Using Deep Learning for Photon Pulse Construction from PolariX TDS images.

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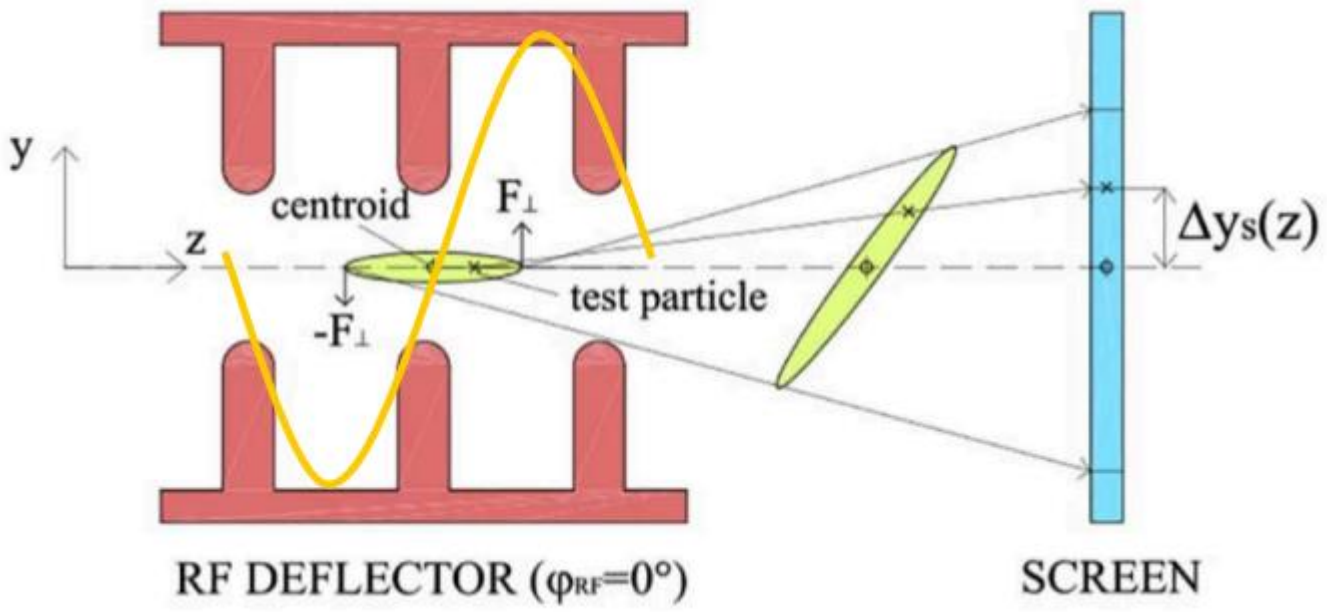
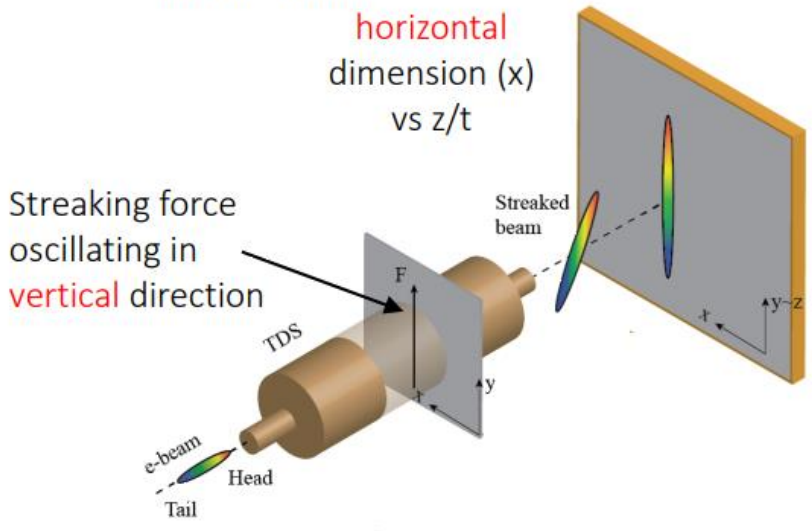
Transverse Deflecting Cavity (TDC)



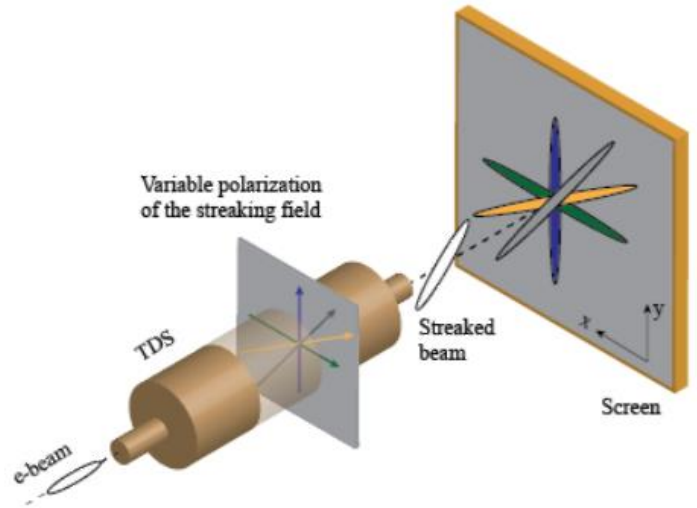
- TDCs use RF fields to impart a time-dependent transverse kick to a bunch, converting the longitudinal coordinate to transverse coordinates.
- Allows for bunch length and longitudinal phase space measurements

PolariX TDS

Conventional TDS: streaking in a fixed polarization (i. e. vertical or horizontal)



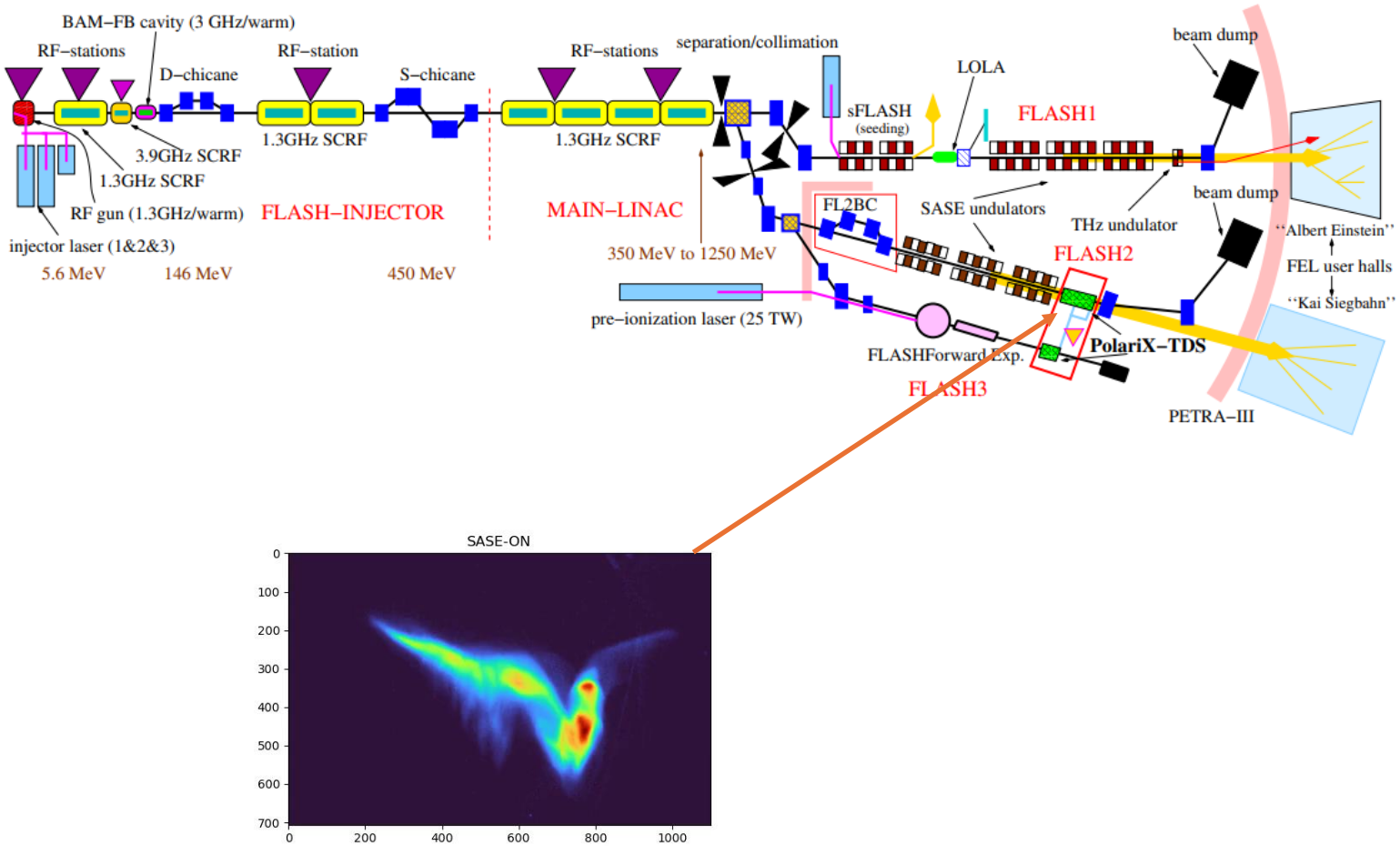
POLARIzable X-band Transverse Deflection Structure – **POLARIX TDS**



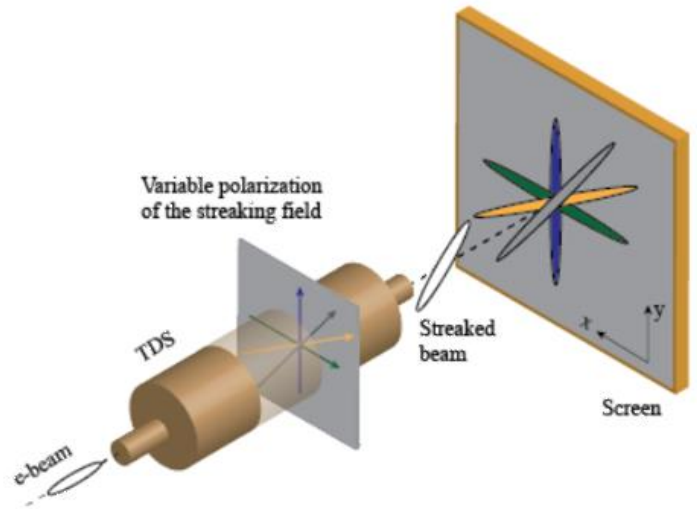
Diagnose multidimensional phase space of electron bunches

P. Craievich et al., PRAB, 23 (11):112001 (2021)

PolariX TDS at FLASH

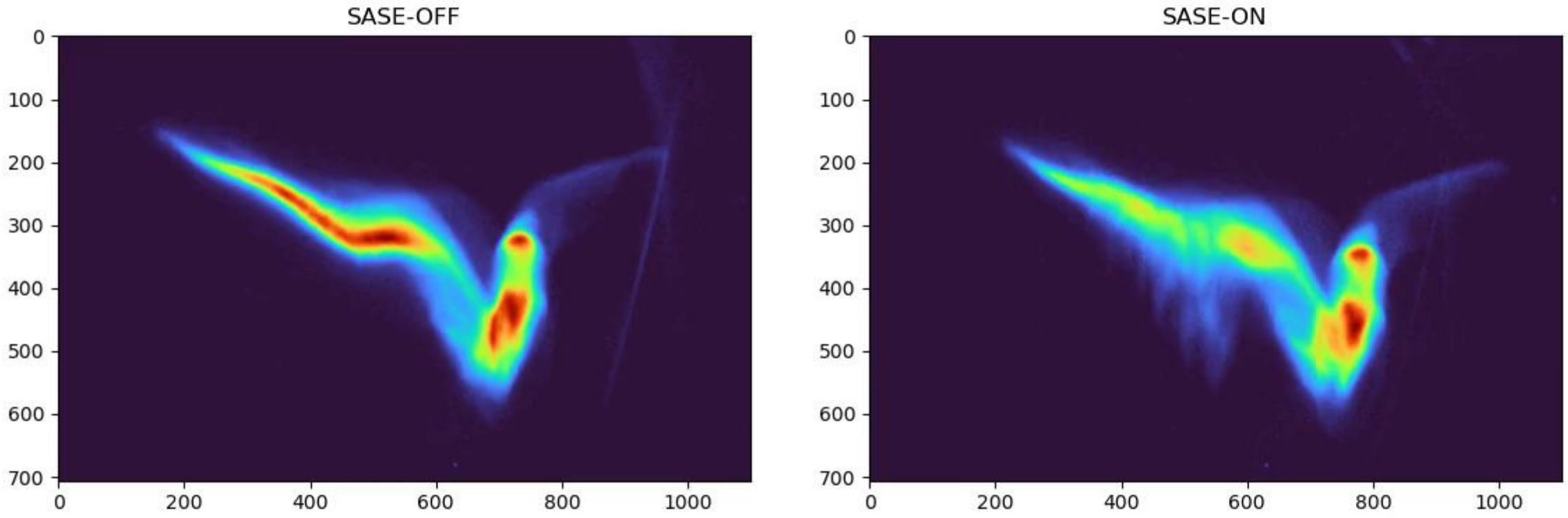


POLARIzable X-band Transverse Deflection Structure – POLARIX TDS

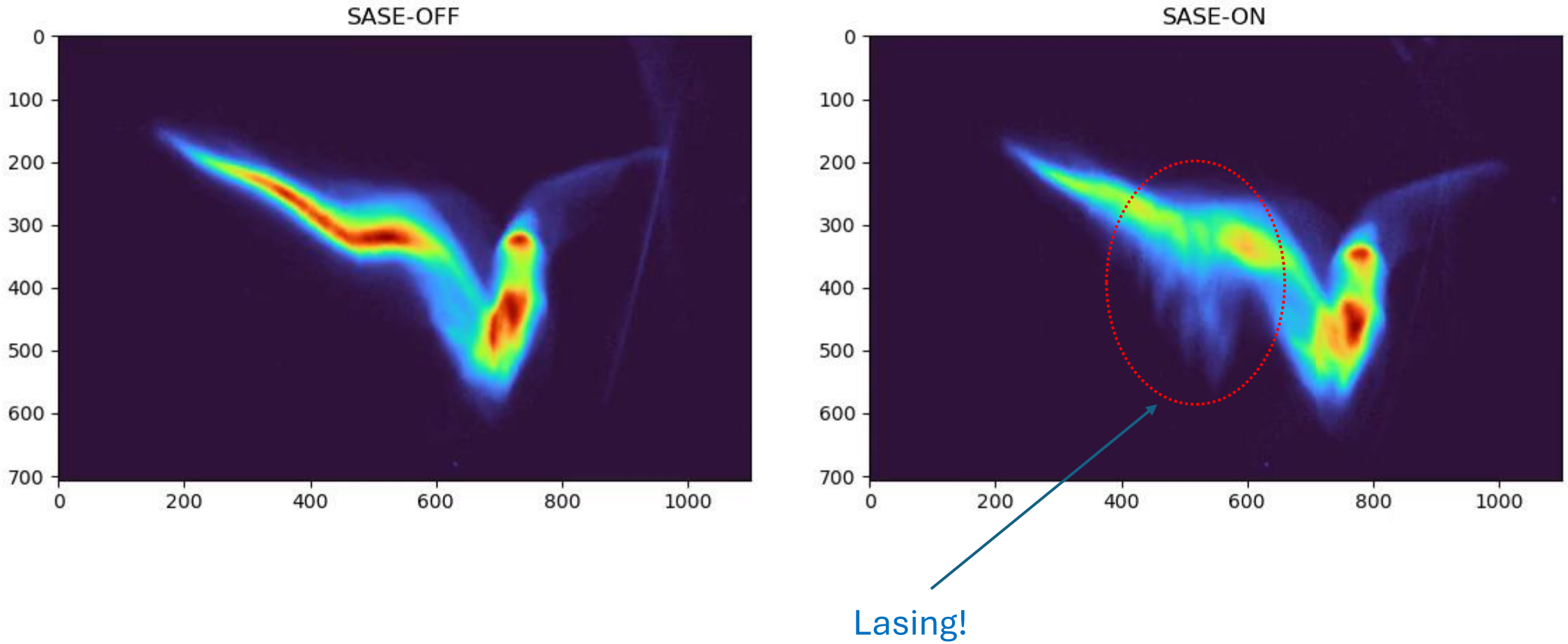


P. Craievich et al., PRAB, 23 (11):112001 (2021)

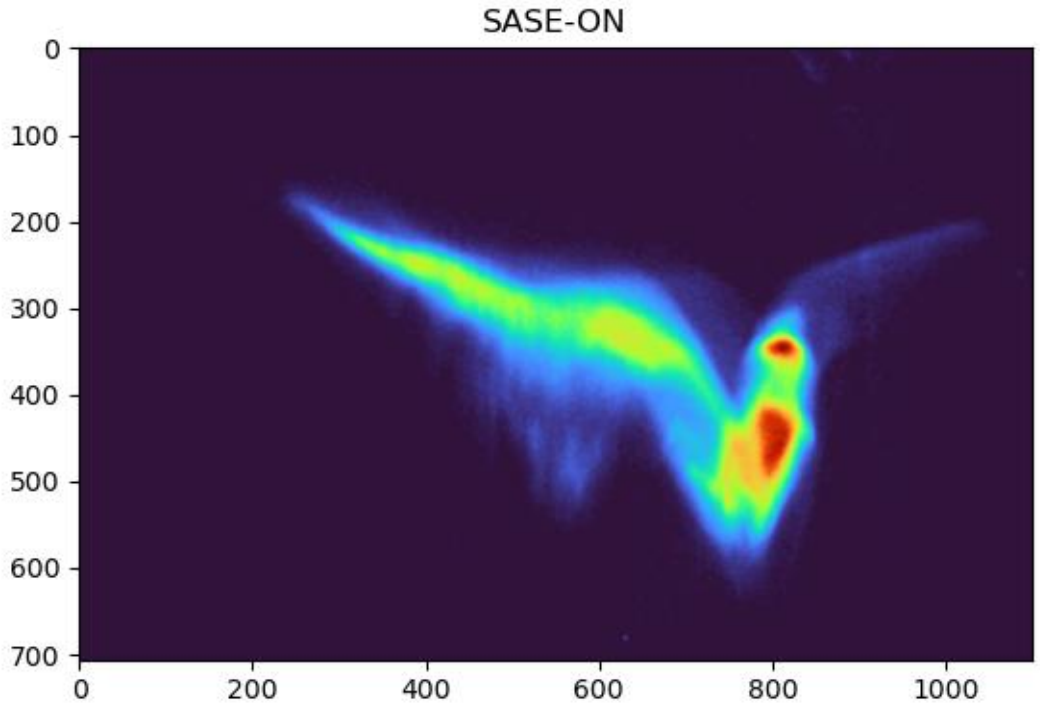
An example from the PolariX TDS

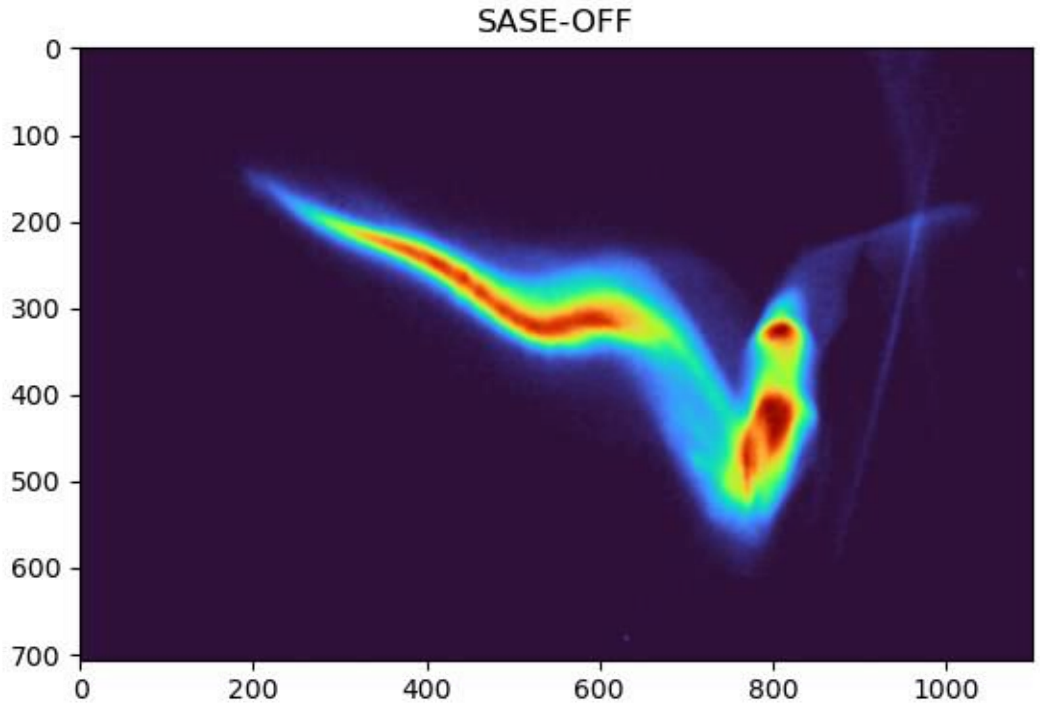


An example from the PolariX TDS

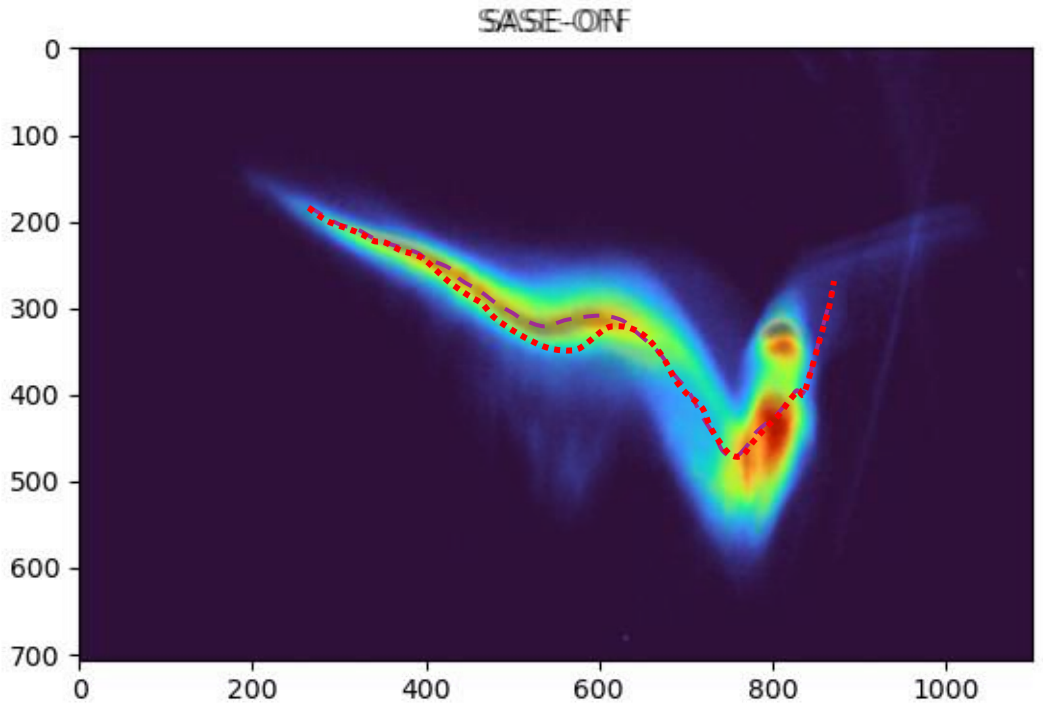


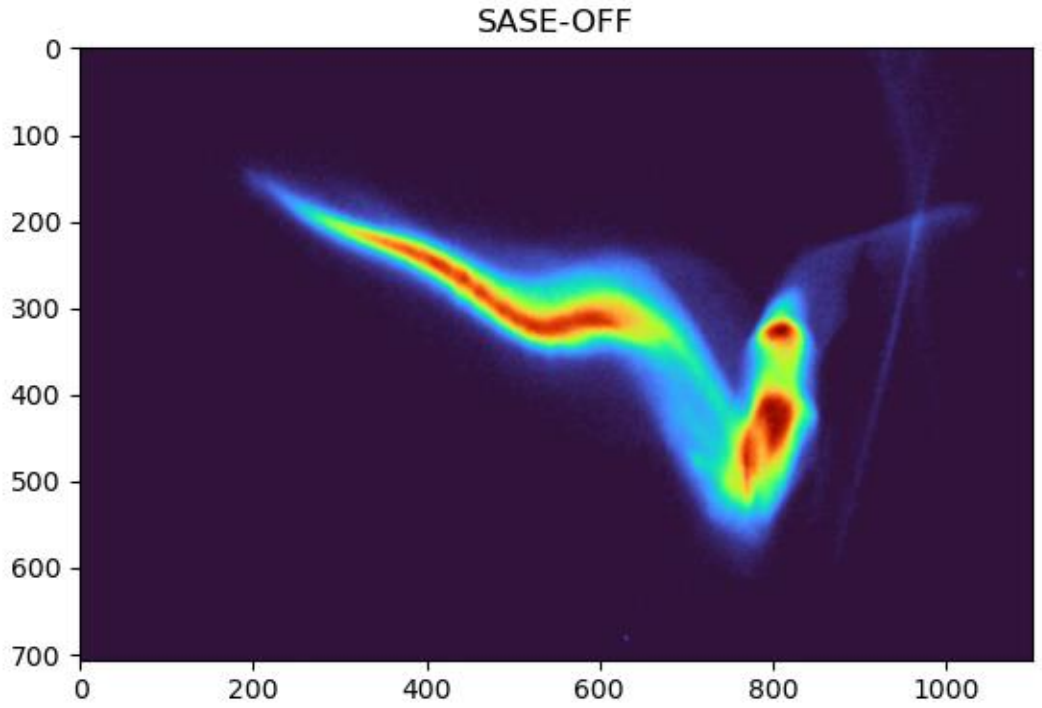
A standard method for photon profile construction





