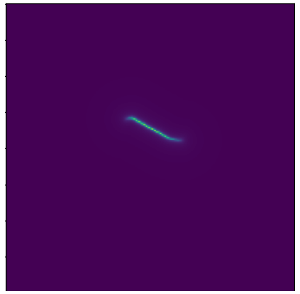

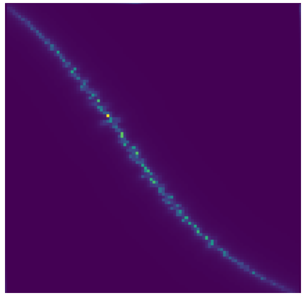

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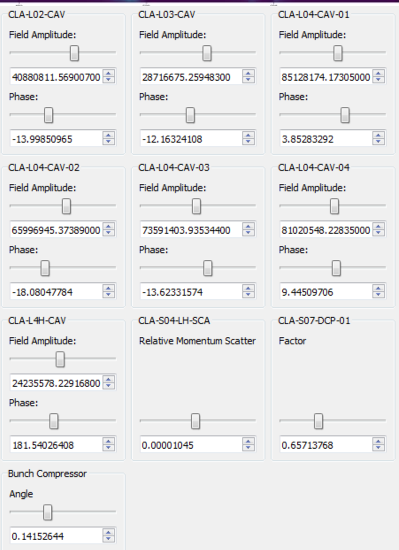

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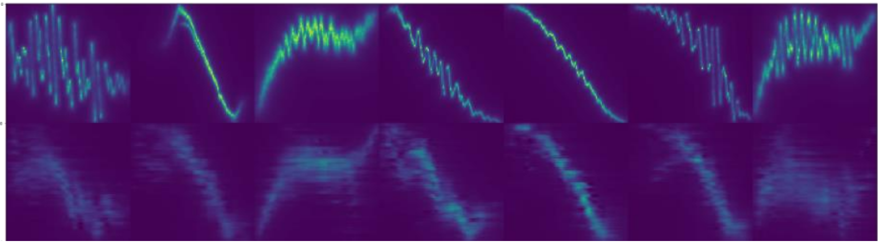
Prediction



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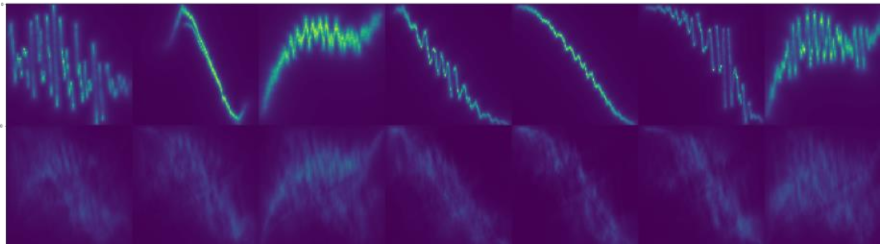

