HELMHOLTZ AI Artificial Intelligence Cooperation Unit

DESY.

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Harnessing Machine Learning for Single-Shot Measurement of Free Electron Laser Pulse Power

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INTRODUCTION

Free electron lasers are essential in many scientific and technological fields. The lasing-off electron power profile for an individual electron bunch is experimentally inaccessible during laser operation. This is a crucial hurdle in the exact reconstruction of the photon pulse profile. To overcome this hurdle, we developed a machine learning model that predicts the temporal power profile of the electron bunch in the lasing-off regime using machine parameters that can be obtained when lasing is on.

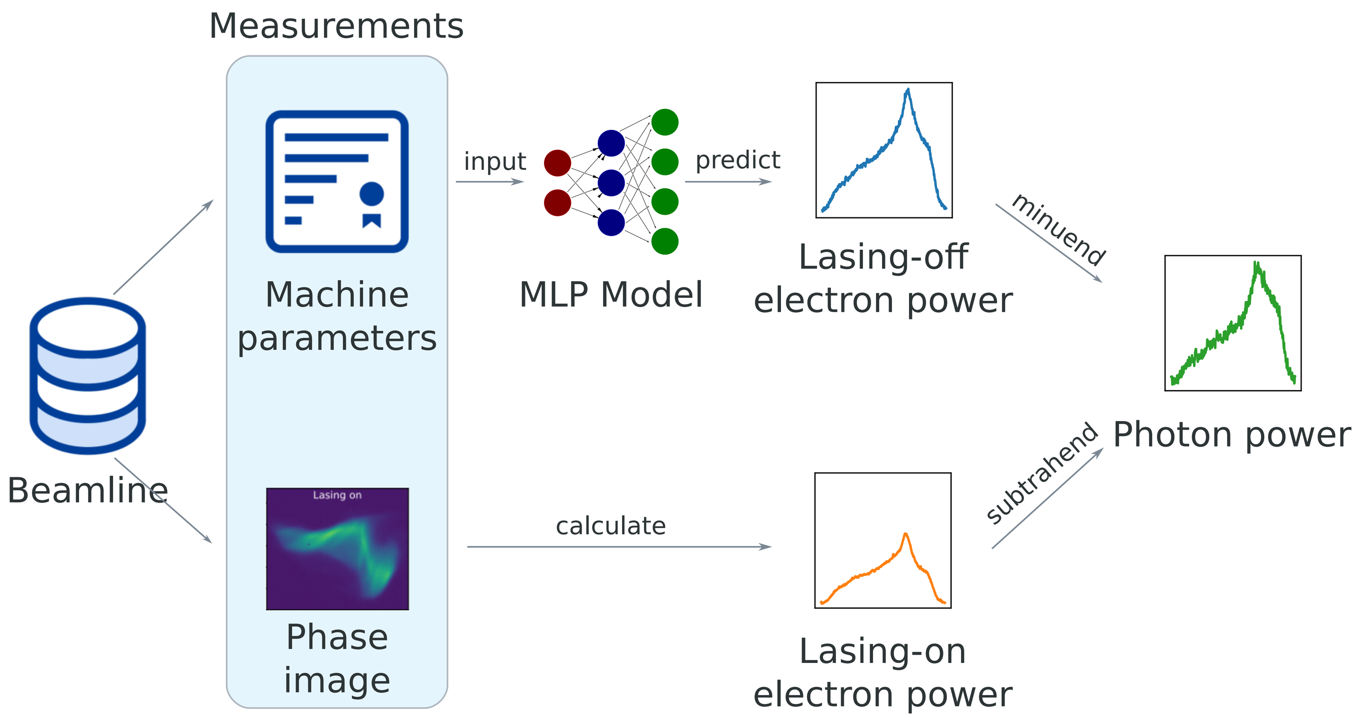

Fig. 1 Overview of the data flow in the project. Lasing off data is inaccessible during regular beamline operation. Therefore, we use machine learning to predict the lasing-off electron energy from beamline parameters (top row).