A standard method for photon profile construction



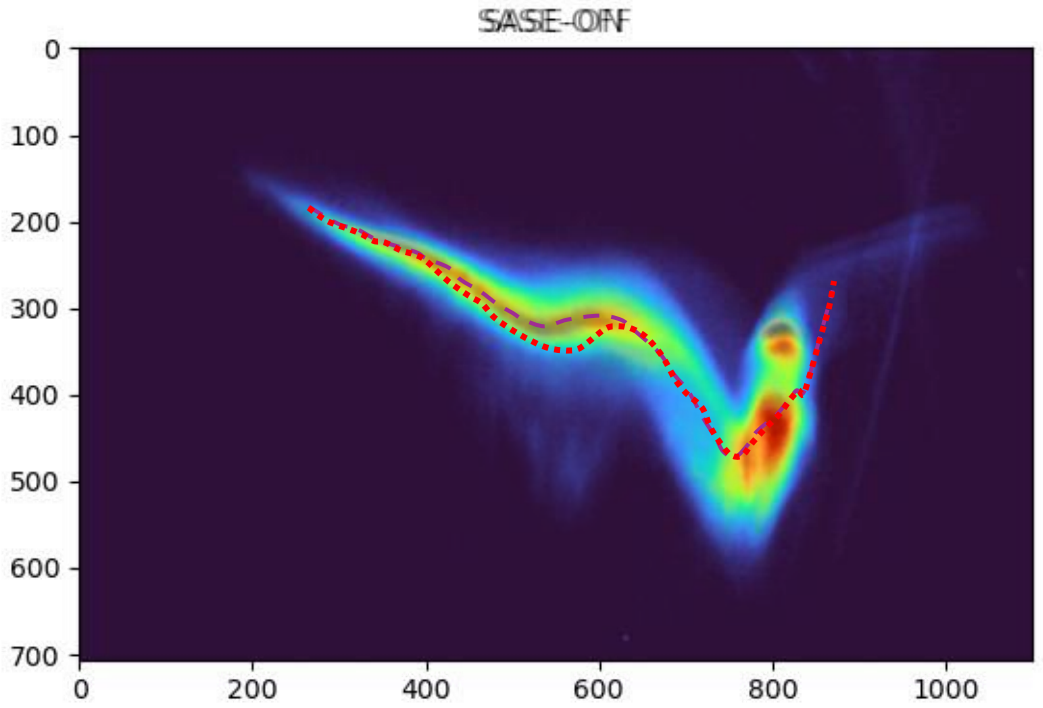


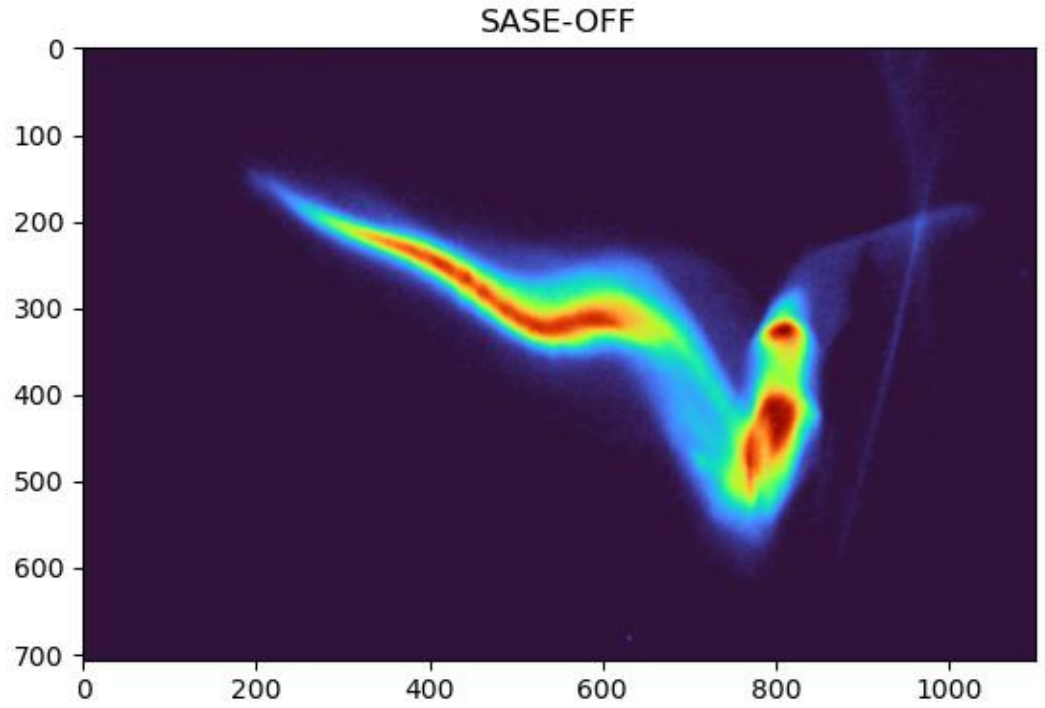
$$\Delta E(t_i) = E_{\mathrm{on}}(t_i) - E_{\mathrm{off}}(t_i)$$

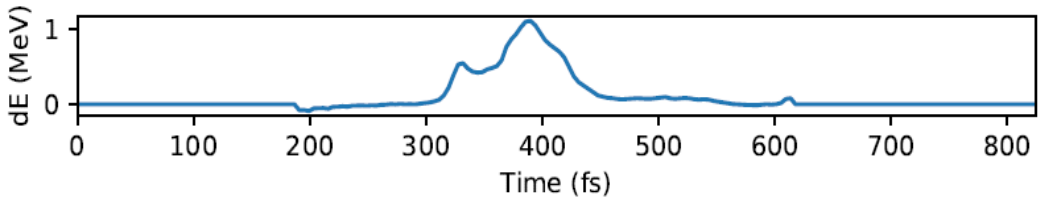
$$P(t_i) = \Delta E(t_i) \cdot \frac{I(t_i)}{e}$$

Behrens, C., Decker, FJ., Ding, Y. *et al., Nat Commun* **5**, 3762 (2014)

A standard method for photon profile construction







$$P(t_i) = \Delta E(t_i) \cdot \frac{I(t_i)}{e}$$

Behrens, C., Decker, FJ., Ding, Y. *et al., Nat Commun* **5**, 3762 (2014)

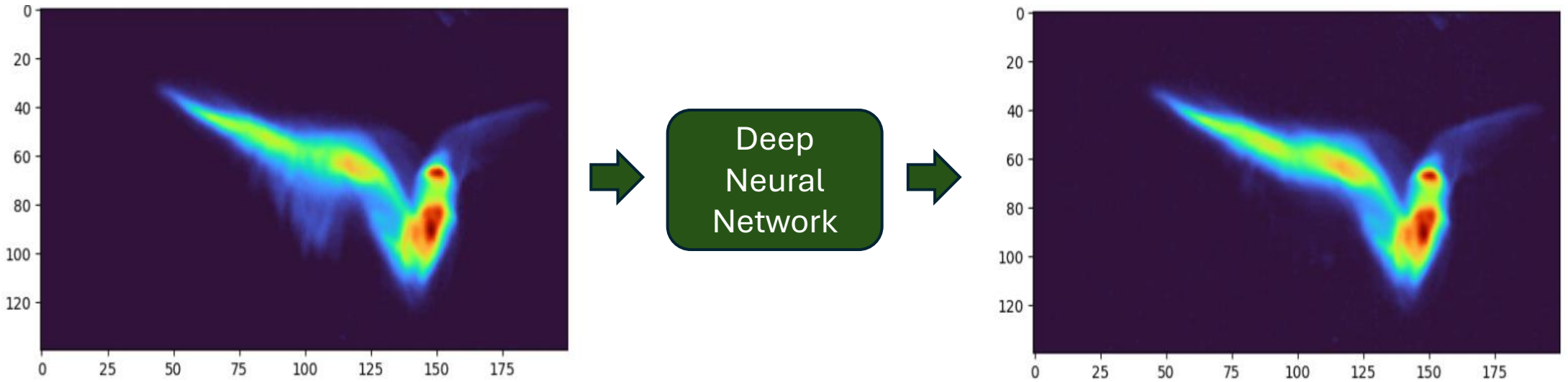
A standard method for photon profile construction

- The difficulty is in finding the lasing-off reference that matches closely with the lasing-on images.

- Imperfect matching or lasing-off reference can create artifacts in the resulting photon profile.

Using U-nets for photon profile construction

- The idea is to use a deep neural network to generate a lasing-off reference image given a lasing-on image.
- This avoids the need to suppress the lasing to take lasing-off references.
- This approach ensures a one-to-one correspondence between the lasing-on and generated lasing-off images, which avoids the need to carefully match and align the images.

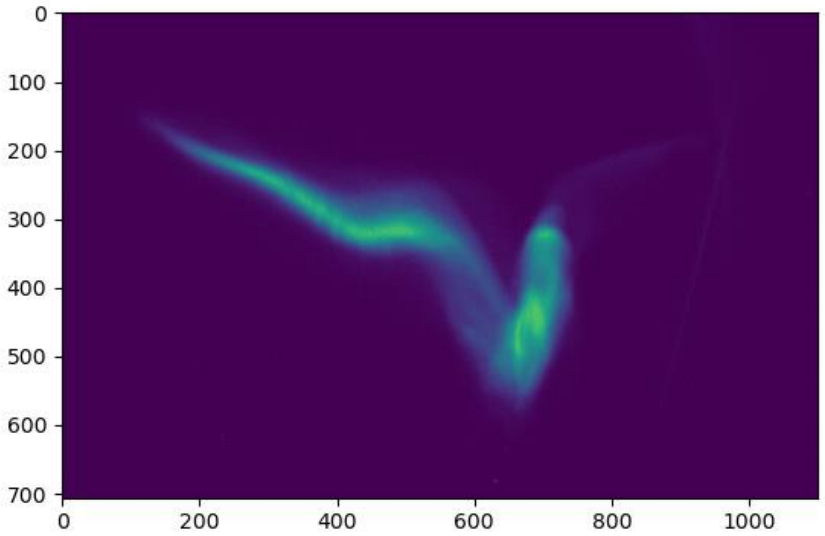


Using U-nets for photon profile construction

- U-Net deep neural network was used for this task.

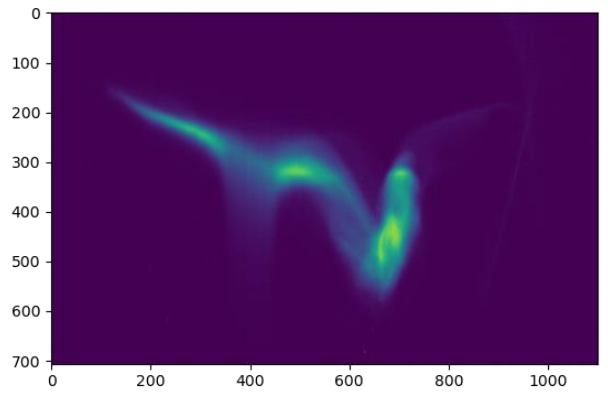
- The network was trained on pairs of *lasing-off* images and artificially augmented *lasing-off* images, designed to resemble *lasing-on* images.

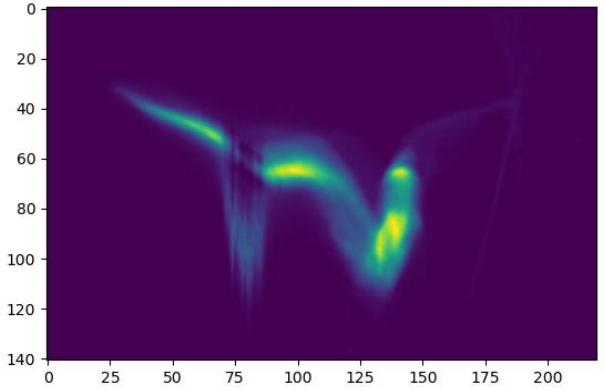
Lasing-OFF image



Augmentation

Trying to mimic Lasing-ON images





Two methods are used for augmentation…

1. Subtract and add Gaussians.

2. Convolving with an asymmetric function

Two methods are used for augmentation…

1. Subtract and add Gaussians.

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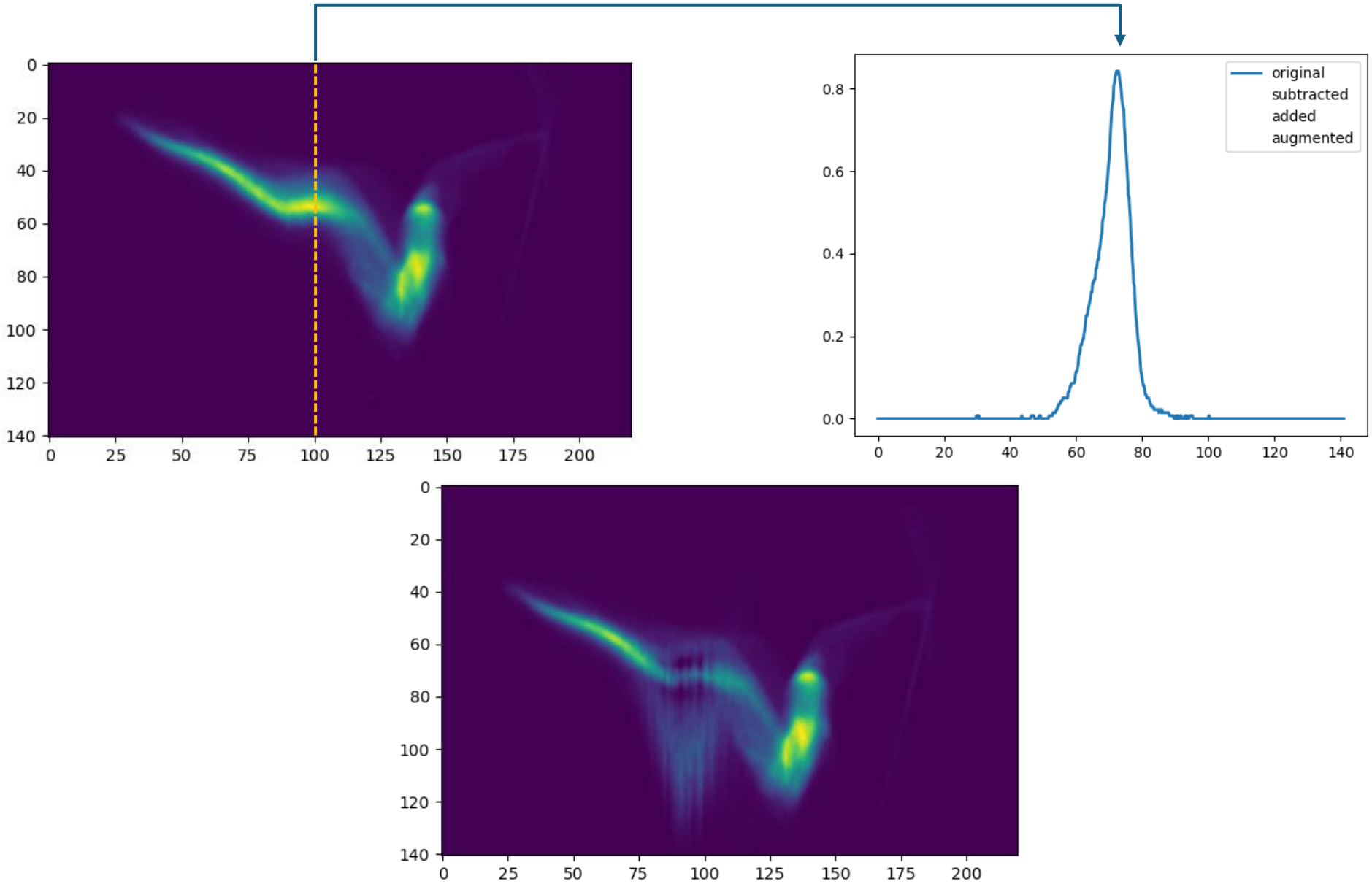
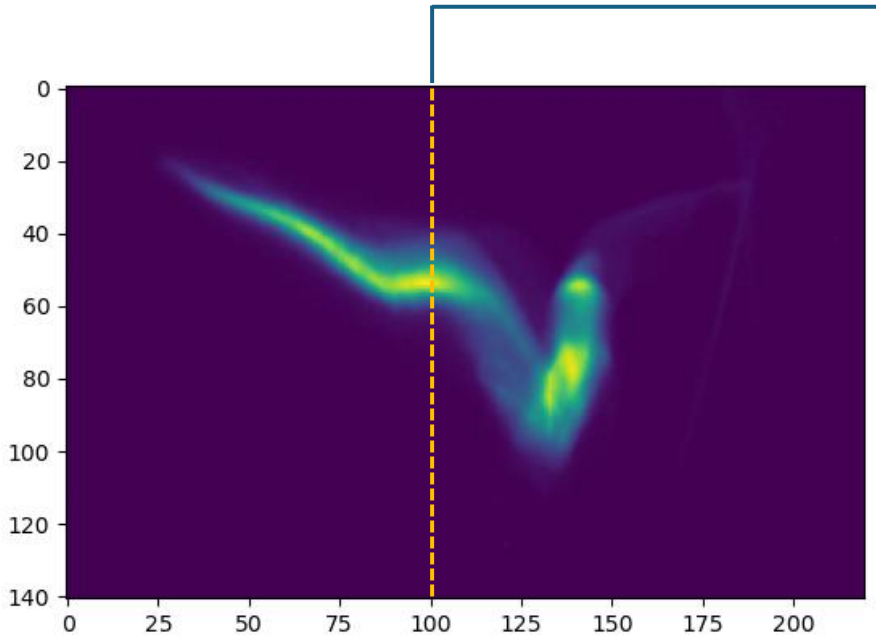
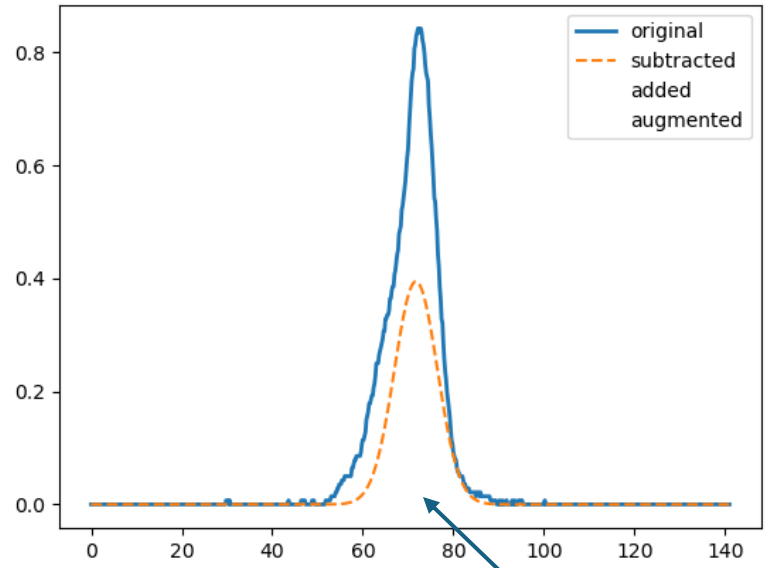
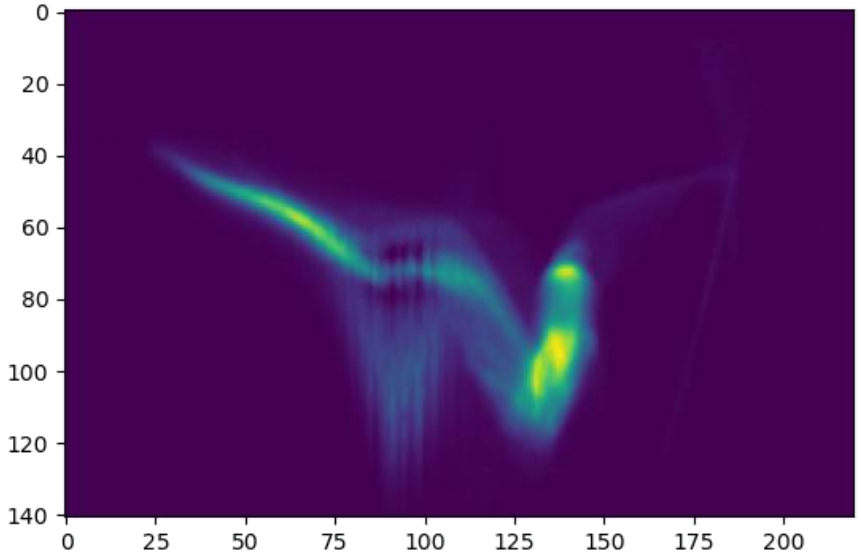
1. Subtract and add Gaussians.