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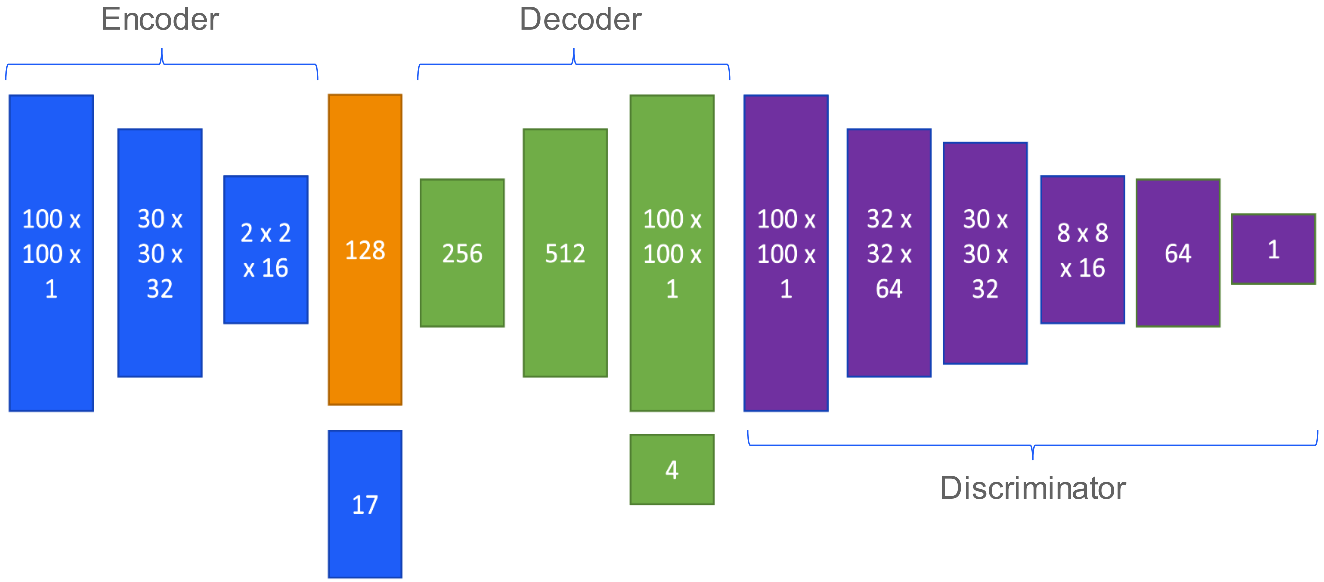

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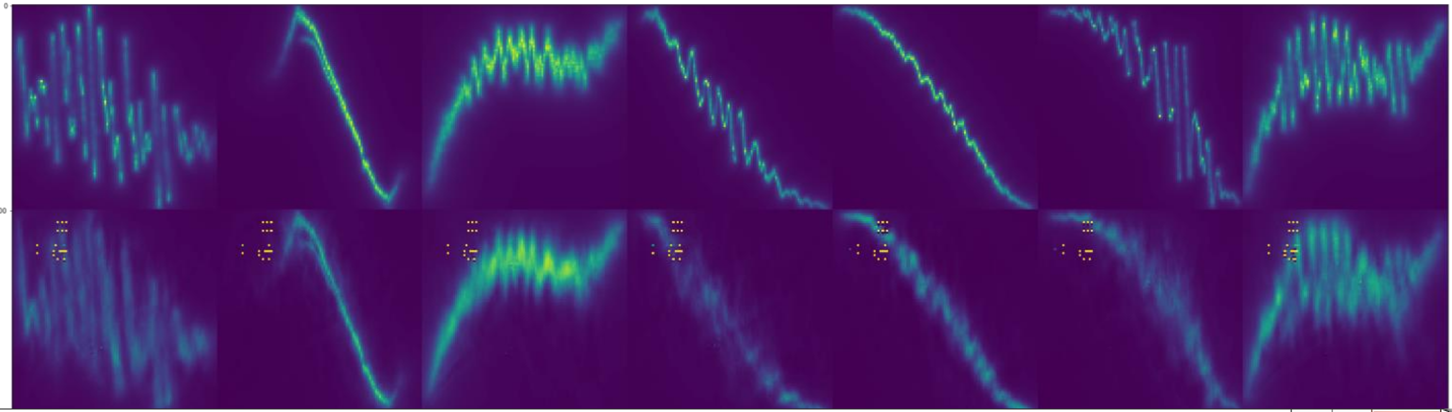

