### **Problem**

Accurate prediction of longitudinal phase space and other

properties of the electron beam are computationally

expensive, but critical to FEL performance.

Each configuration takes a few minutes to simulate.

A dataset of 10,000 start-to-end simulations of the accelerator was generated using the simulation code ASTRA and Elegant. Using the 60 burch distributions produced, DS images were created by calculating the maximum and minimum values of the z-positions and beam energies for each individual distribution and binning the particles in a 2D histogram defined by this region of interest to create 100×100 pixel images. We can use this to train a machine learning system.





Ground Truth

Prediction



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. Fixed Extent – The whole of the LPS graph.

0.14152644

Field Amplitude

85128174.17305000

81020548.22835000

0.65713768

## **Results**

Ϋ́Υ

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

Science and Technology Facilities Council





Prediction DNN autoencoder model produces better images, but blurred

Ground Truth

Prediction



Solution

Using machine learning, we create a surrogate model

Simpler models as used in previous works lack the predictive

Simple CNN based model produces low

power for fine structure details critical for FEL performance

quality fine structure details

of the simulation that runs in linear time.

## **Rapid Search**

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



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.

## **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.

		Automatical State	-	Carpenants Materiality		12.5	
						Simulator output	_
-	-	1000					
	100	The same					
		Anna Anna II					
		1000 2		Same a	-		
	ALC: NO	Contractor Networkski		CLASSING NO.			
	103						
		-				and the test	
1 1 1 1		And in case				n m n m un m un	
		**					
	and the second sec	1.000	Provide Lines				



<>> 10 / 10 / 10 9

Science and Technology Facilities Council

[[3.28381260e-04 4.70795682e-04 7.86763239e+07 8.43499599e+07[]

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

# Problem

## Accurate prediction of longitudinal phase space and other properties of the electron beam are computationally expensive, but critical to FEL performance. Each configuration takes a few minutes to simulate.

A dataset of 10,000 start-to-end simulations of the accelerator was generated using the simulation code ASTRA and Elegant. Using the 6D bunch distributions produced, LPS images were created by calculating the maximum and minimum values of the z-positions and beam energies for each individual distribution and binning the particles in a 2D histogram defined by this region of interest to create 100×100 pixel images. We can use this to train a machine learning system.





**Facilities Council** 





#### **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.



0 14152644

# **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

**Ground Truth** 



Prediction

DNN autoencoder model produces better images, but blurred

**Ground Truth** 

Prediction



Science and Technology Facilities Council 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!



Draw Desired Plot

Export as YAML

Simulator output



[[3.28381260e-04 4.70795682e-04 7.86763239e+07 8.43499599e+07]]

# **Rapid Search**

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

LPS Generator				
e 54.3996 - 1.112e+03.1075e+09.1038e+09.1000e+09 54.3998 - 55.0 -	A MARINE A	CLA-L02-CAV Pield Amplitude:	CLA-L03-CAV Field Amplitude: 25379321.22644800 Phase: -14.87506314 CLA-L04-CAV-03 Field Amplitude: 80201552.20792800 Phase: -21.73741780 CLA-S04LH-SCA ILPS Generator - Draw L	CLA-104-CAV-01 Field Amplitude: 82487735.97240500 * Phase: 0.65070902 * CLA-104-CAV-04 Field Amplitude: 75863415.67425999 * Phase: CLA-507-DCP-01 Phase: CLA-507-DCP-01 ************************************
[[2.92294238e-04 4.93655941e-04 3.90404528e+07 4.32997086e+07]]	Draw Desired Plot			Clear



# **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.