1. Subtract and add Gaussians.

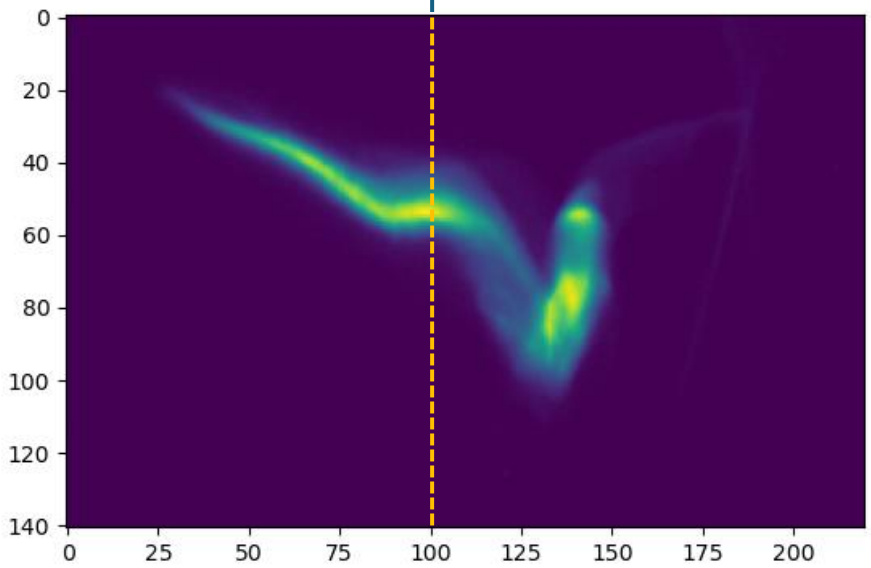


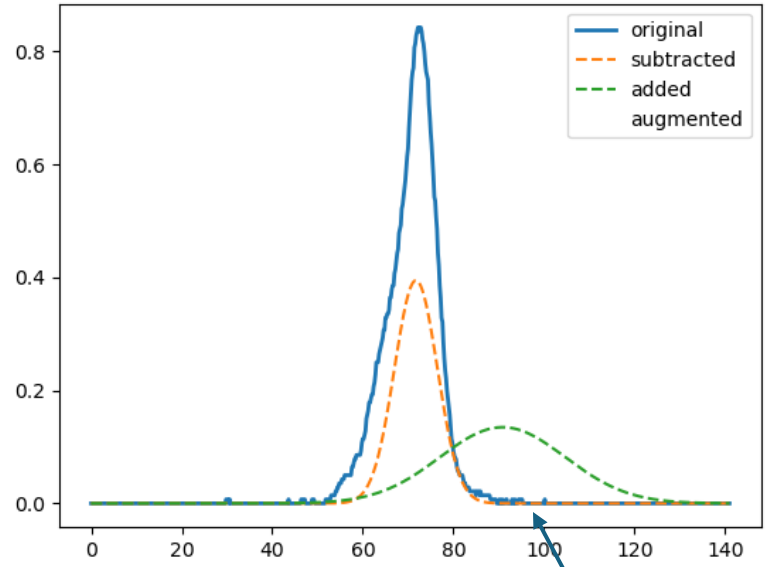


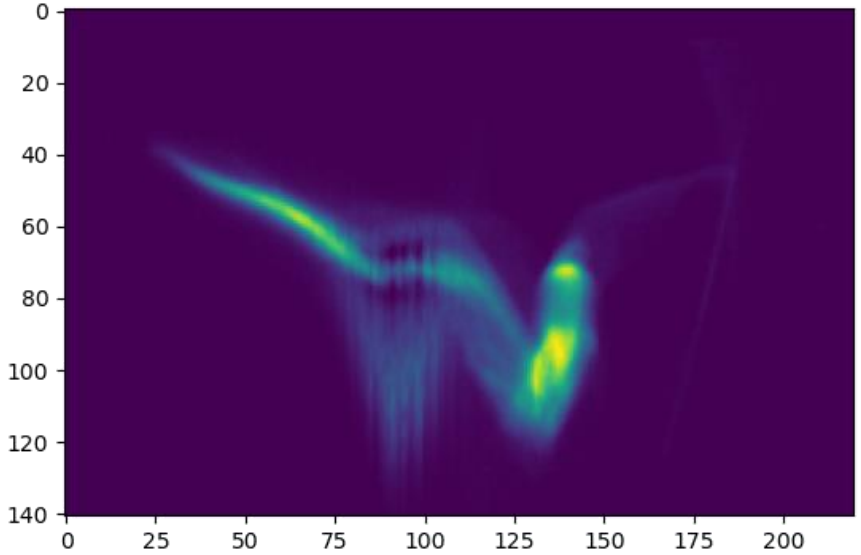


Subtract a Gaussian from near the centroid

1. Subtract and add Gaussians.

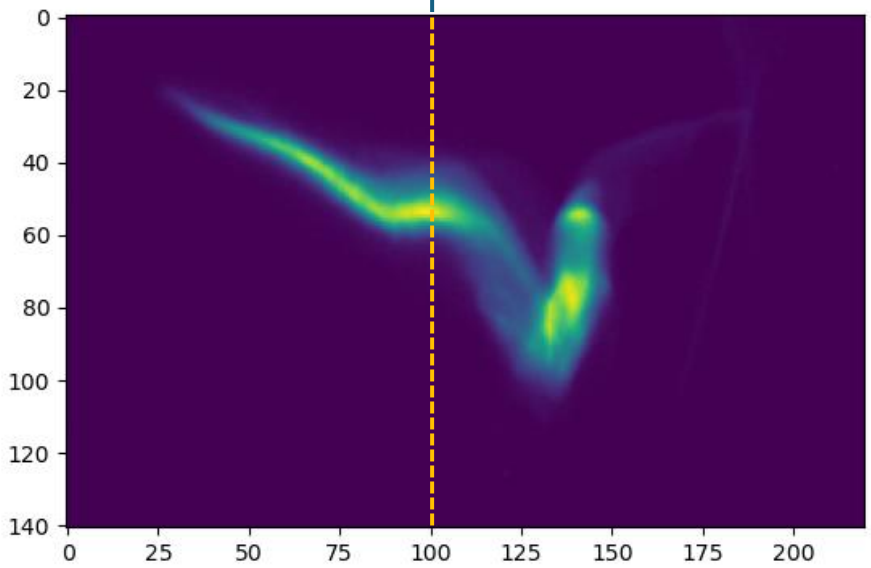


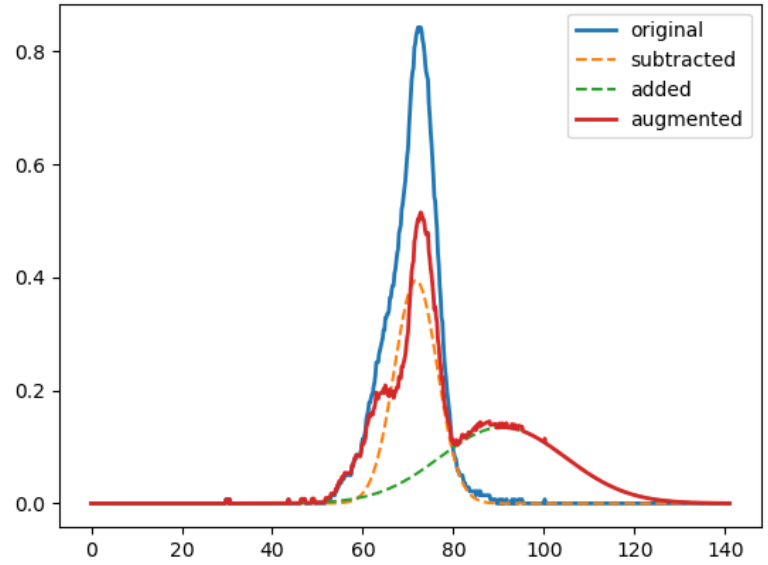


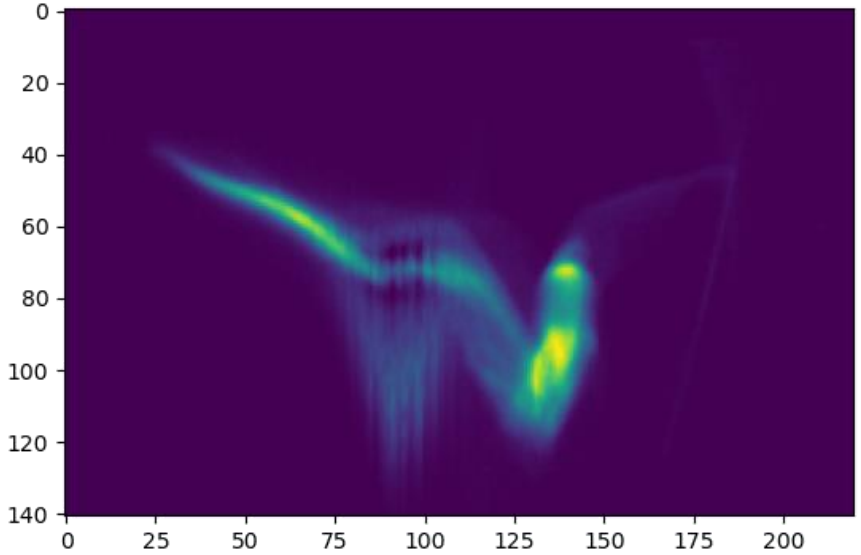


Add another Gaussian to the right of the centroid (corresponding to lower energies).

1. Subtract and add Gaussians.

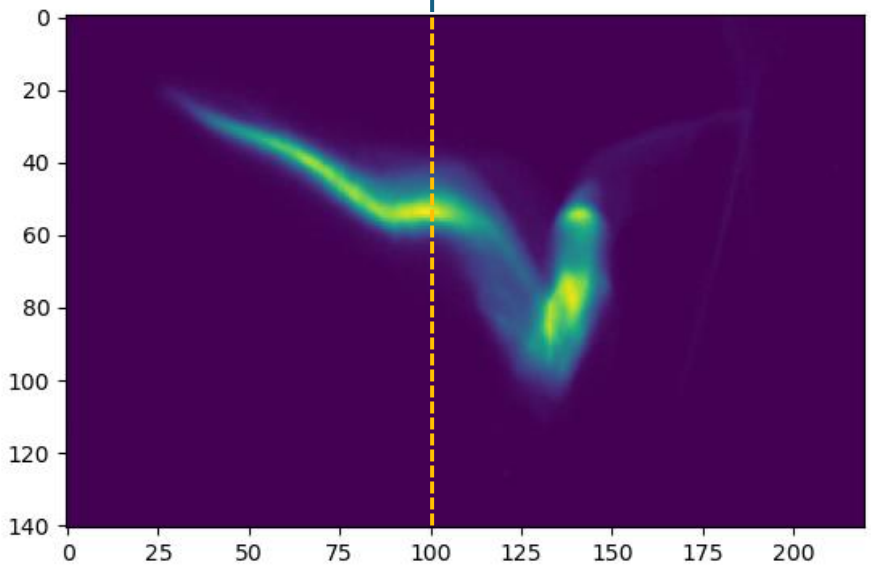


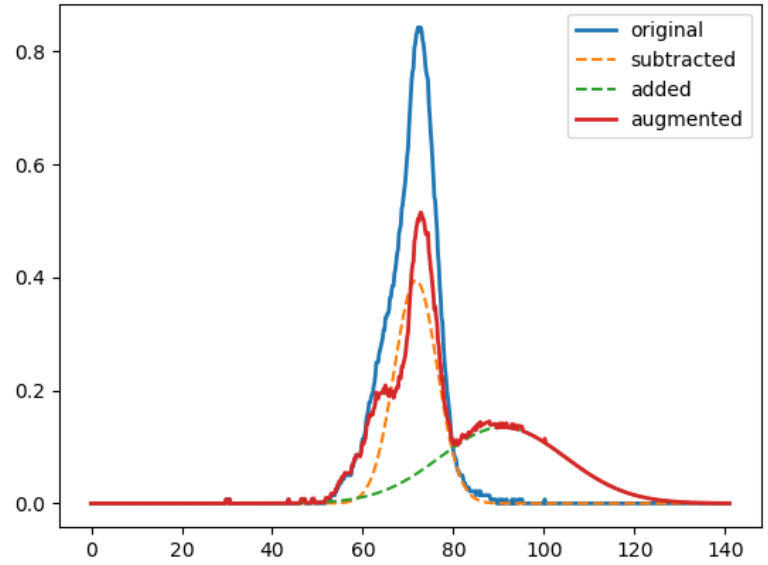


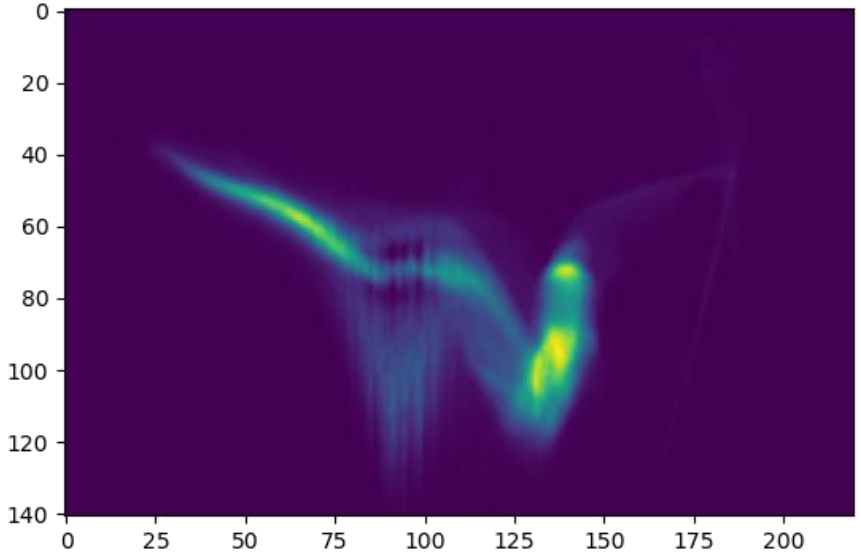


Do this for each slice in the image. Set an augmentation window outside of which the augmentation is not applied.

1. Subtract and add Gaussians.







Parameters to vary:

- Height and width of the subtracted and added Gaussians.
- Offset between the Gaussians.
- Location, shape and width of the augmentation window.

Do this for each slice in the image. Set an augmentation window outside of which the augmentation is not applied.

Two methods are used for augmentation…

1. Subtract and add Gaussians.

2. Convolving with an asymmetric function

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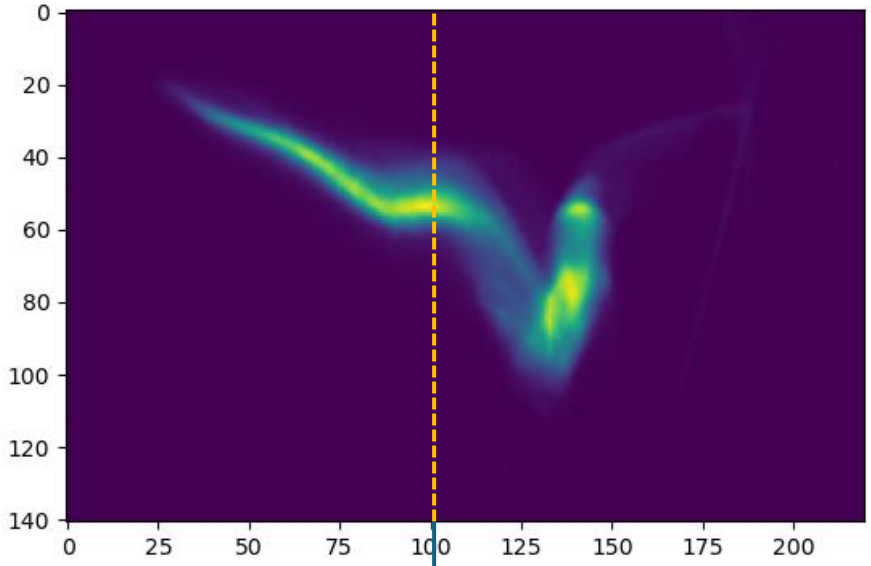
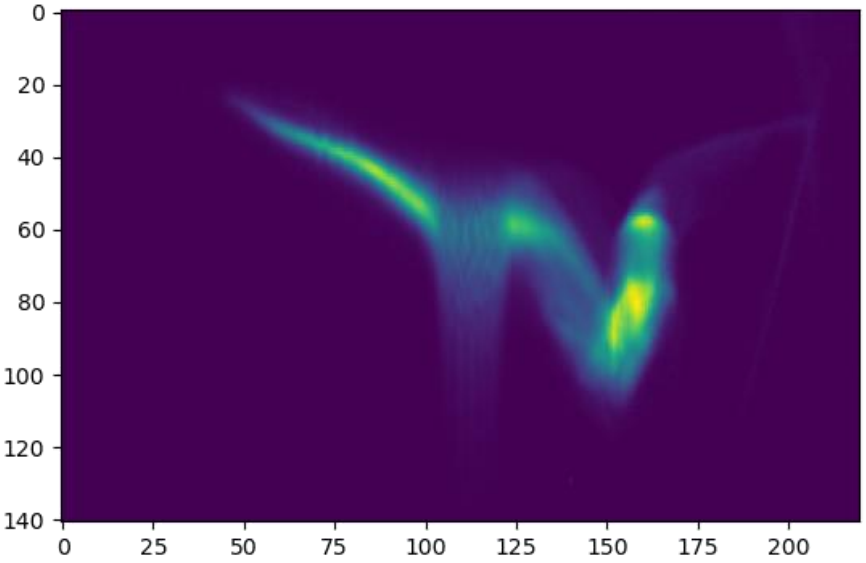
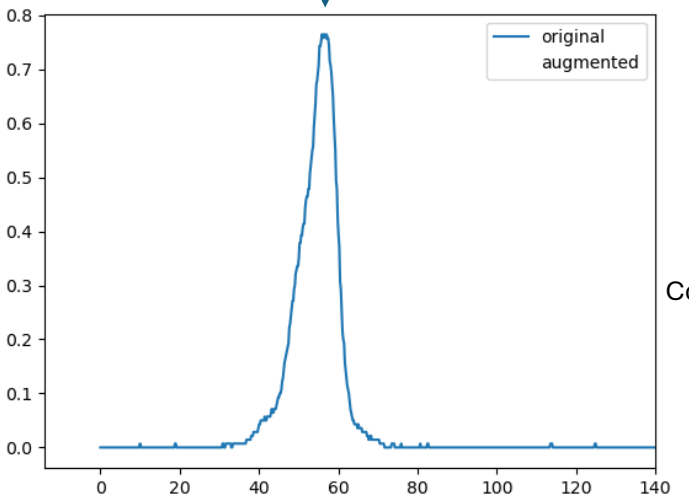
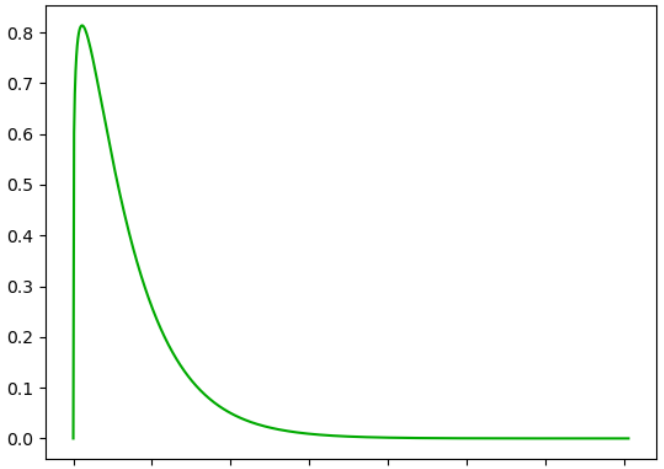