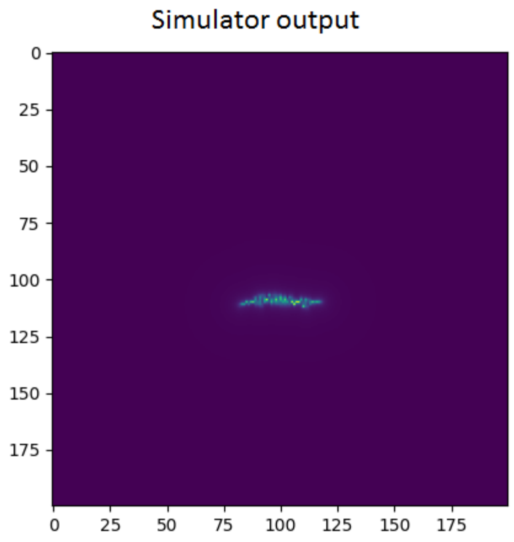

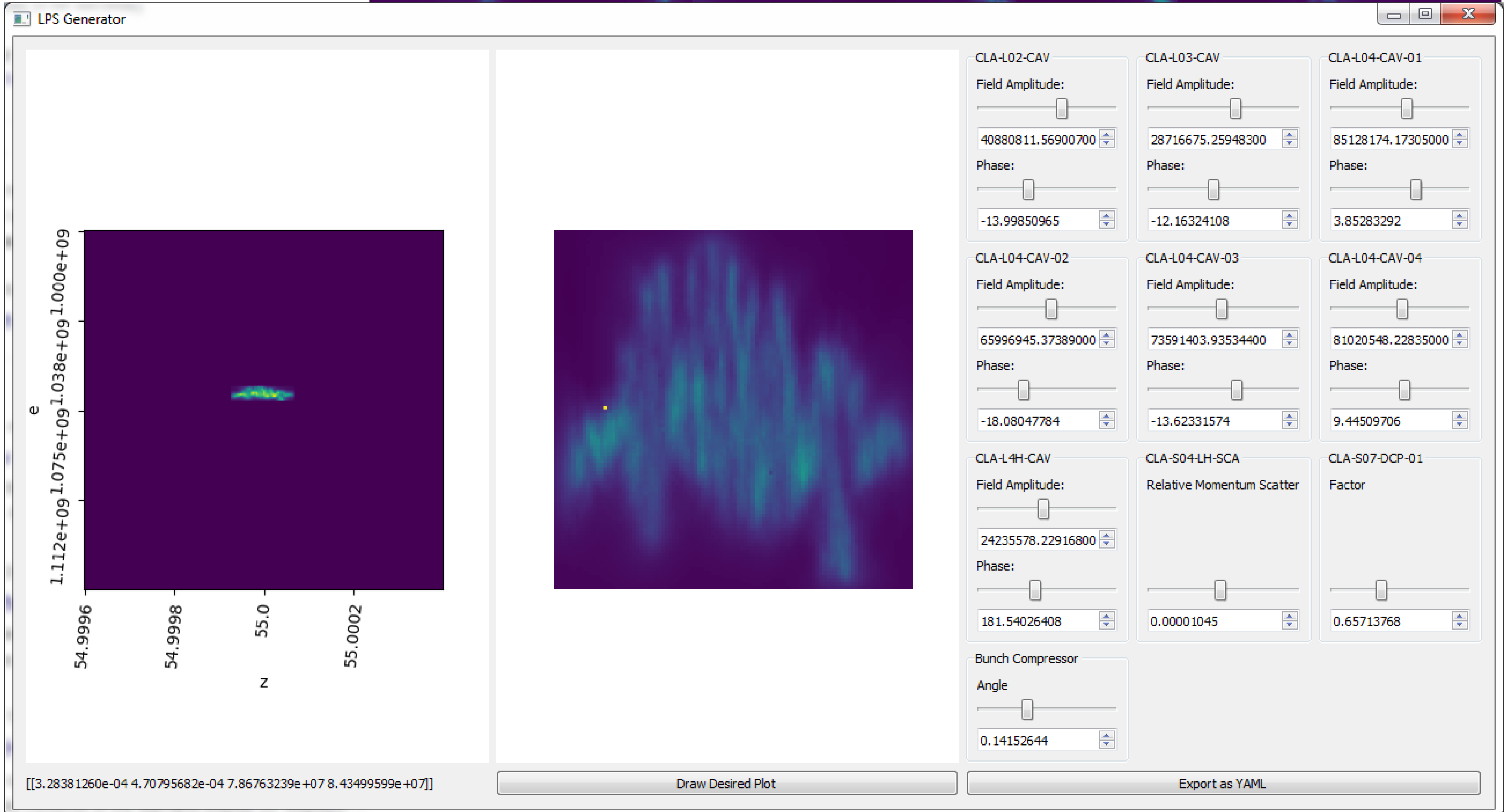

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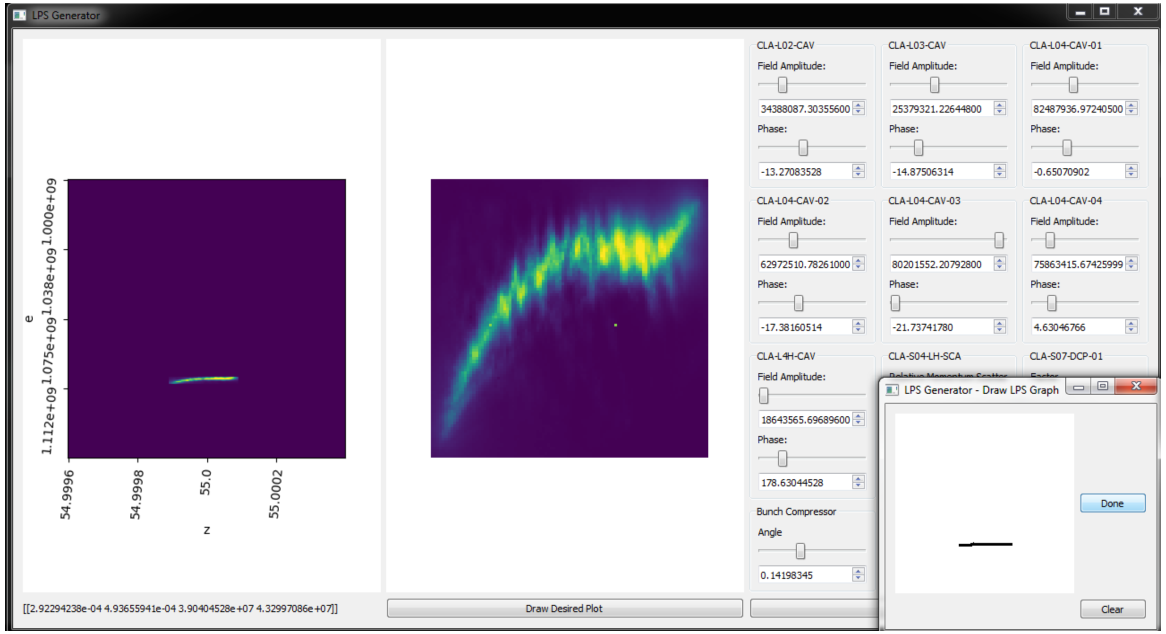

