

High Rep-Rate Data Acquisition for the Extreme Light Laser

Nathaniel Tamminga¹, Scott Feister², Chris Orban¹, Joseph Snyder³, Kyle Frische⁴, Benjamin Knight⁴, Michael Dexter⁴, Anil Patnaik⁴

¹⁾ Department of Physics, The Ohio State University, Columbus, Ohio 43210, USA

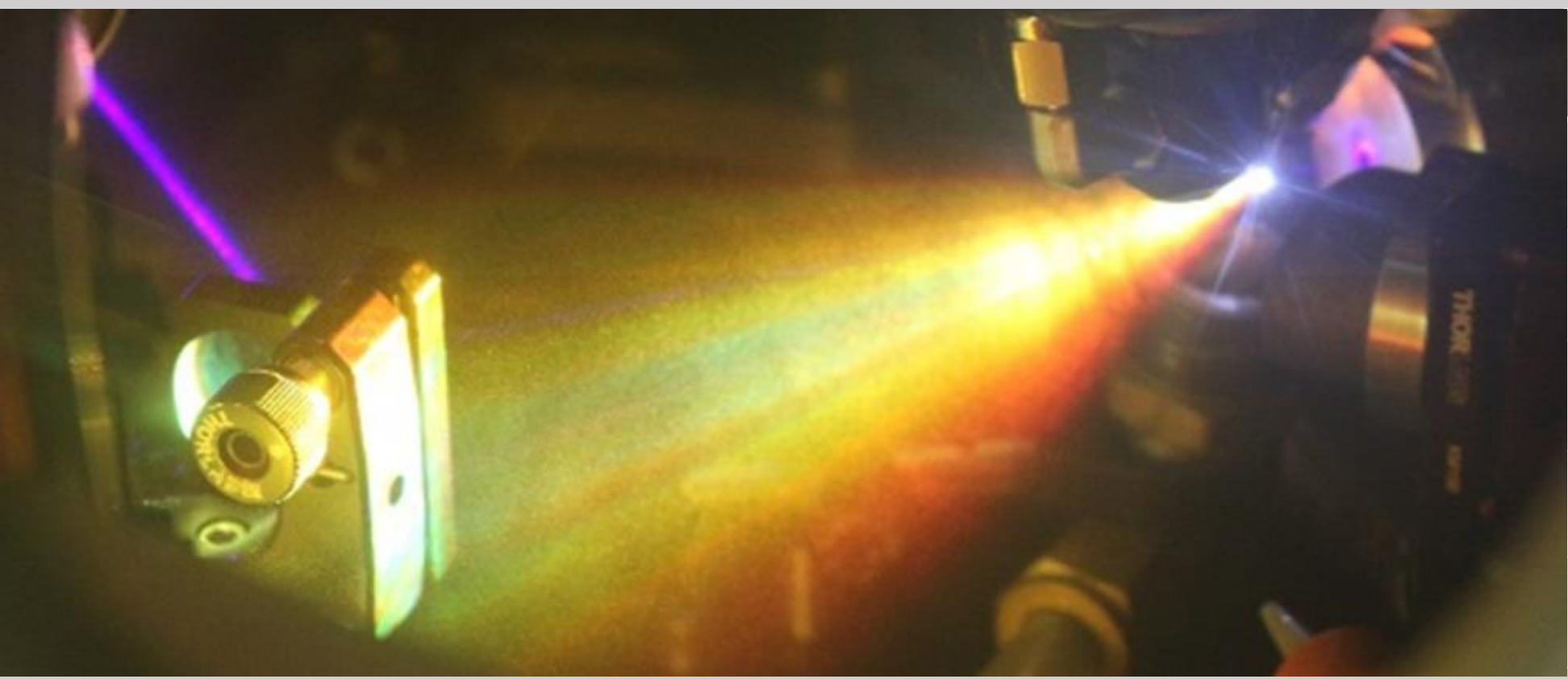
²⁾ Department of Computer Science, California State University Channel Islands, Camarillo, California 93012, USA

³⁾ Department of Mathematical and Physical Sciences, Miami University, Hamilton, Ohio 45011, USA

⁴⁾ Department of Engineering Physics, Air Force Institute of Technology, Dayton, Ohio 45433, USA