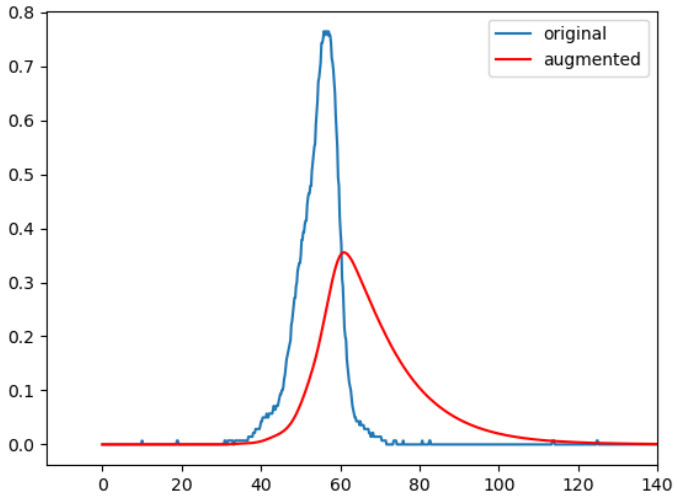




Convolution

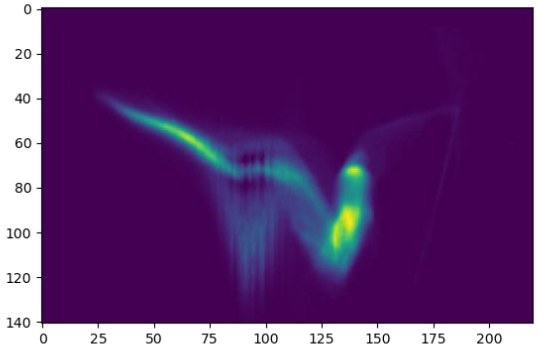


Gamma function

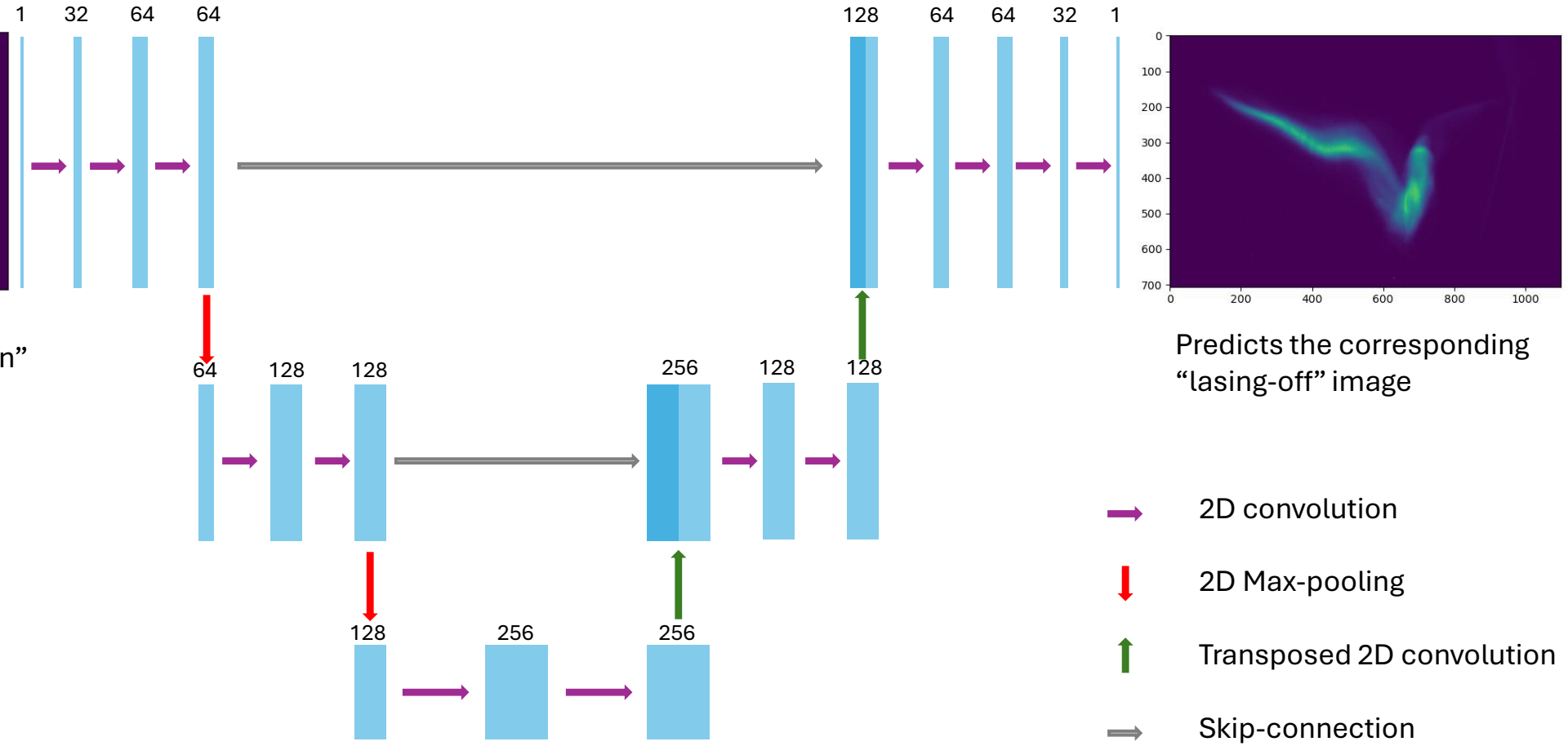


The U-Net architecture

Input



Give the augmented “lasing-on” image as input



Output

Predicts the corresponding “lasing-off” image

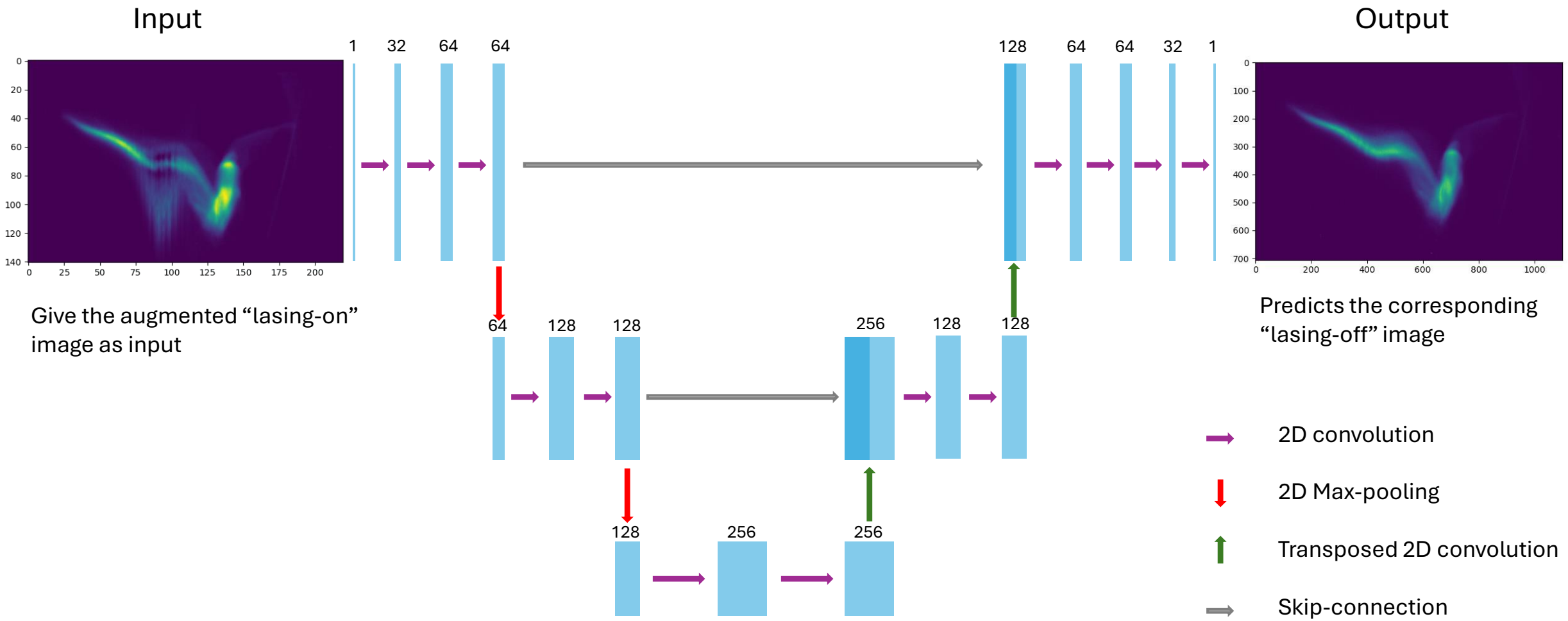
2D convolution

2D Max-pooling

Transposed 2D convolution

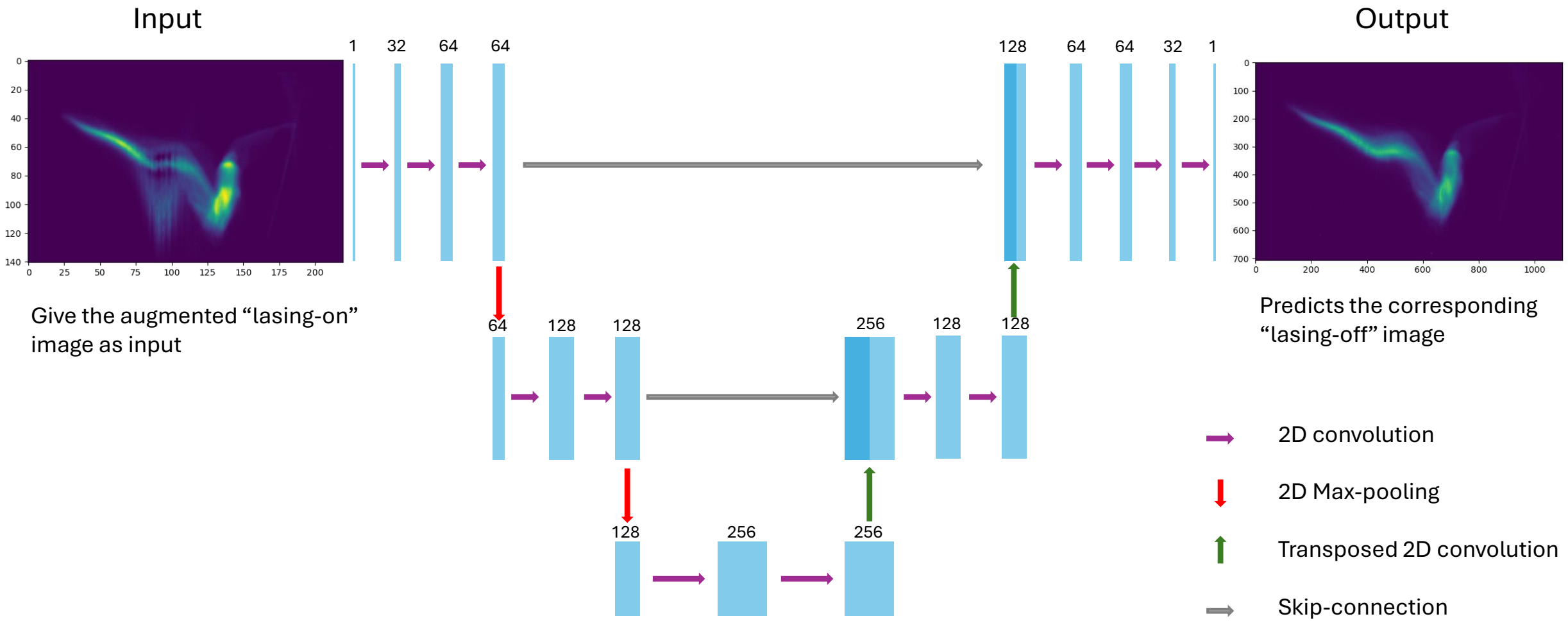
Skip-connection

The U-Net architecture



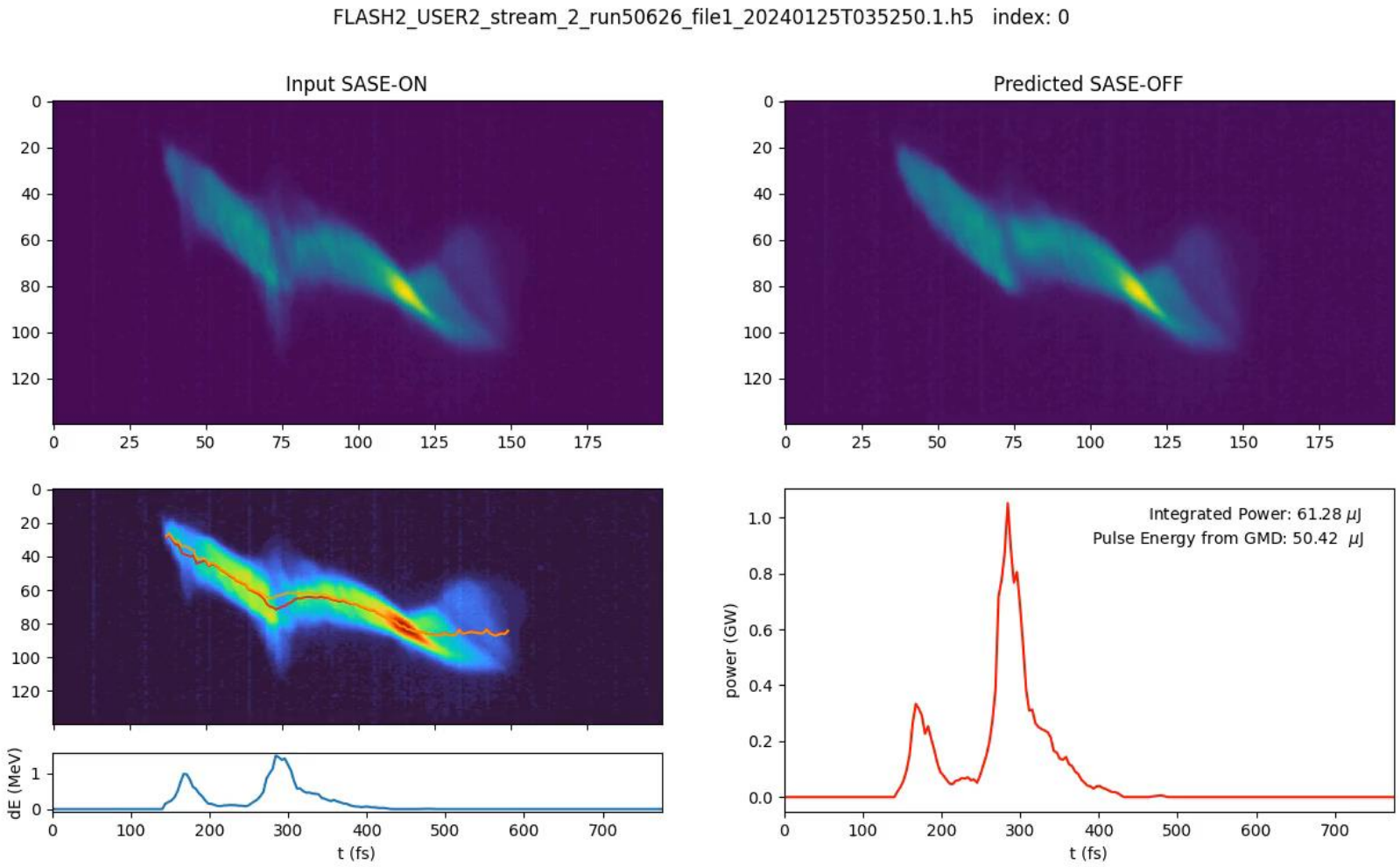
Trained the model with 7332 synthetic training samples

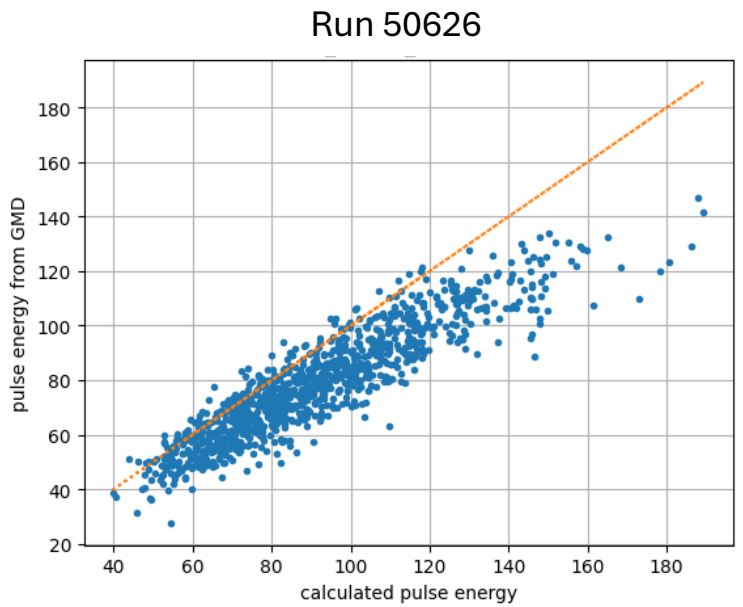
The U-Net architecture



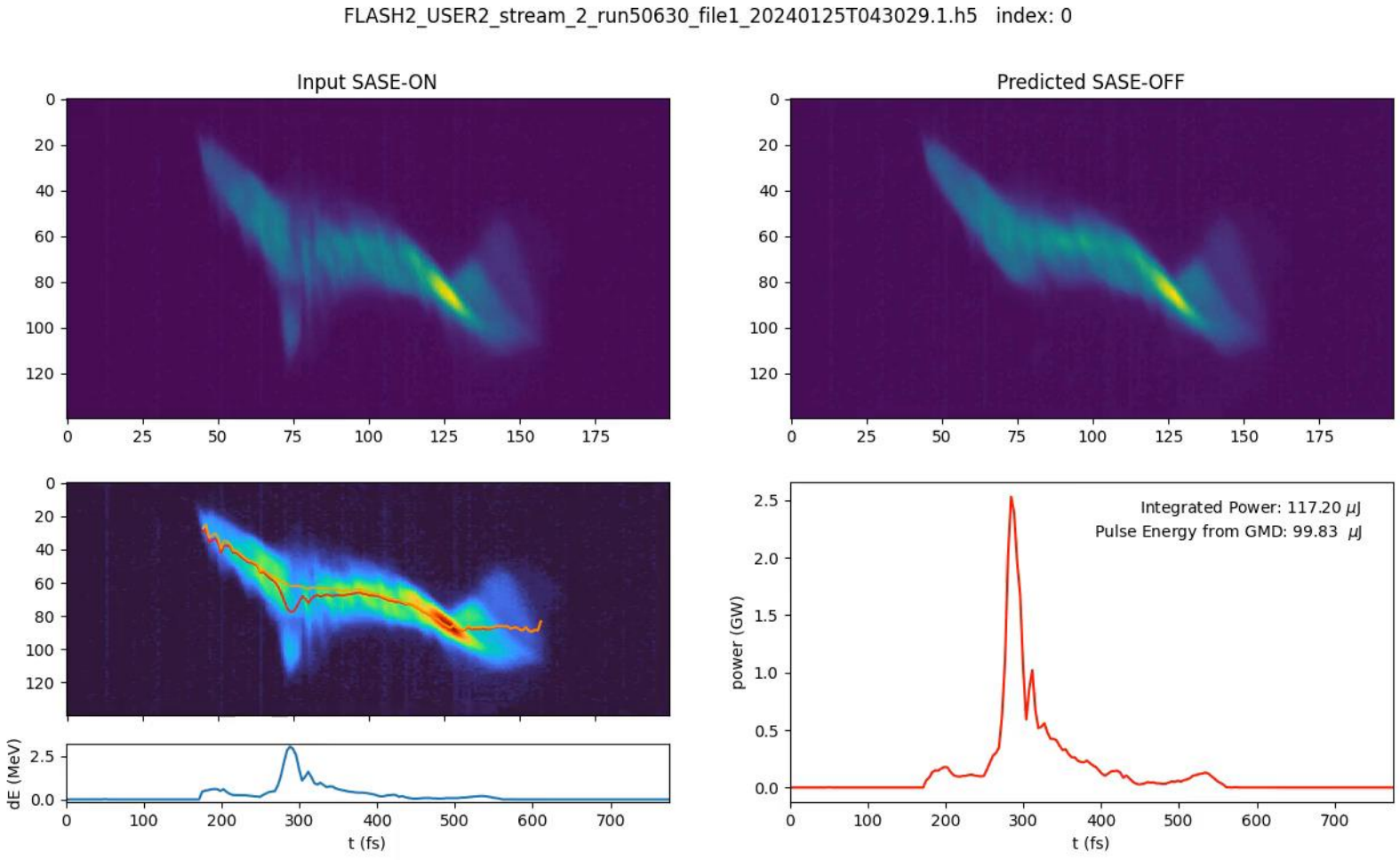
The question is, does it work well with real lasing-on images?

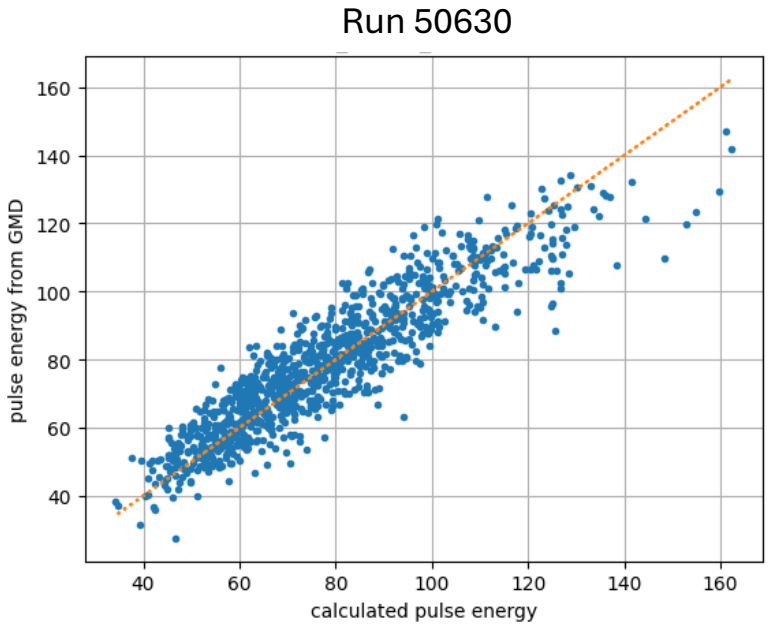
Results


FLASH2_USER2_stream_2_run50626_file1_20240125T035250.1.h5 index: 0
Input SASE-ON
Predicted SASE-OFF
dE (MeV)
t (fs)
power (GW)
Integrated Power: 61.28 μJ
Pulse Energy from GMD: 50.42 μJ