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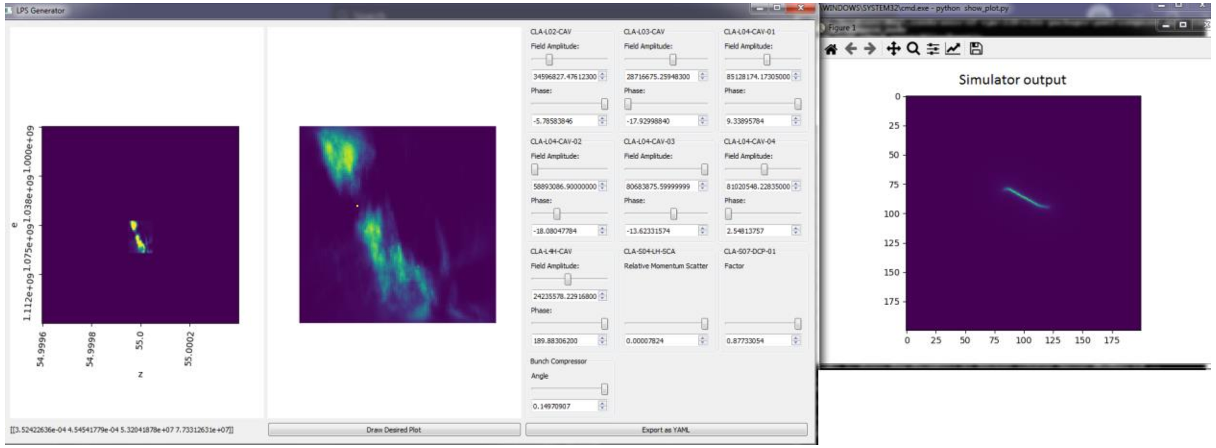

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