METHODOLOGY

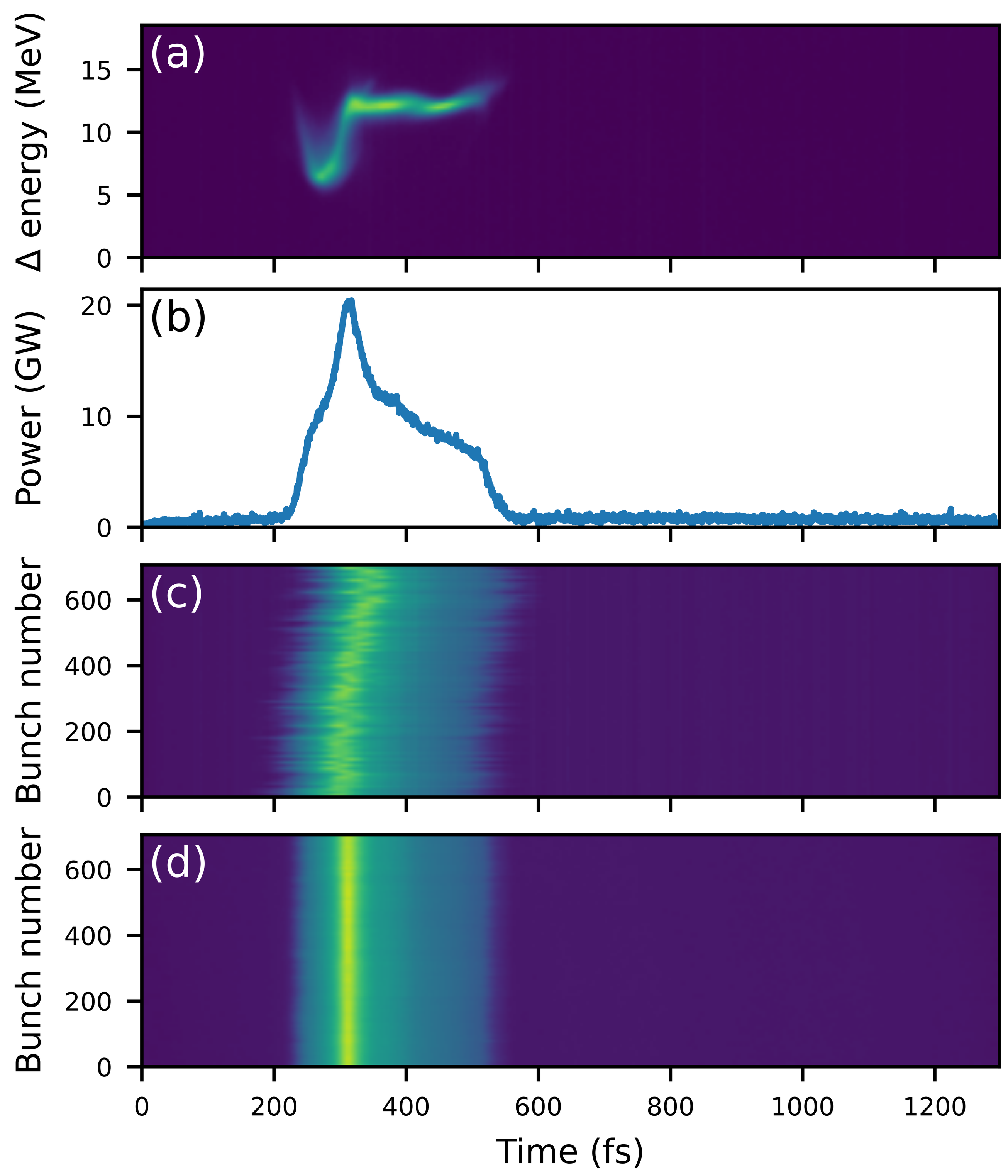

Fig. 2 Data processing. Longitutinal phase images of electron energy vs. time (a) were used to calculate electron power profiles per bunch (b). To correct for jitter, electron power profiles for the entire dataset (c) were aligned by their peaks (d).

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RESULTS

A multi-layer-perceptron was trained on a training dataset of 2261 pairs of machine parameters as input and lasing-off power profiles as labels and converged nicely. Predicted temporal power profiles matched the measured profiles in the 282 test datasets very well. The predictions of the MLP model have a significantly lower mean squared error than power profiles determined with other state-of-the-art methods, underpinning the superiority of our model.