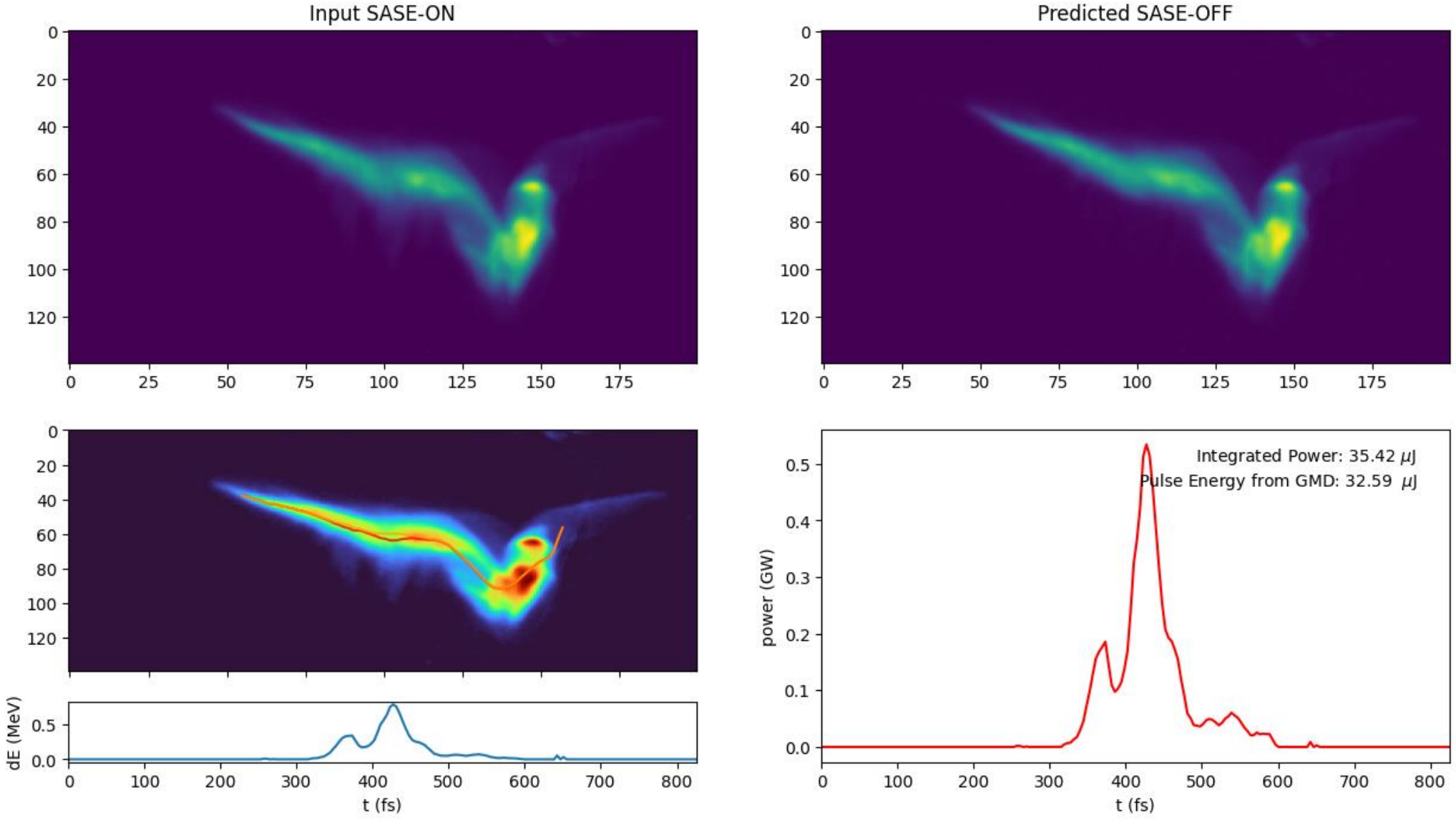

Run 50626
pulse energy from GMD
calculated pulse energy

Results

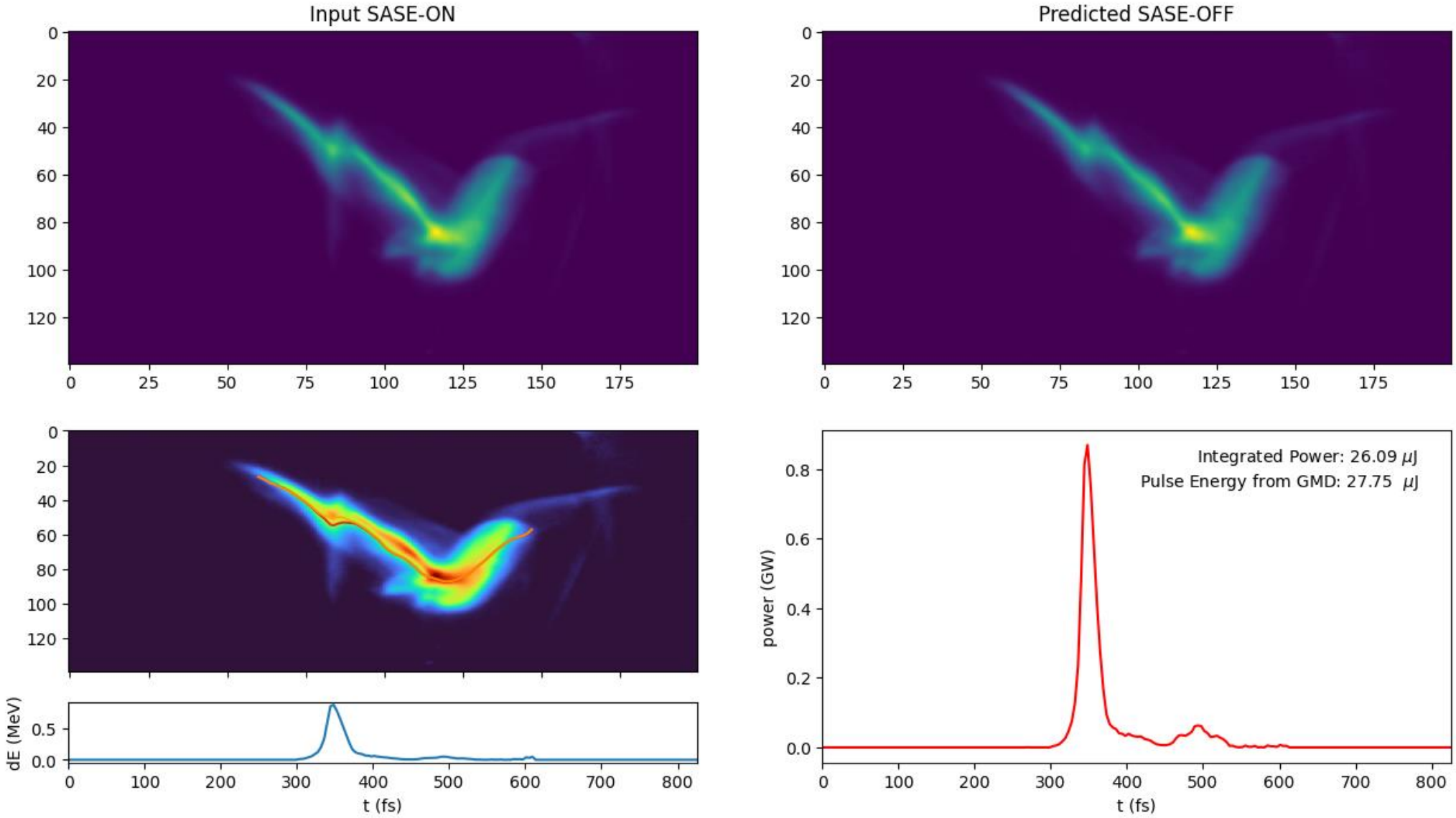

FLASH2_USER2_stream_2_run50630_file1_20240125T043029.1.h5 index: 0
Input SASE-ON
Predicted SASE-OFF
dE (MeV)
t (fs)
power (GW)
Integrated Power: 117.20 μJ
Pulse Energy from GMD: 99.83 μJ


Run 50630
pulse energy from GMD
calculated pulse energy

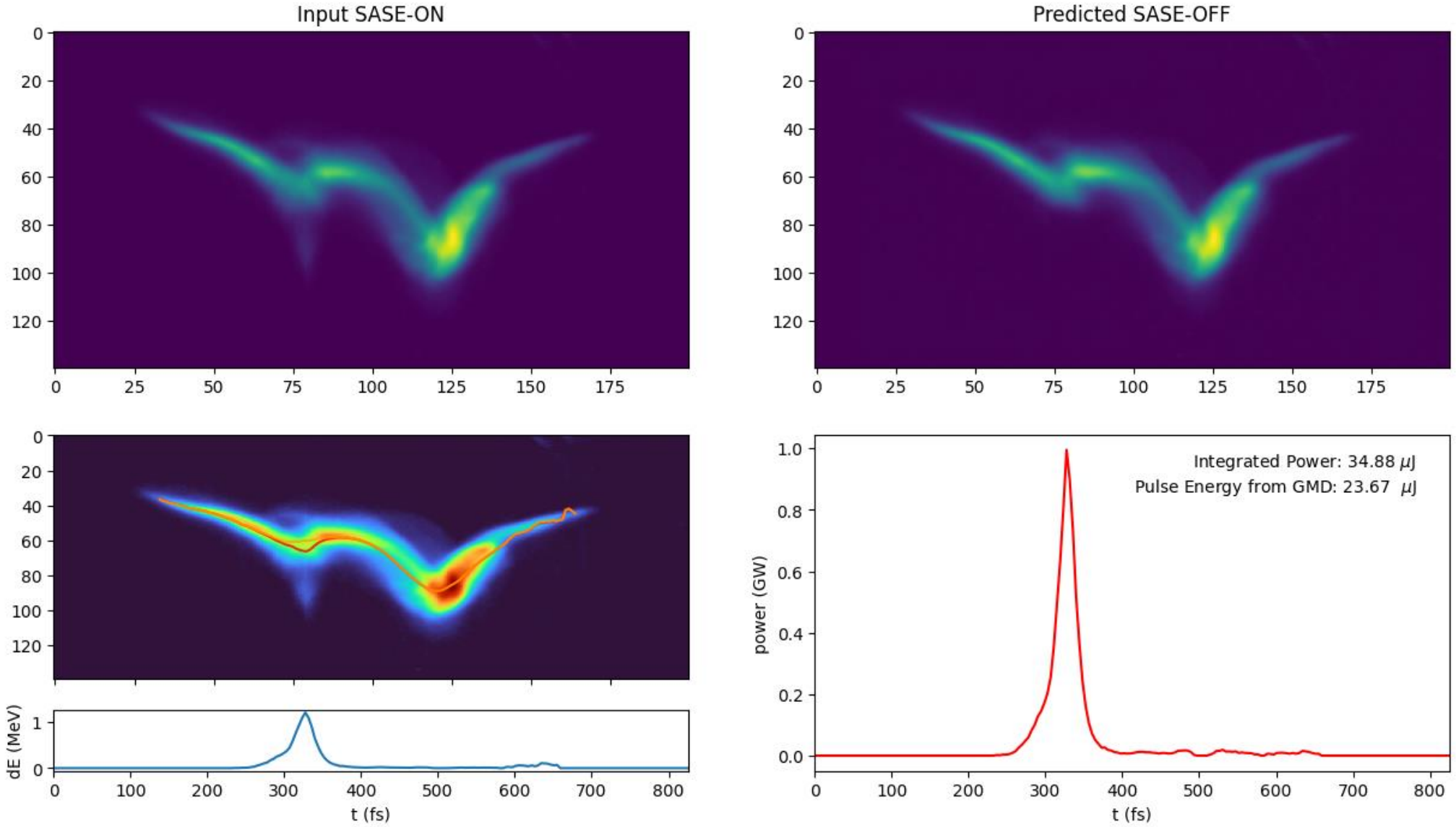
Results


Input SASE-ON
Predicted SASE-OFF
dE (MeV)
t (fs)
power (GW)
Integrated Power: 35.42 μJ
Pulse Energy from GMD: 32.59 μJ

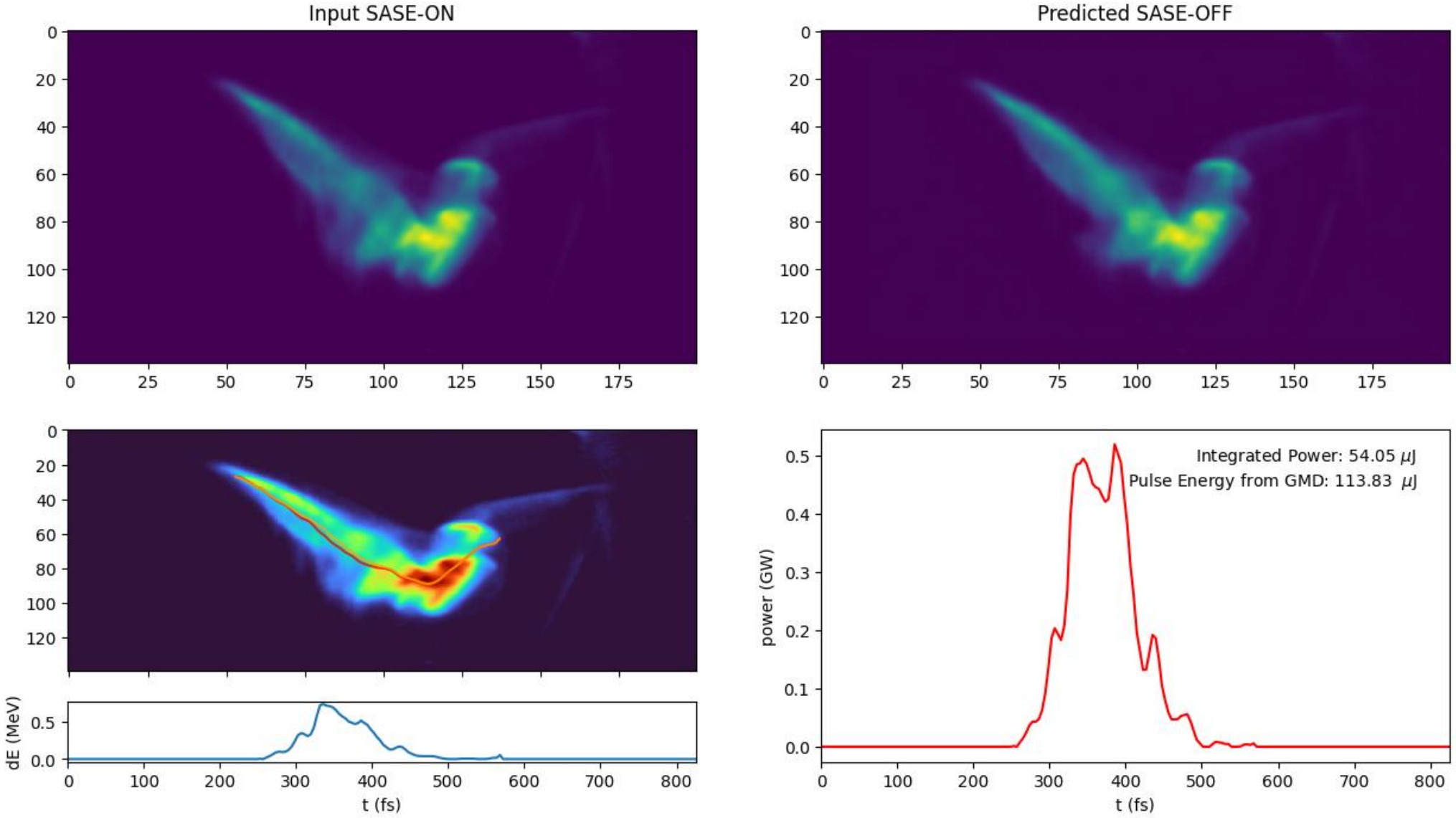
Results


Input SASE-ON
Predicted SASE-OFF
dE (MeV)
t (fs)
power (GW)
Integrated Power: 26.09 μJ
Pulse Energy from GMD: 27.75 μJ

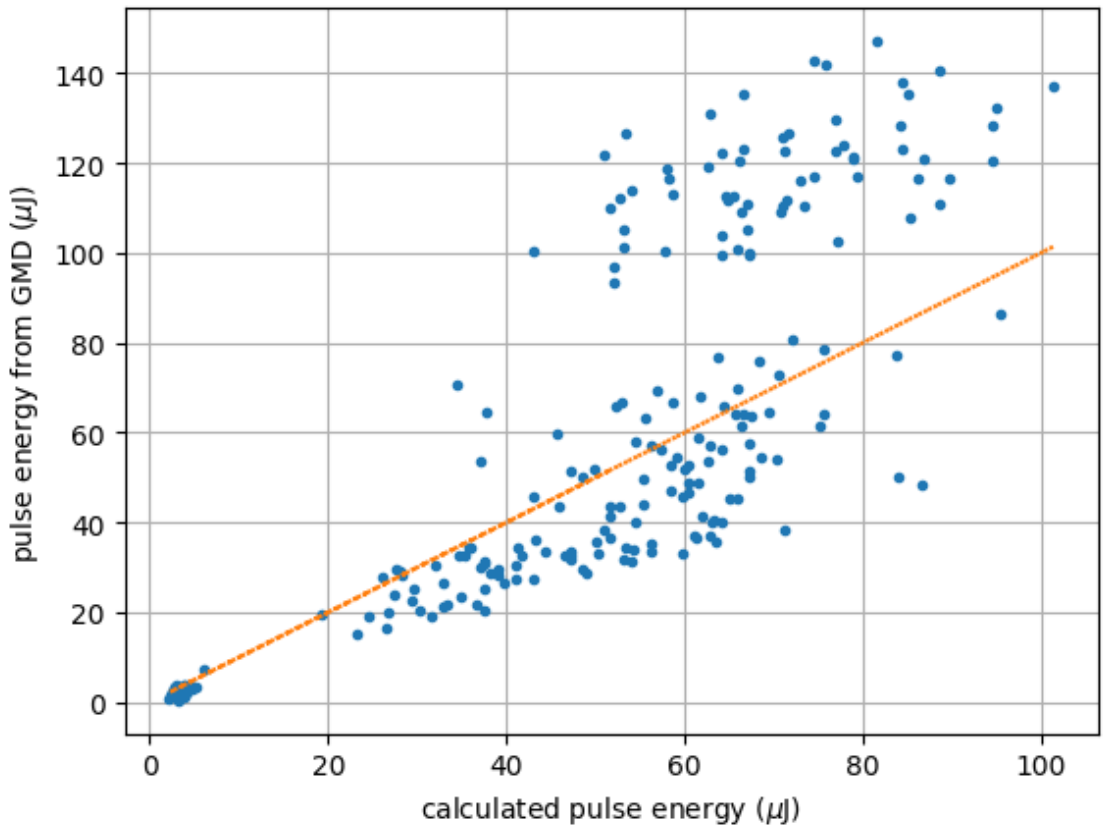
Results


Input SASE-ON
Predicted SASE-OFF
dE (MeV)
t (fs)
power (GW)
Integrated Power: 34.88 μJ
Pulse Energy from GMD: 23.67 μJ

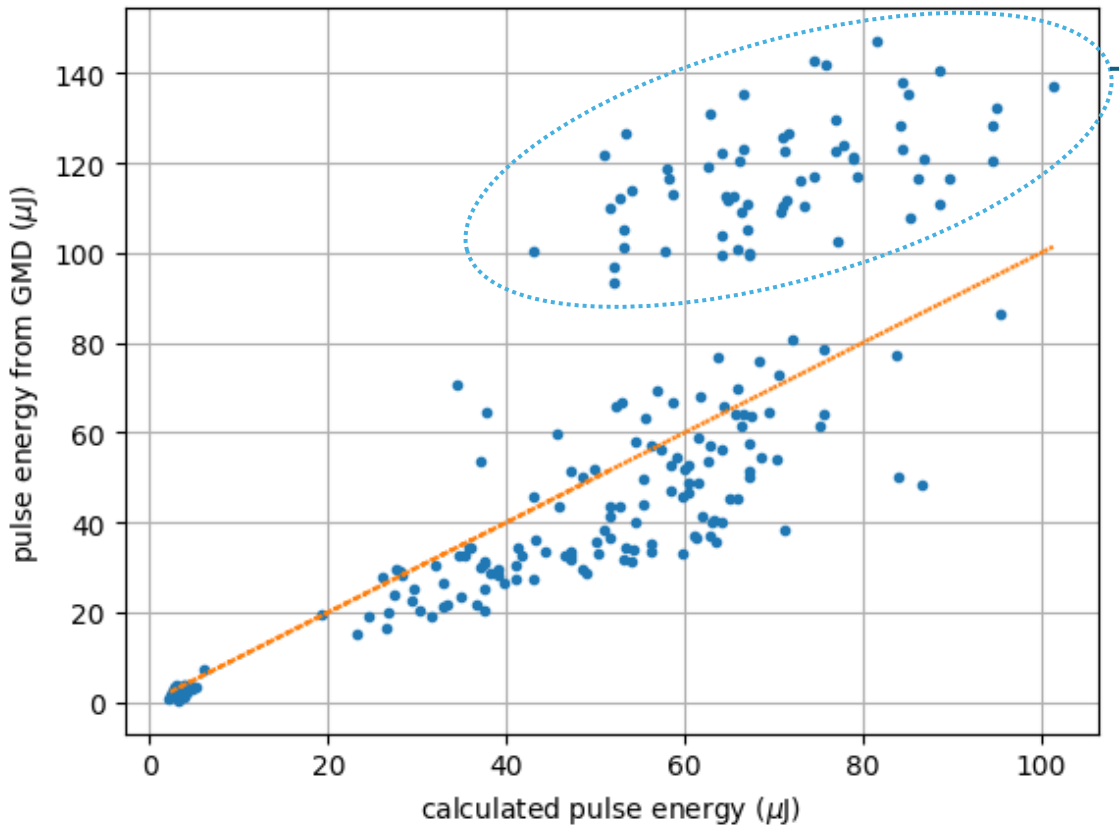
Results

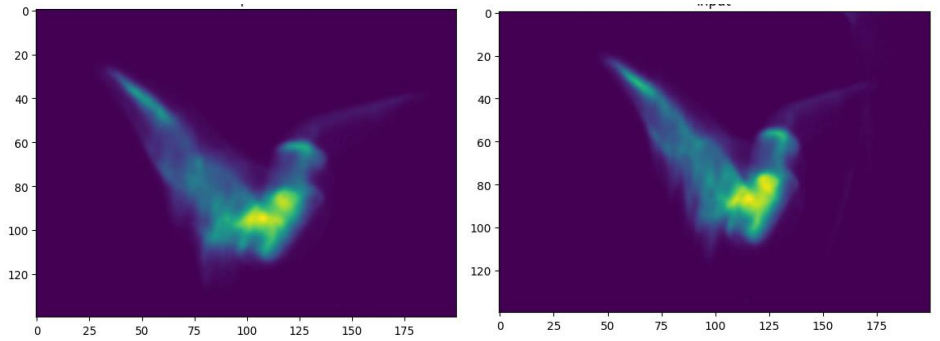

Input SASE-ON
Predicted SASE-OFF
dE (MeV)
t (fs)
power (GW)
Integrated Power: 54.05 μJ
Pulse Energy from GMD: 113.83 μJ

Results


pulse energy from GMD (μJ)
calculated pulse energy (μJ)
0
20
40
60
80
100
120
140

Results

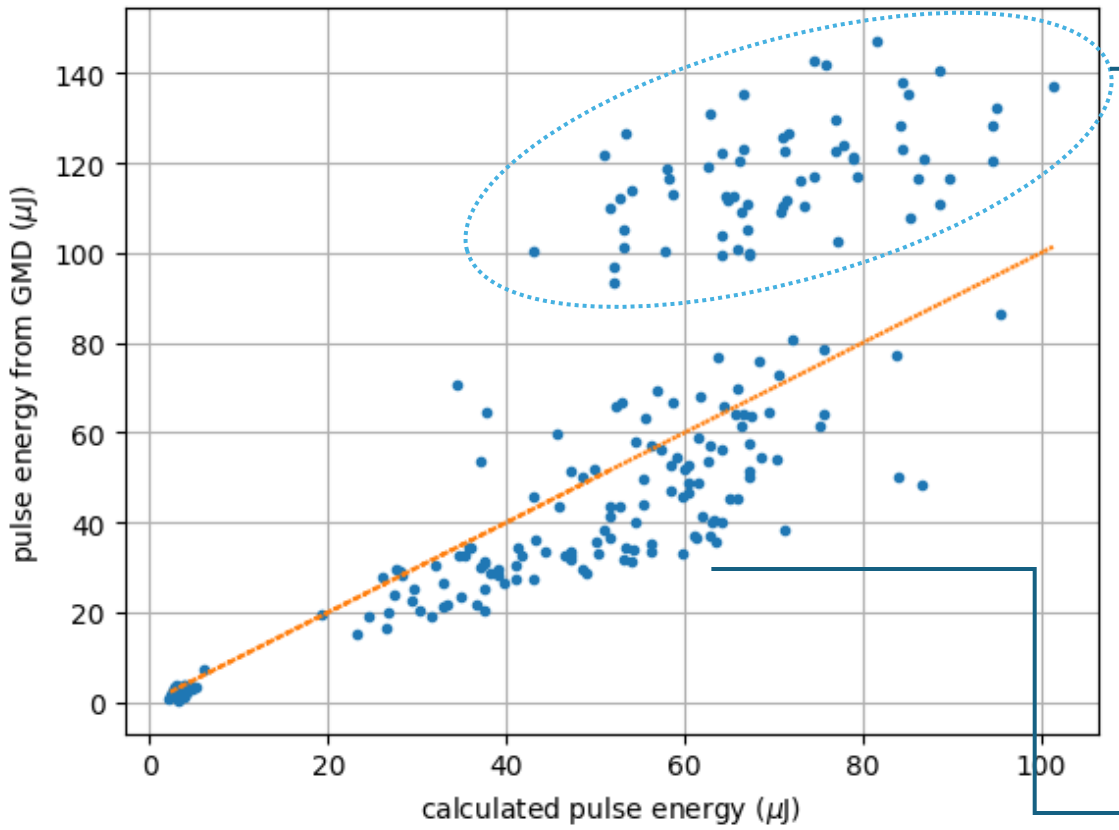


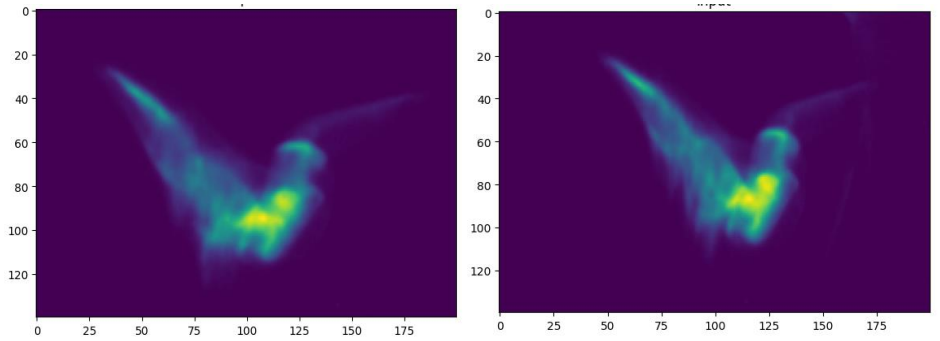


Long pulses

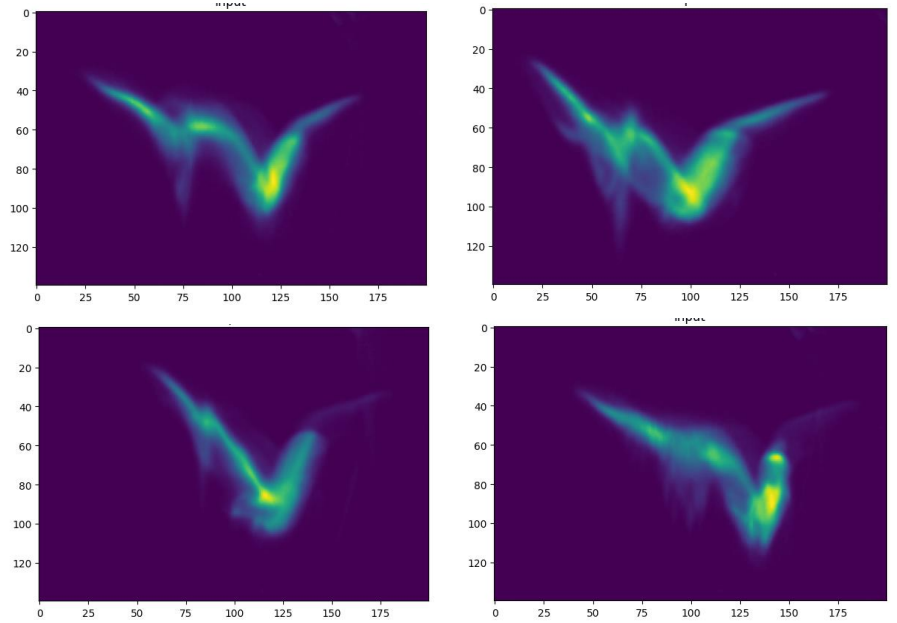
Results

The model works best with short pulses.



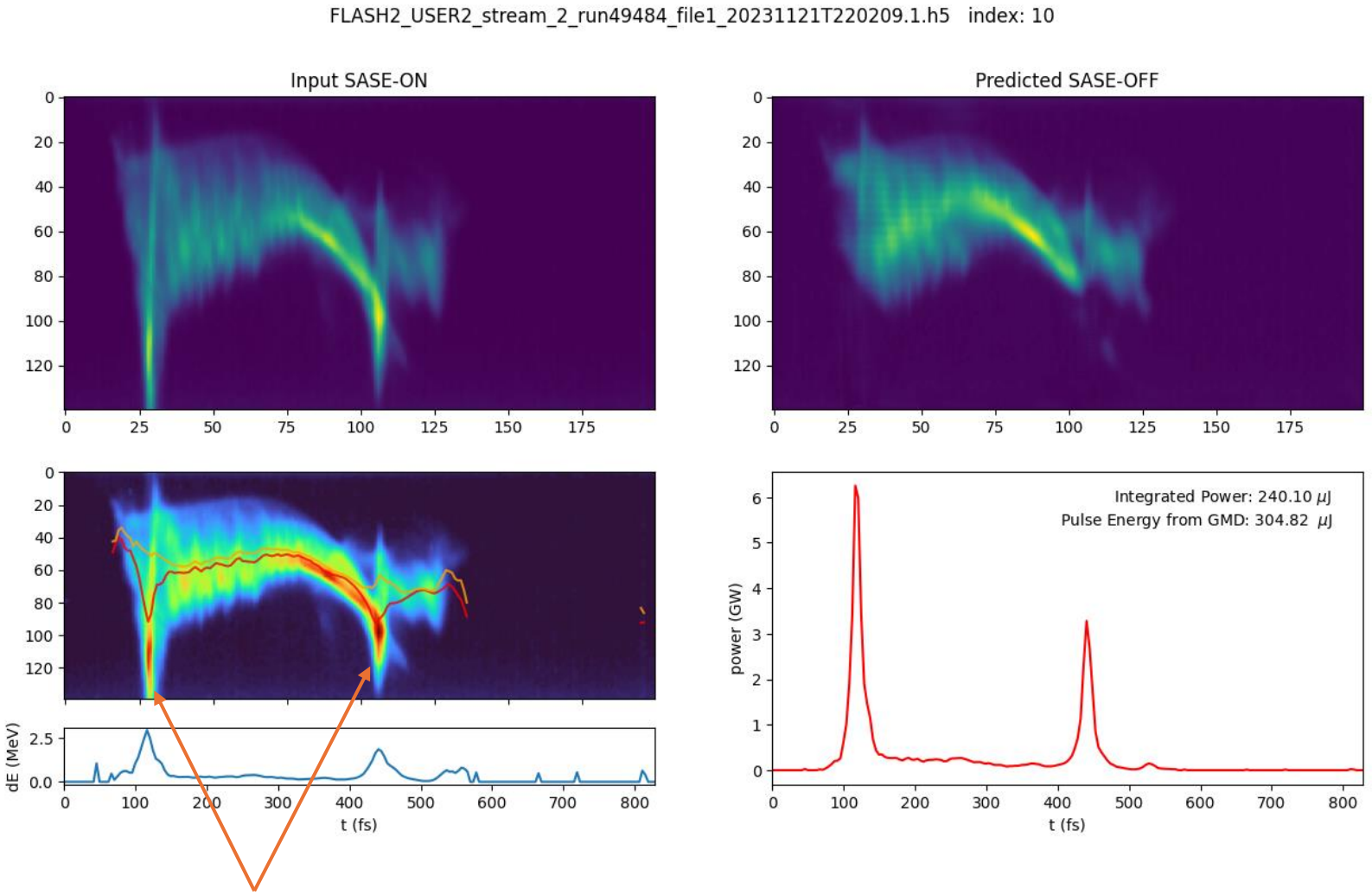


Long pulses



Short pulses

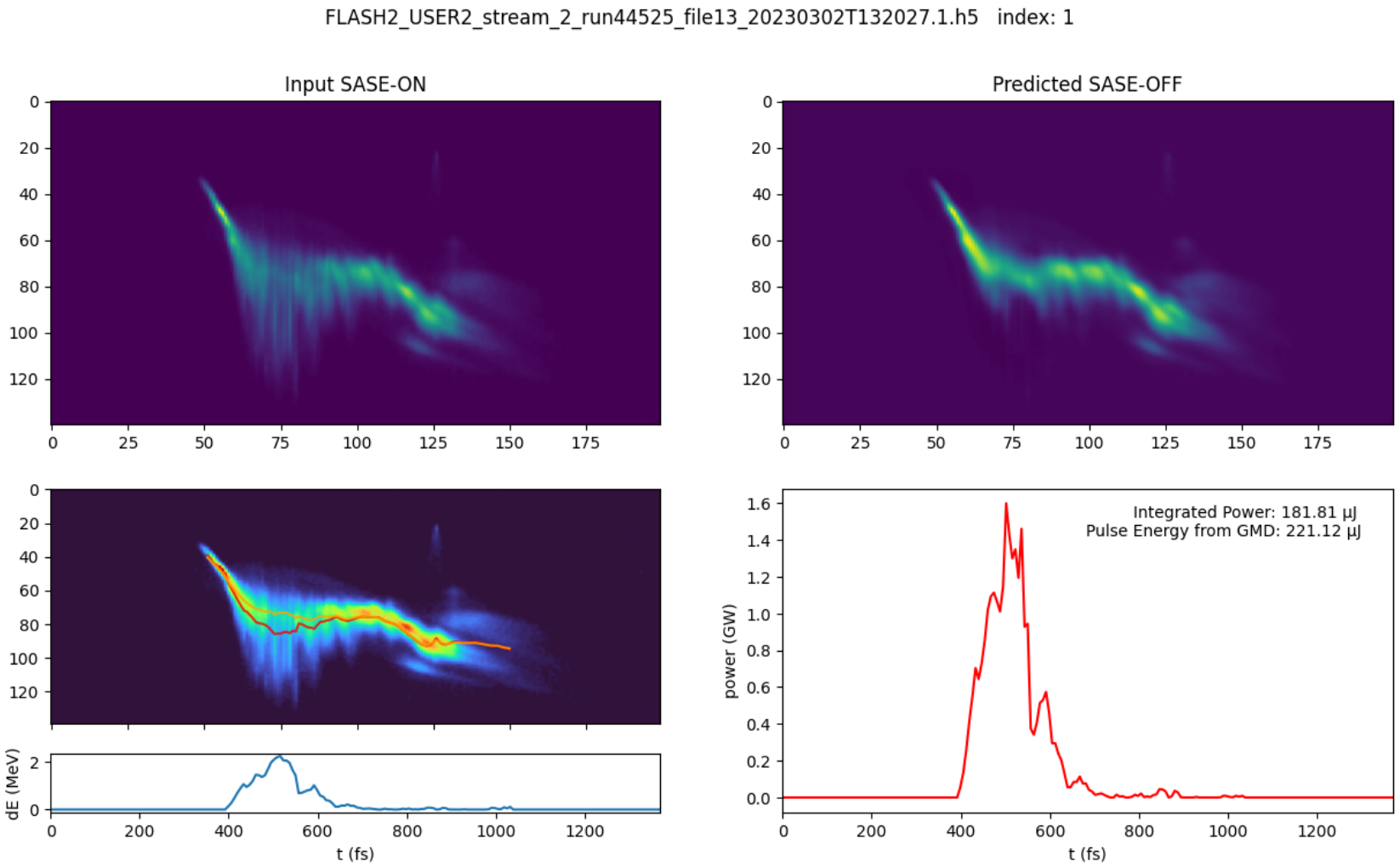
Examples where it doesn’t work so well



Mistakes these two features as SASE

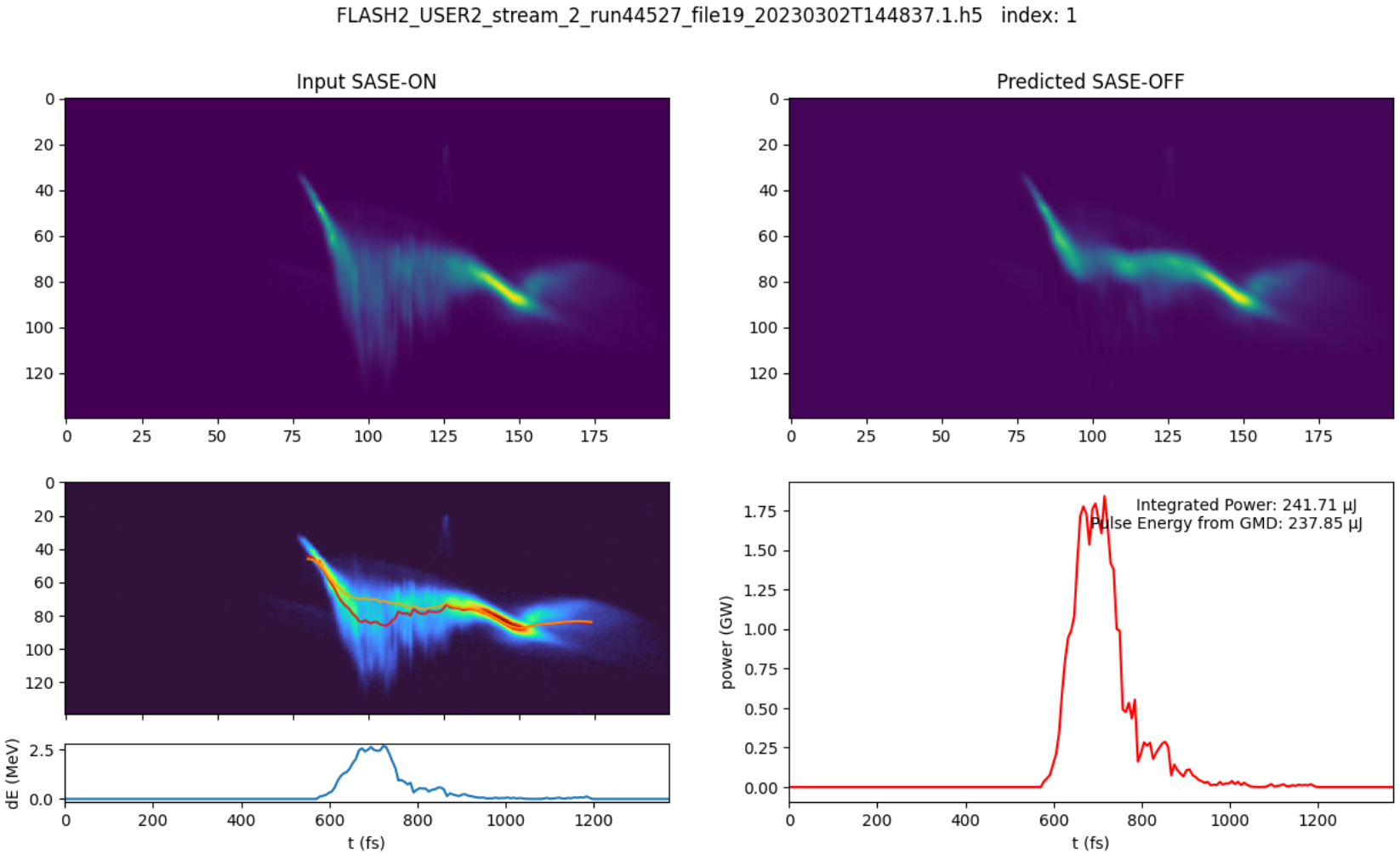
- Sharp features in the phase space are mistaken for SASE.

Examples where it doesn’t work so well



- Model struggles with long SASE pulses.

Examples where it doesn’t work so well



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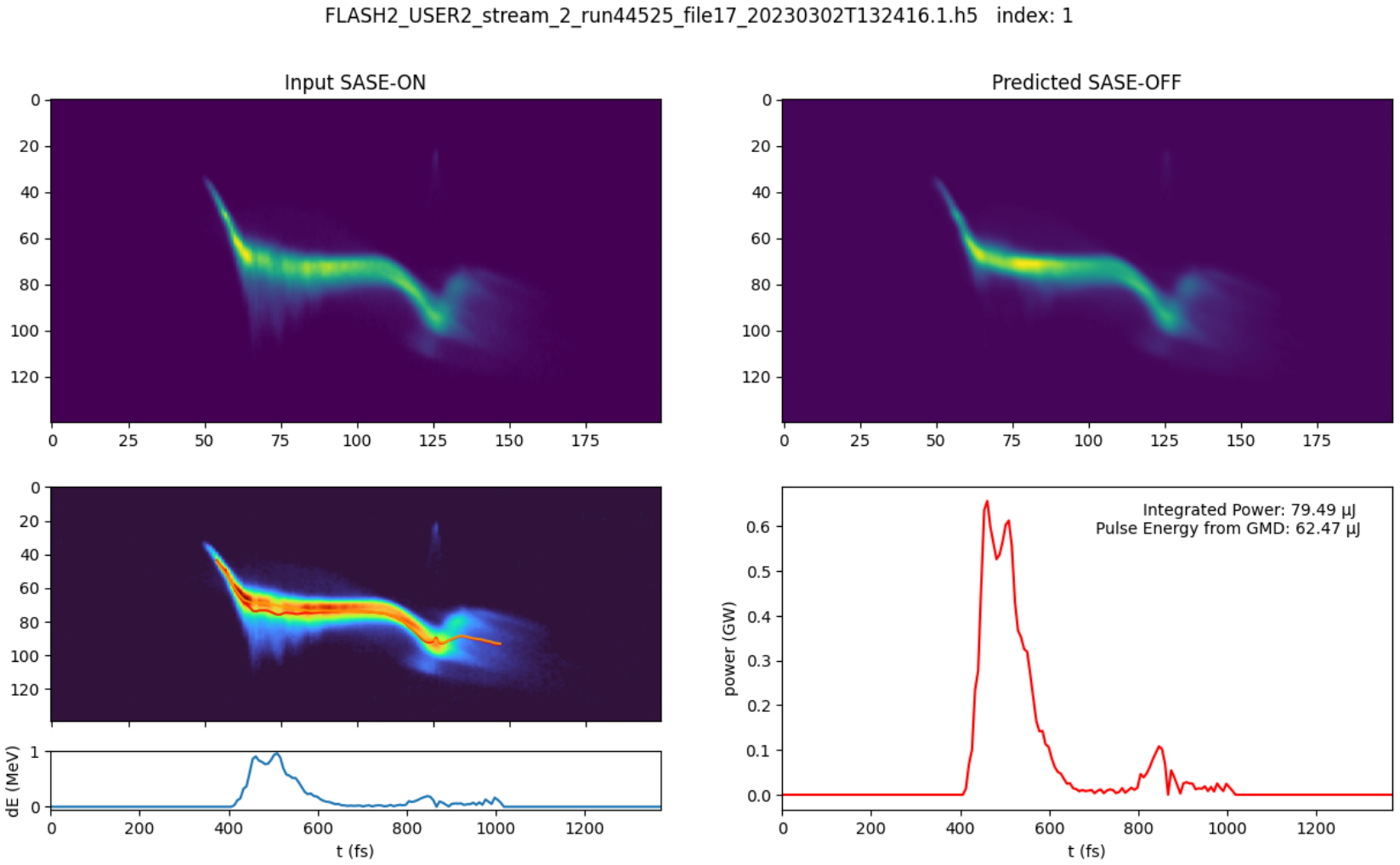
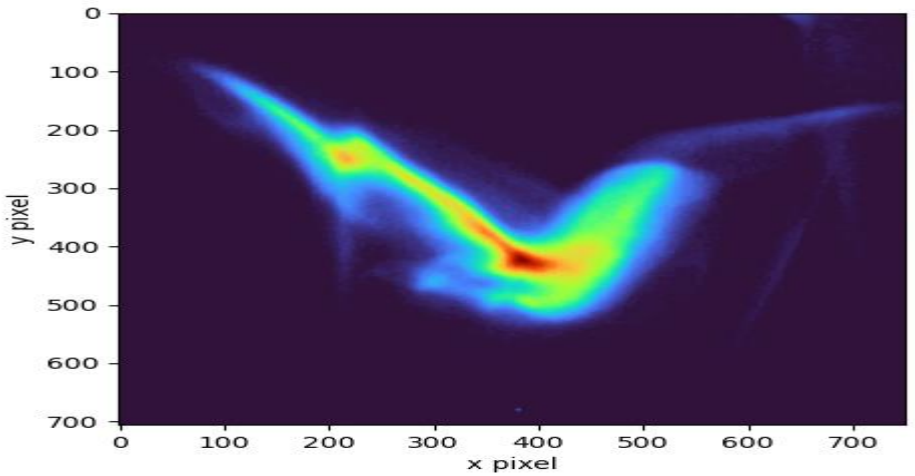
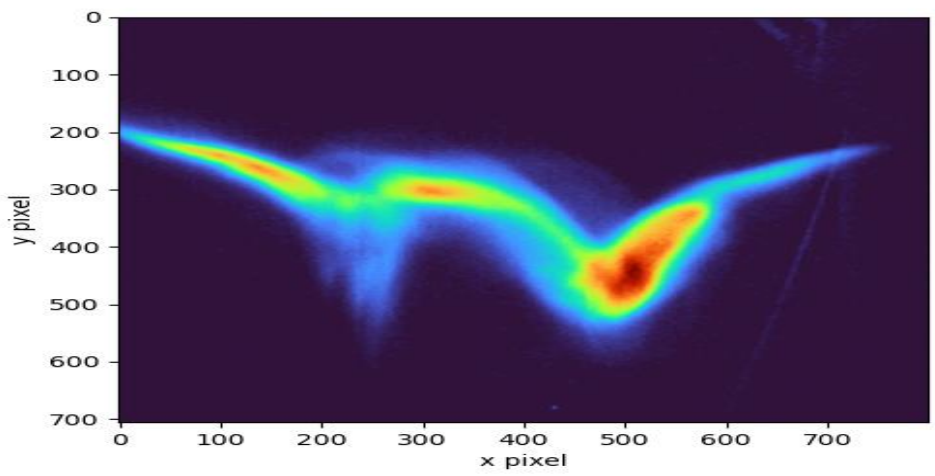
Examples where it doesn’t work so well

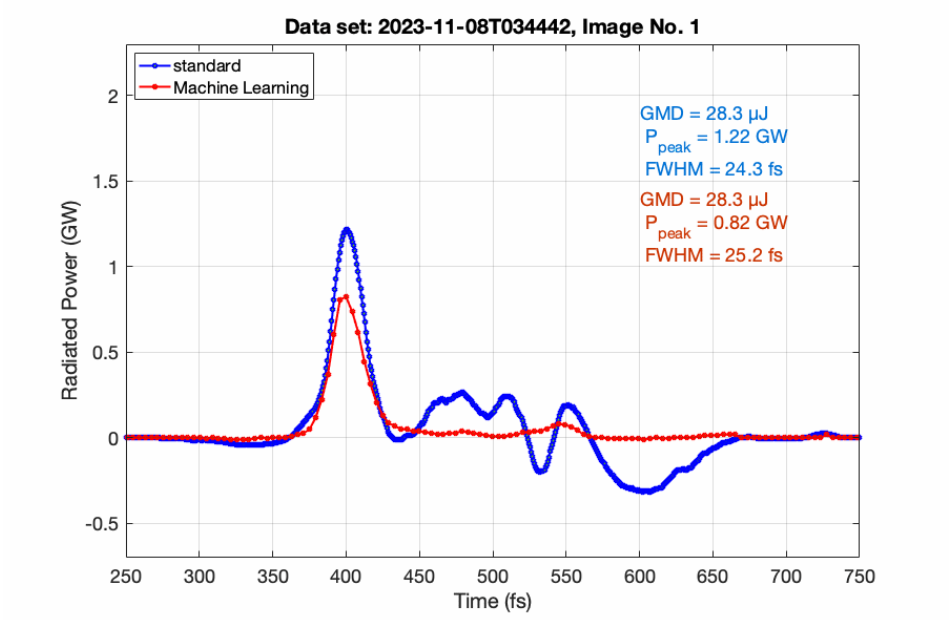


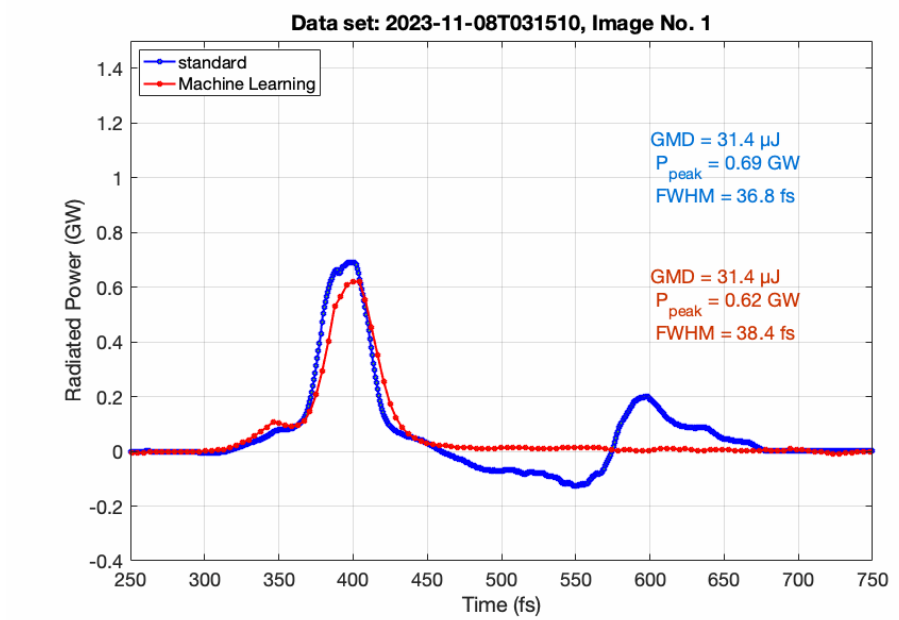
- Model struggles with long SASE pulses.