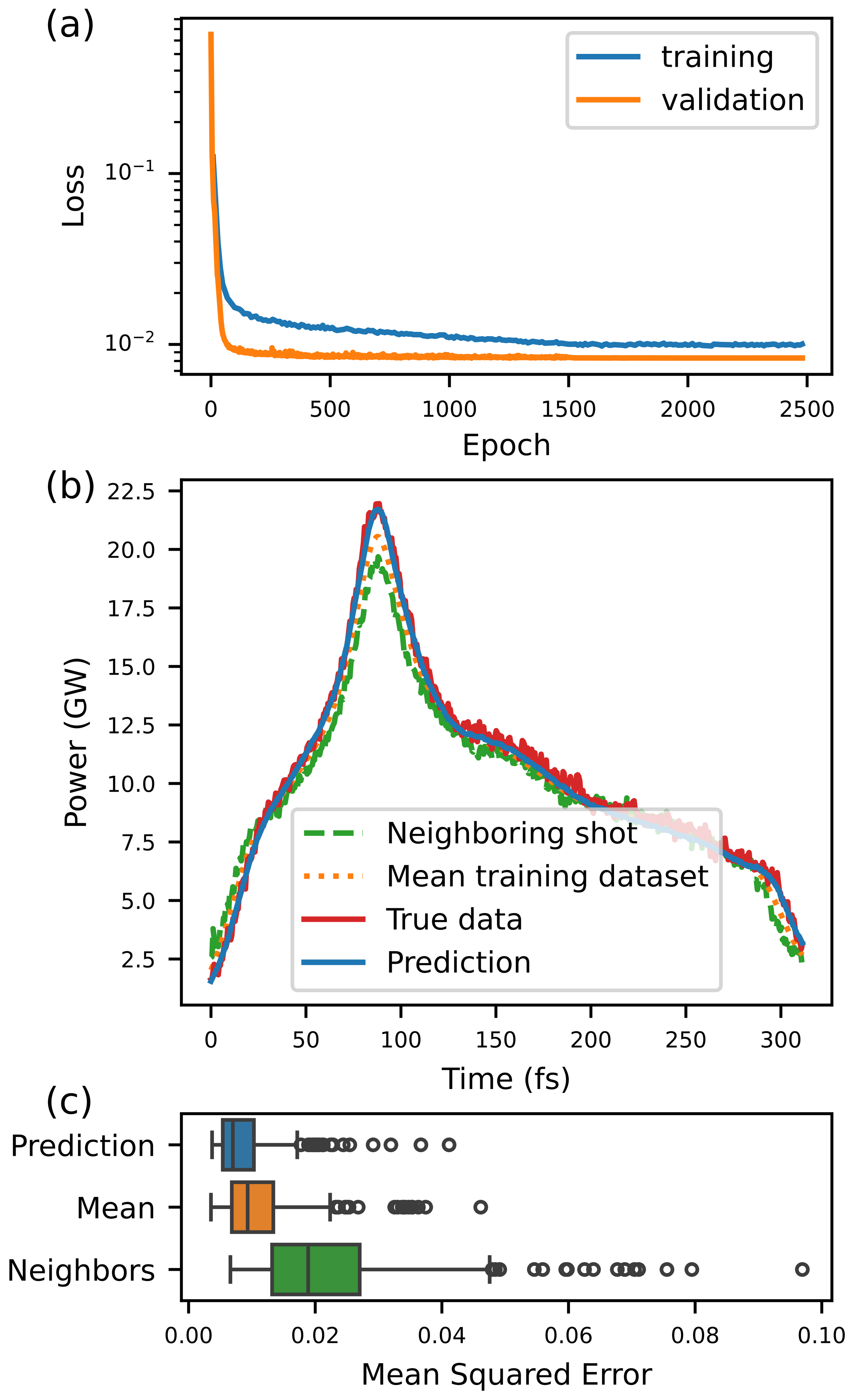

Fig. 3 Model performance. (a) Training and validation loss. The validation loss islower than the training loss, because we used a dropout of 0.43 during training. (b) Predictions for individual shots (blue line) matched the actual measurements (red line) better than measurementsfrom previous shots (dashed green line) and better than the mean of all measurements in the trainingdata (dotted orange line). (c) Boxplots of all mean squared errors in the test dataset. (Prediction) Mean squared error between the predictions and the measurements in the test dataset. (Mean) Mean squared error between the measurements in the test dataset and the mean of all measurements in the training dataset. (Neighbors) Mean squared error between adjacent measurements in the test dataset. The numbers at the right of (c) represent the median (interquartile range) of the errors as well as the number of observations n. All errors were statistically significantly different from each other (p<0.01) as determined by a Wilcoxon signed-rank test followed by a Bonferroni correction for multiple comparisons.

CONCLUSION

Unlike conventional methods, our machine-learning-driven approach makes the lasing-off temporal power profile accessible for single shots, offering a non-invasive and efficient method for characterizing free electron laser radiation pulses. In the future we will test the machine learning model during regular operation aiming to enable single-shot measurements of the X-ray pulse structure in real-time. This can open new avenues for scientific discovery for a wide range of FEL experiments.

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