Comparison between the standard and U-net based method



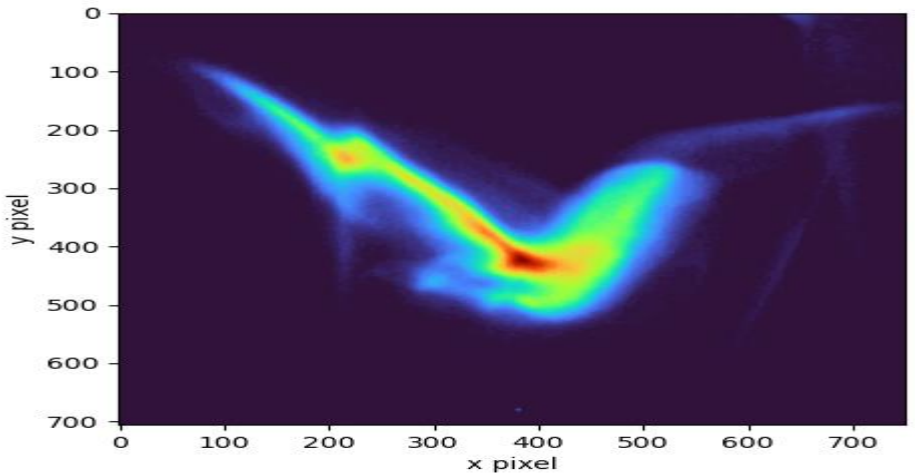


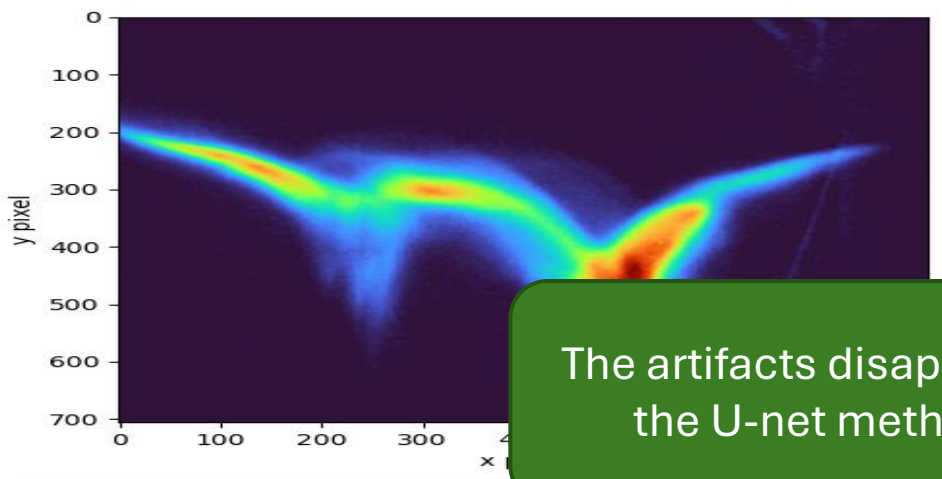




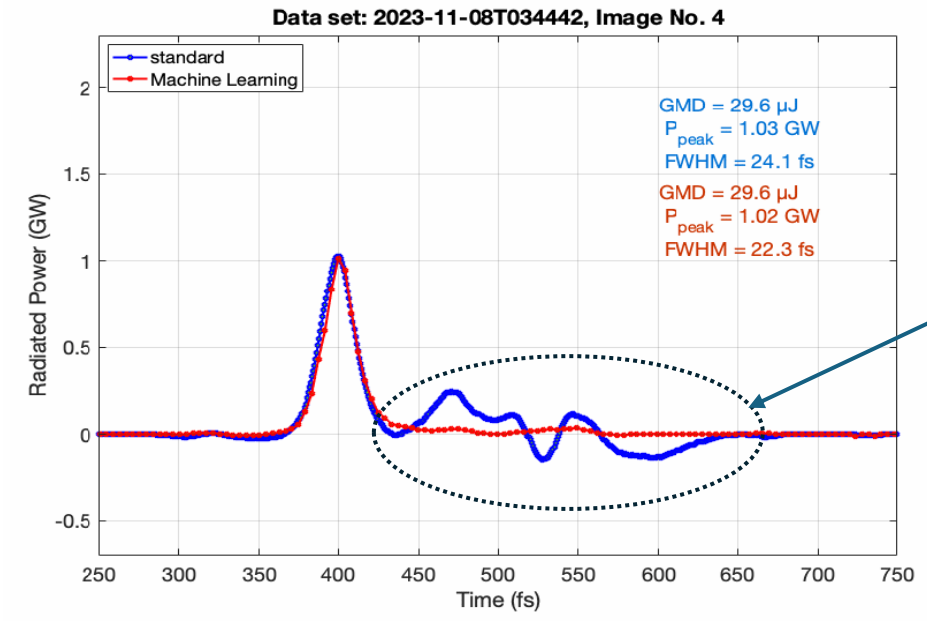
Courtesy: Christopher Gerth

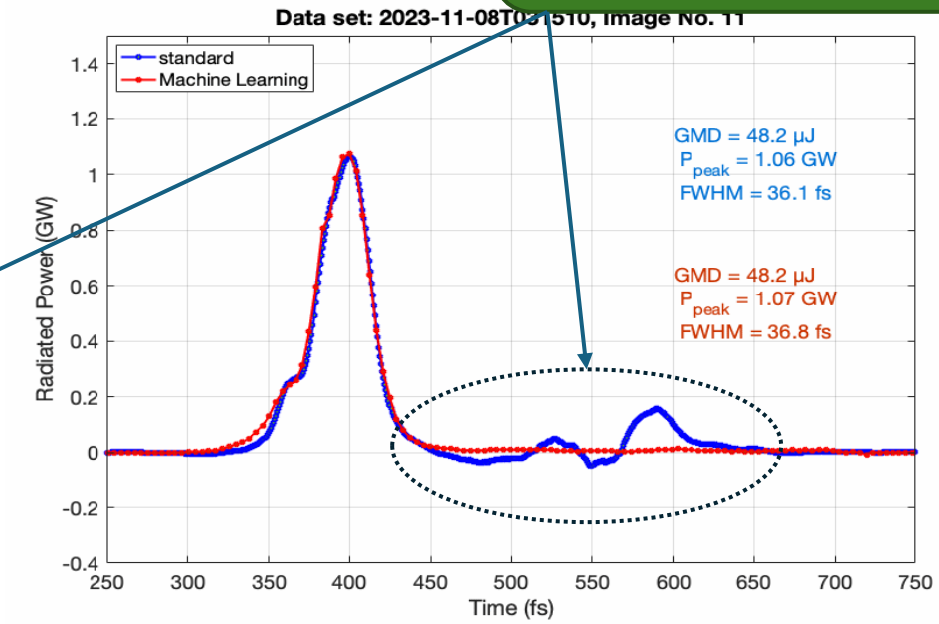
Comparison between the standard and U-net based method





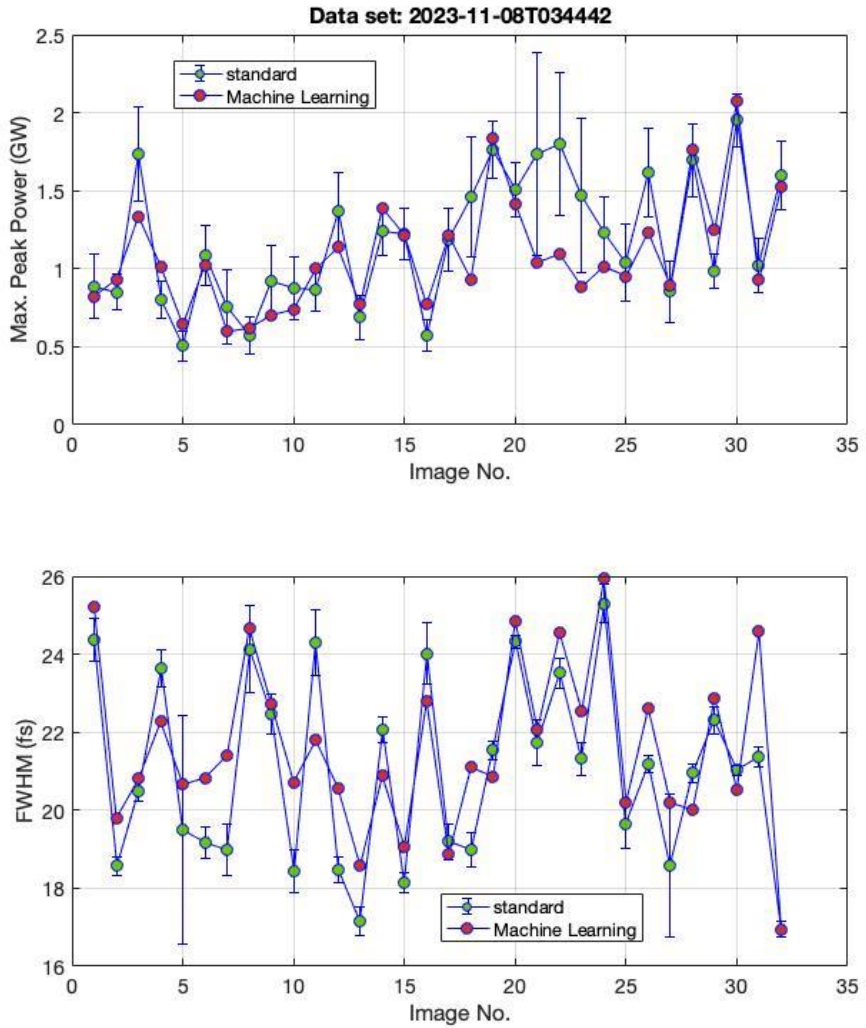
The artifacts disappear in the U-net method!



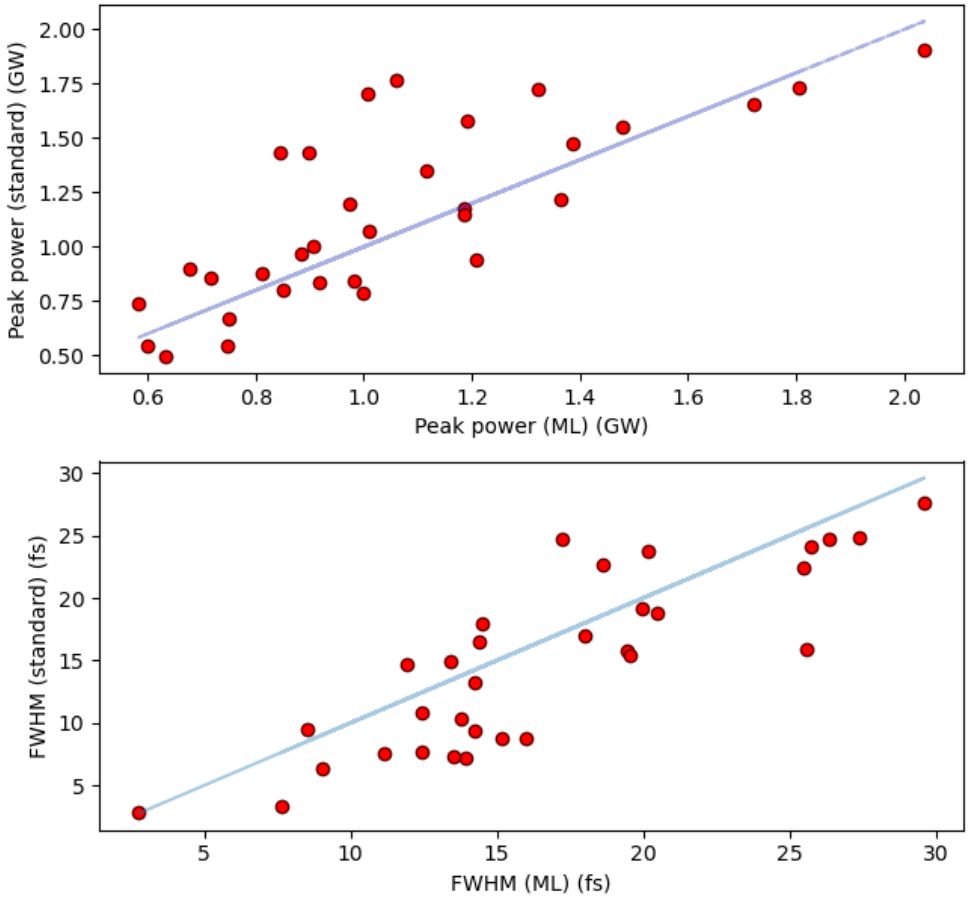


Courtesy: Christopher Gerth

Comparison between the standard and U-net based method



- In general, a good correlation between the standard method and U-net method.



Courtesy: Christopher Gerth

Conclusion

- This method works best for short pulses. Shows a good correlation with the GMD measurements.
- Works with a relatively low number of training samples.
- Any sharp features in the phase space are mistaken for lasing.
- For longer pulses, the results show a large spread, mainly underestimating the pulse energy.
- Needs fine-tuning when using for bunch shapes the model hasn’t encountered.

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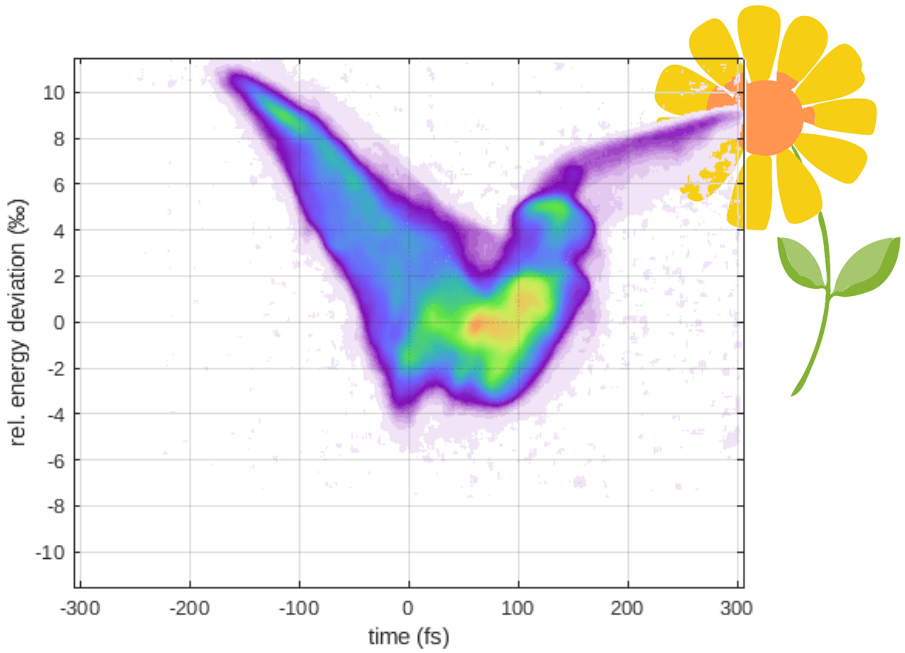
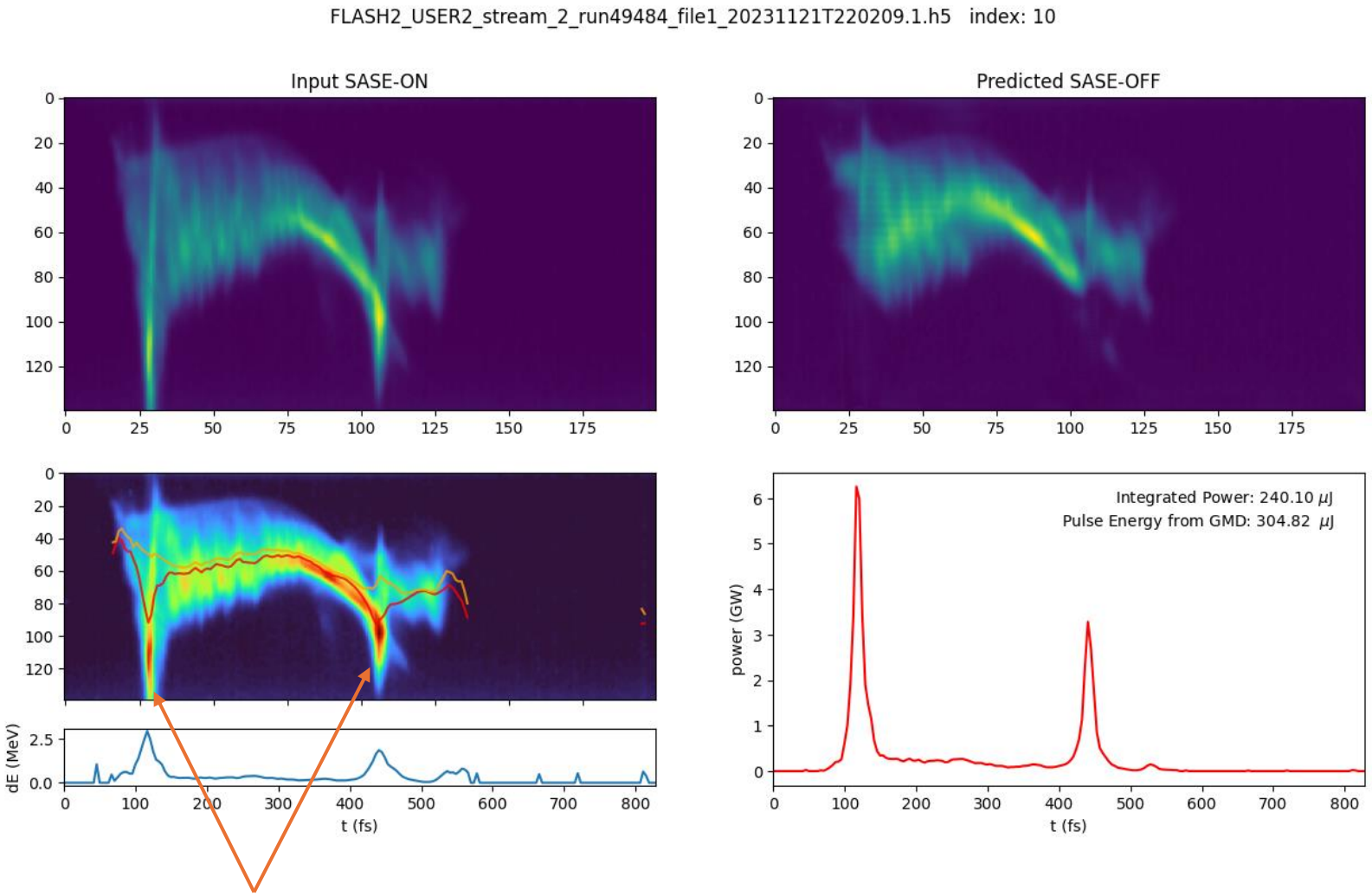
Special thanks to Gesa Goetzke, Stefan Düsterer and Christopher Gerth for helping me access the Maxwell computational resources at DESY.

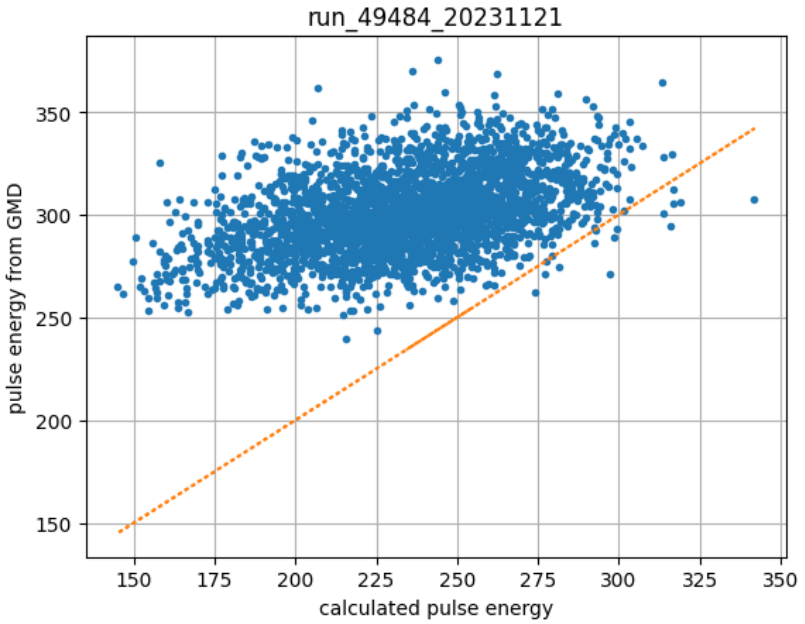

rel. energy deviation (‰)
10
8
6
4
2
0
-2
-4
-6
-8
-10
-300
-200
-100
0
100
200
300
time (fs)

Thank you!

November 21, 2023

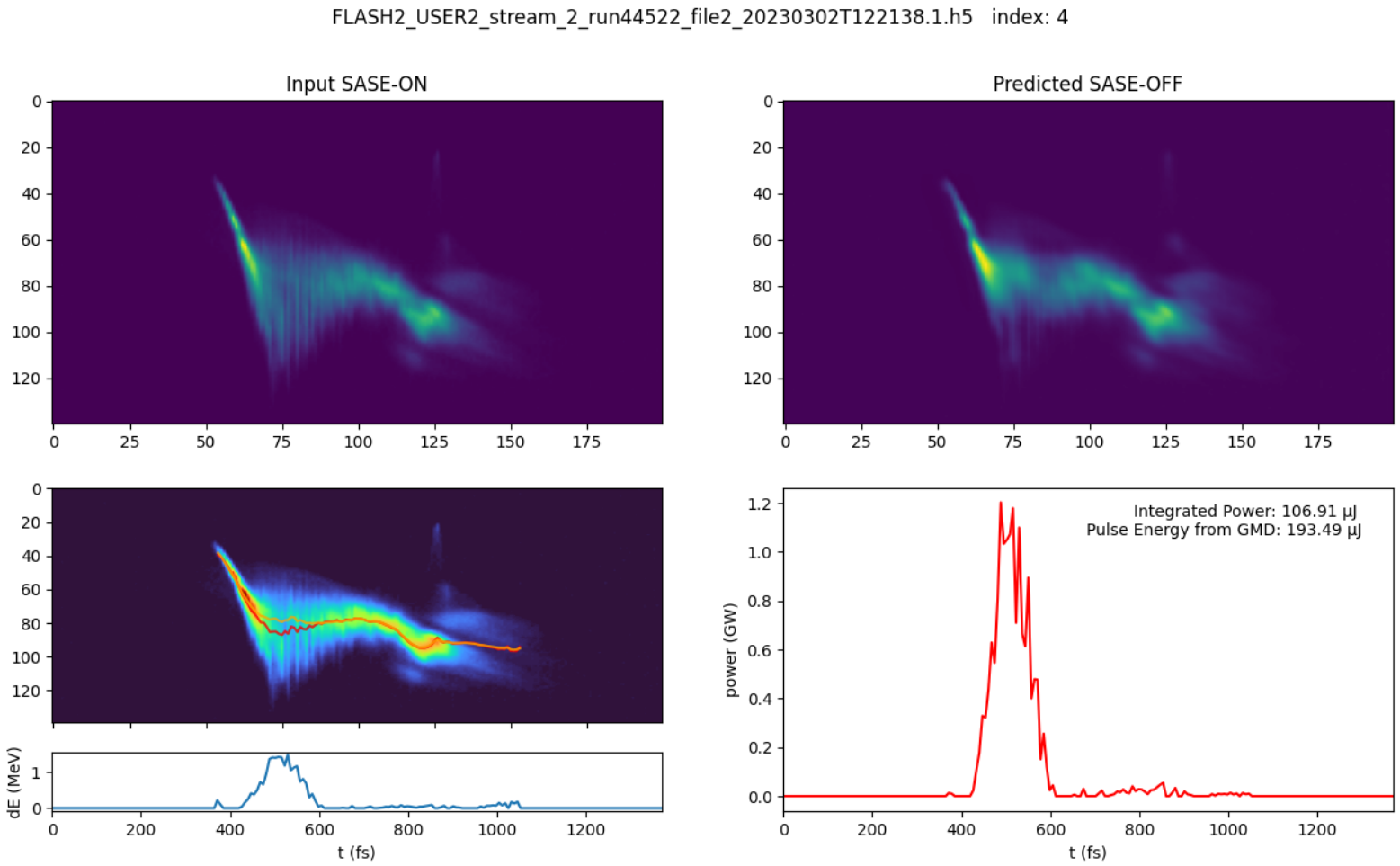


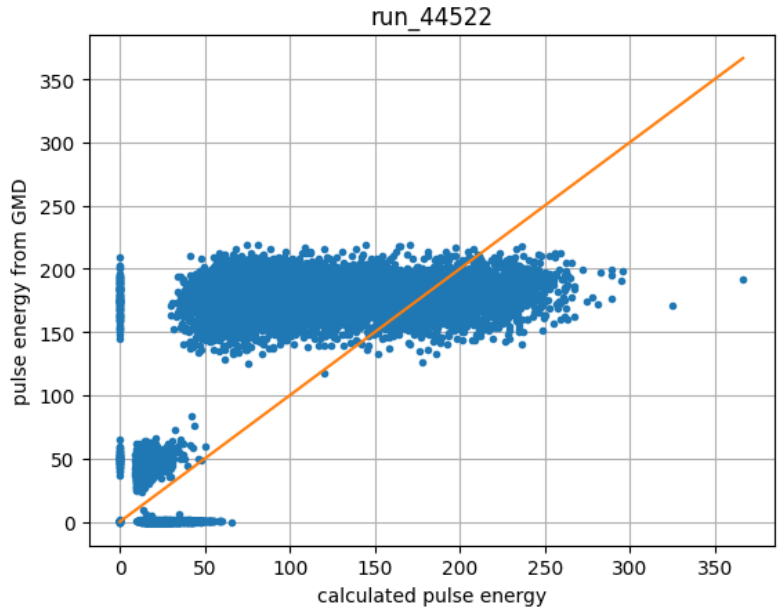
Shows little correlation: Model not suitable for long SASE pulses



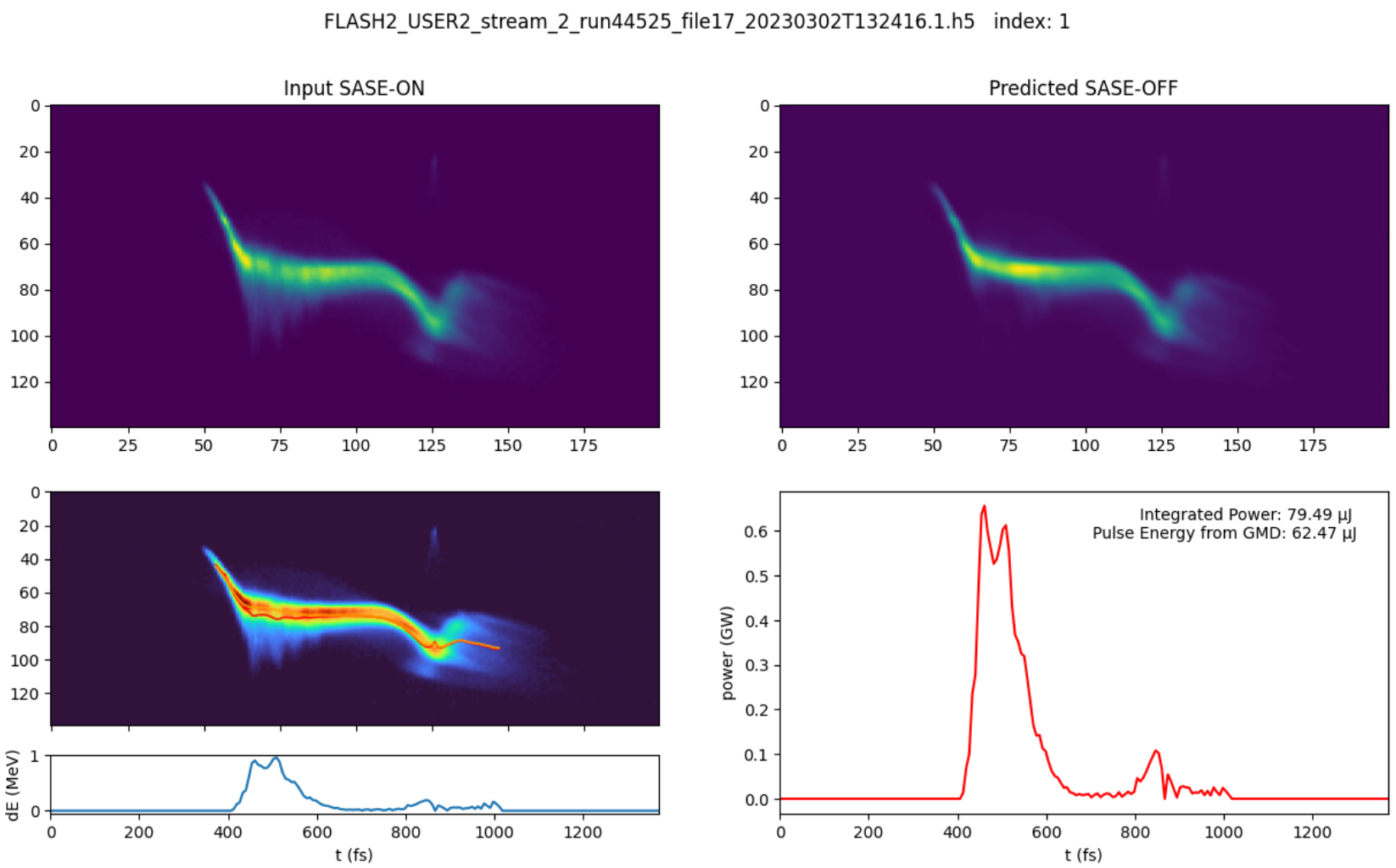
Mistakes these two features as SASE

March 02, 2023 : Run 44522

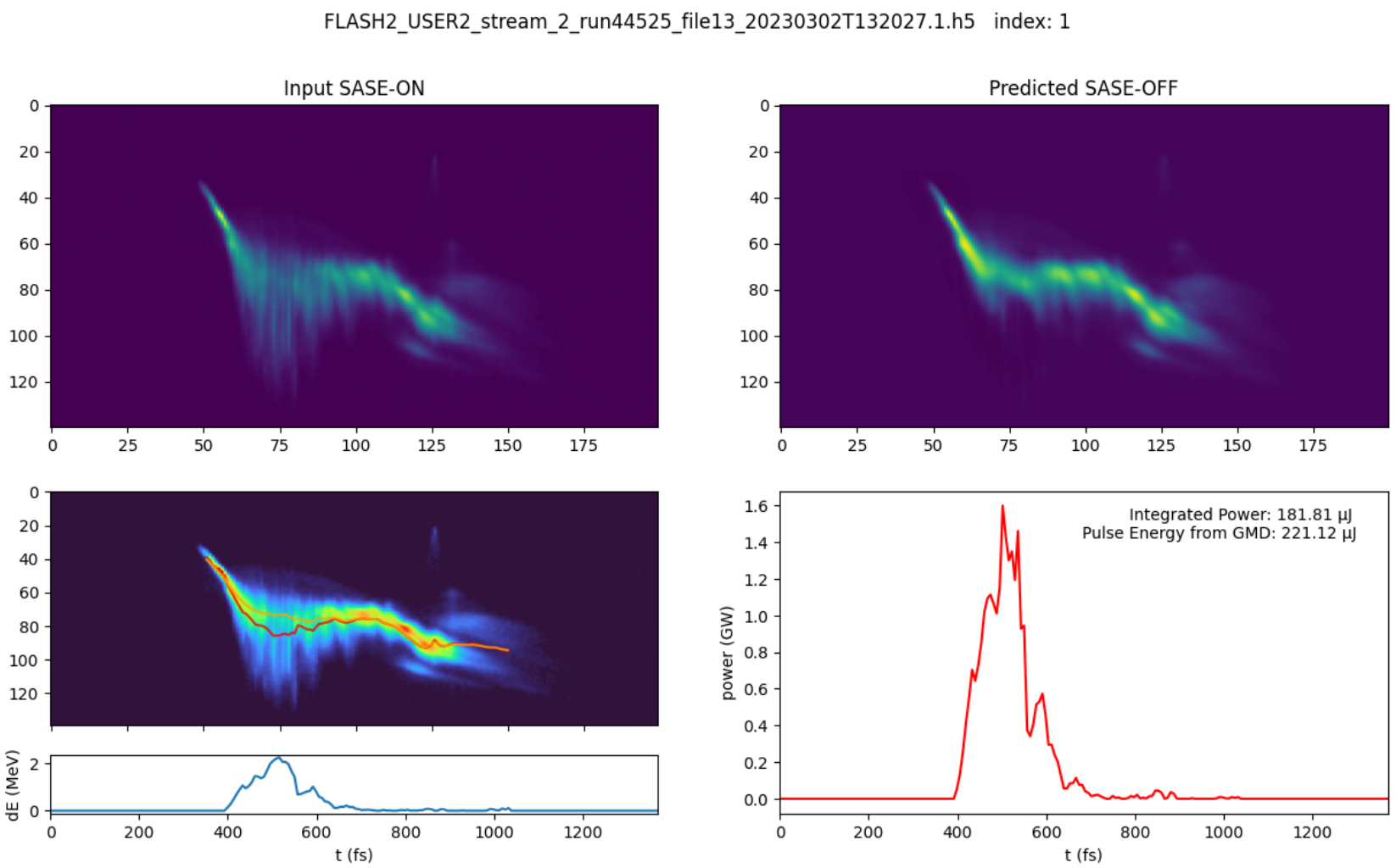




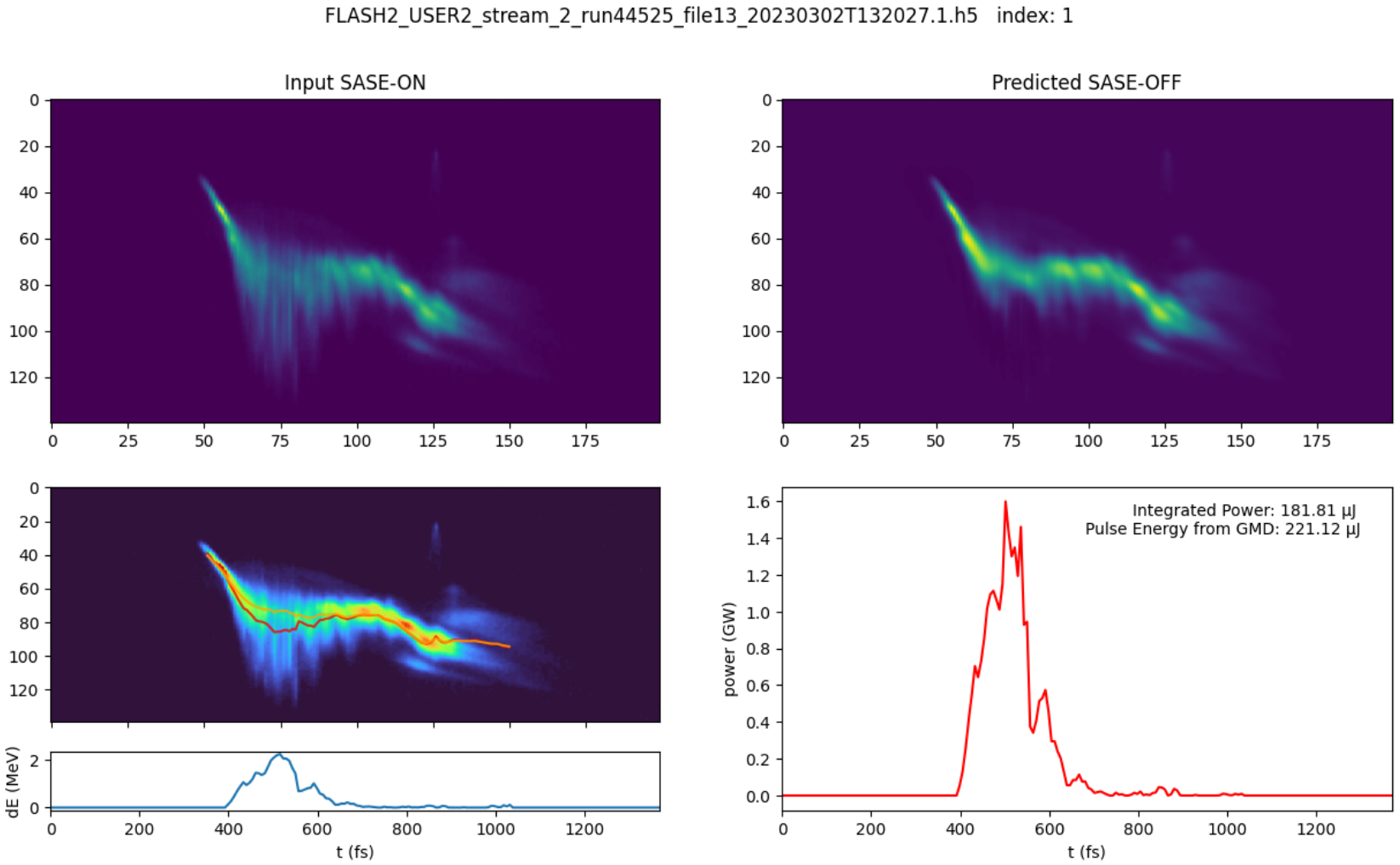
March 02, 2023 : Run 44525

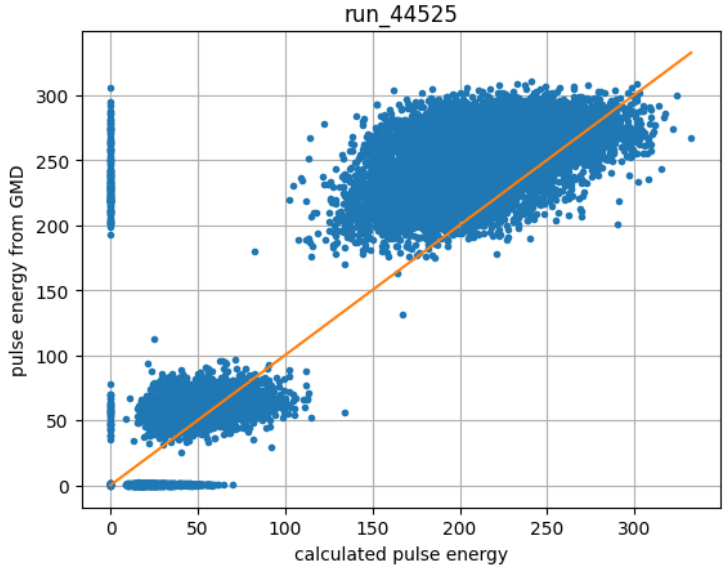


March 02, 2023 : Run 44525

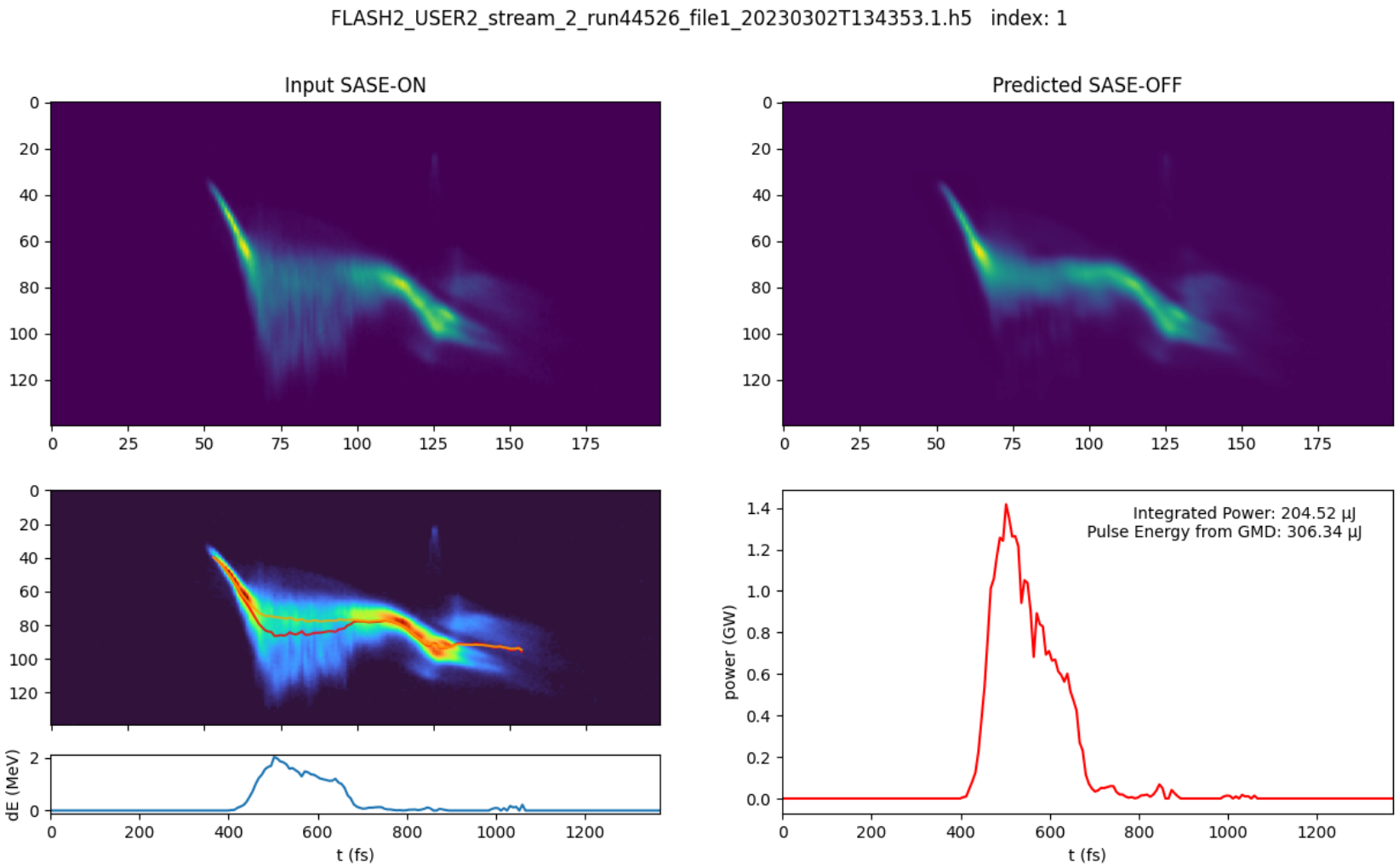


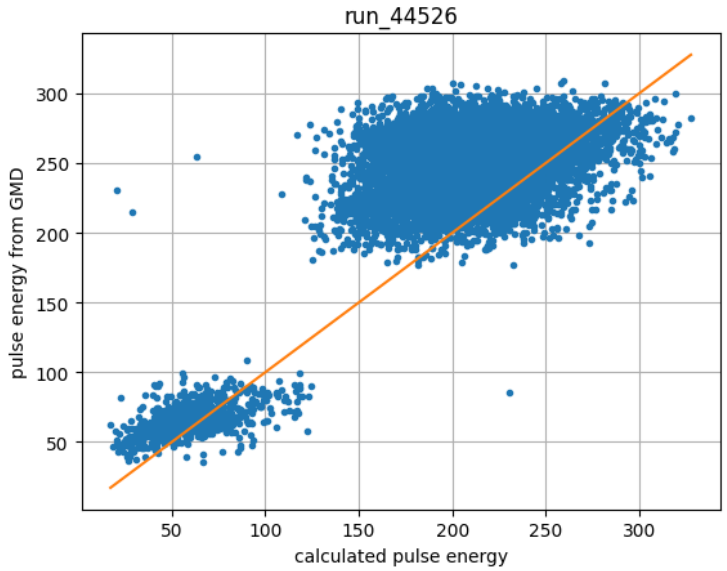
March 02, 2023 : Run 44525





March 02, 2023 : Run 44526





March 02, 2023 : Run 44527