Abstract

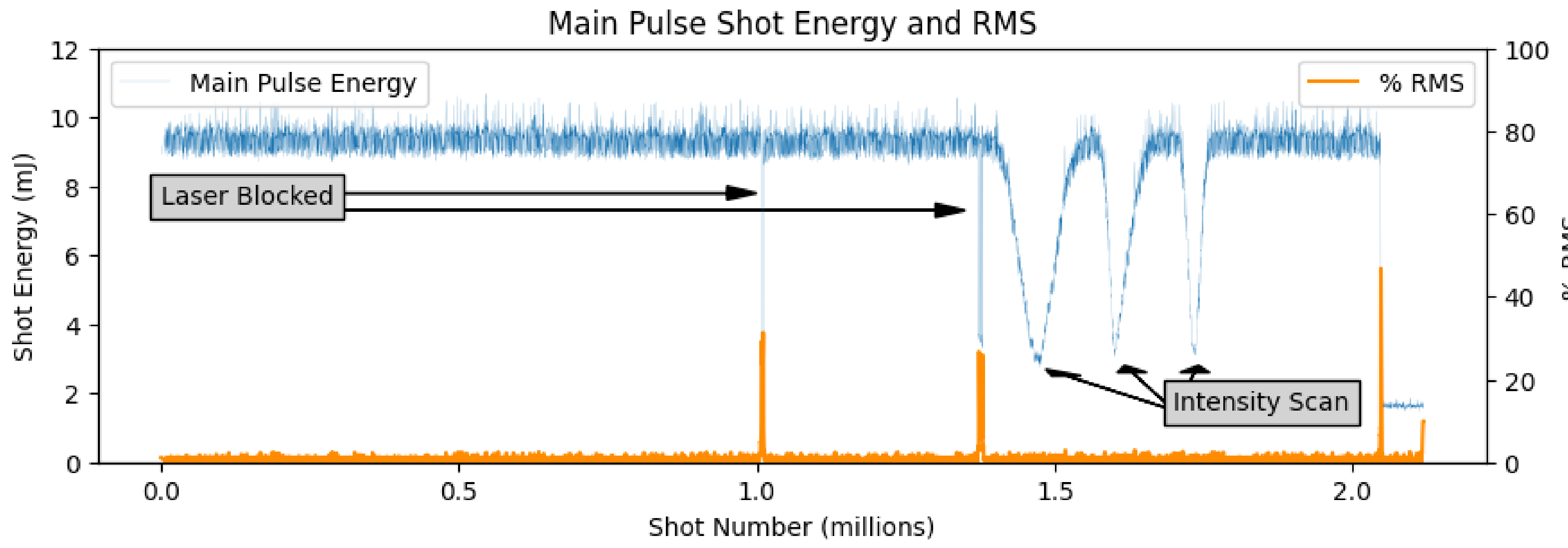
The extreme light laser lab at Wright-Patterson Air Force Base features a 10 mJ class ultra-intense laser that is used for a variety of research projects. The laser system produces 1000 shots per second with intensities approaching 10^{19} W cm⁻², making it a data rich platform for investigating ultra-intense laser science [1,2]. I present preliminary results from an effort to improve the data acquisition system in an NSF/DOE funded collaboration between AFIT, Ohio State University and Prof. Scott Feister and California State University Channel Islands. The improved system is now capable of collecting single shot data for $\sim 10^6$ consecutive shots or more. Ultimately, we plan to utilize this capability in machine learning applications, with the goal of fully automating the laser controls in order to optimize the laser interactions in real time.



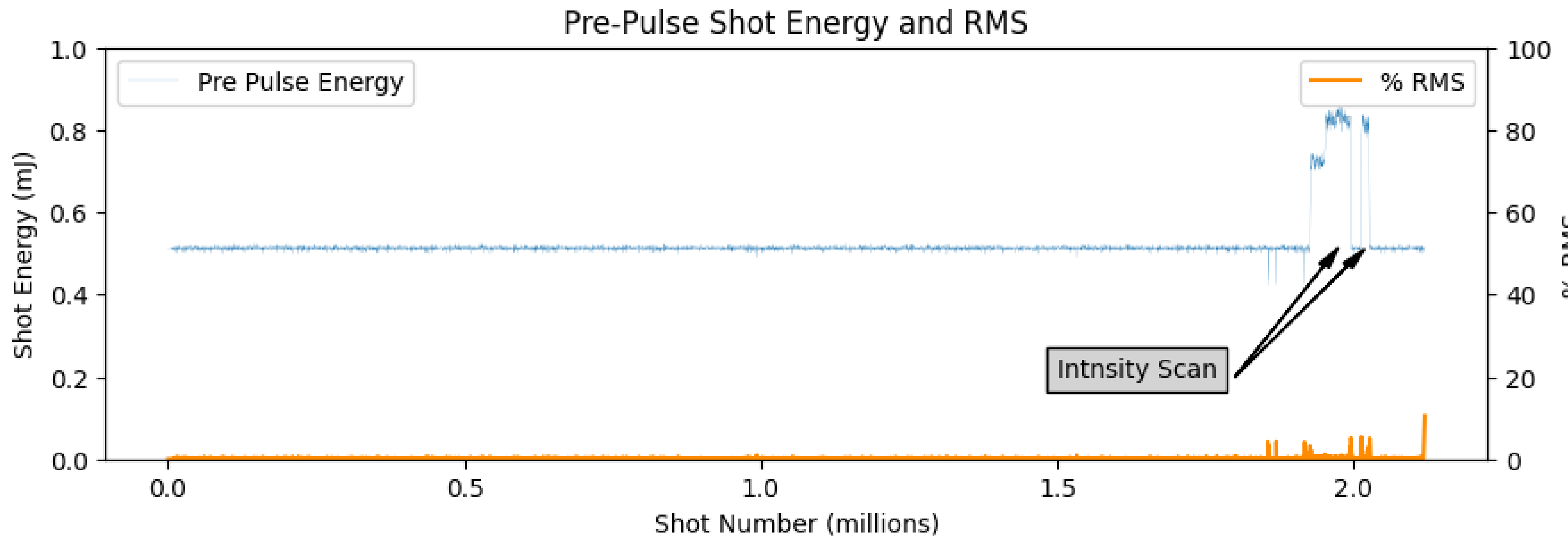
Modified KM Labs Red Dragon Laser

Wavelength	785nm
Spot Size	0.8μm x 0.9μm
Bandwidth (FWHM)	35nm
Pulse Width (FWHM)	40fs
Average Power	9.7 mJ

Main and Pre-Pulse Data



We have achieved a small amount of RMS in our Main Pulse measurements, with the only significant error coming from intentional quick blocking of the main pulse.



We have achieved a small amount of RMS in our Pre-Pulse measurements.

We have clean single shot diode measurements for over 10^6 shots, which is one of the largest laser-plasma data sets. This data will be used to train a neural network to optimize the laser output. Our electron spectrometer collects data at a rate of 10 Hz. In this recent experiment, we mainly got electrons with energies between 50-300keV. This data set is a good step to getting our neural network training data set.

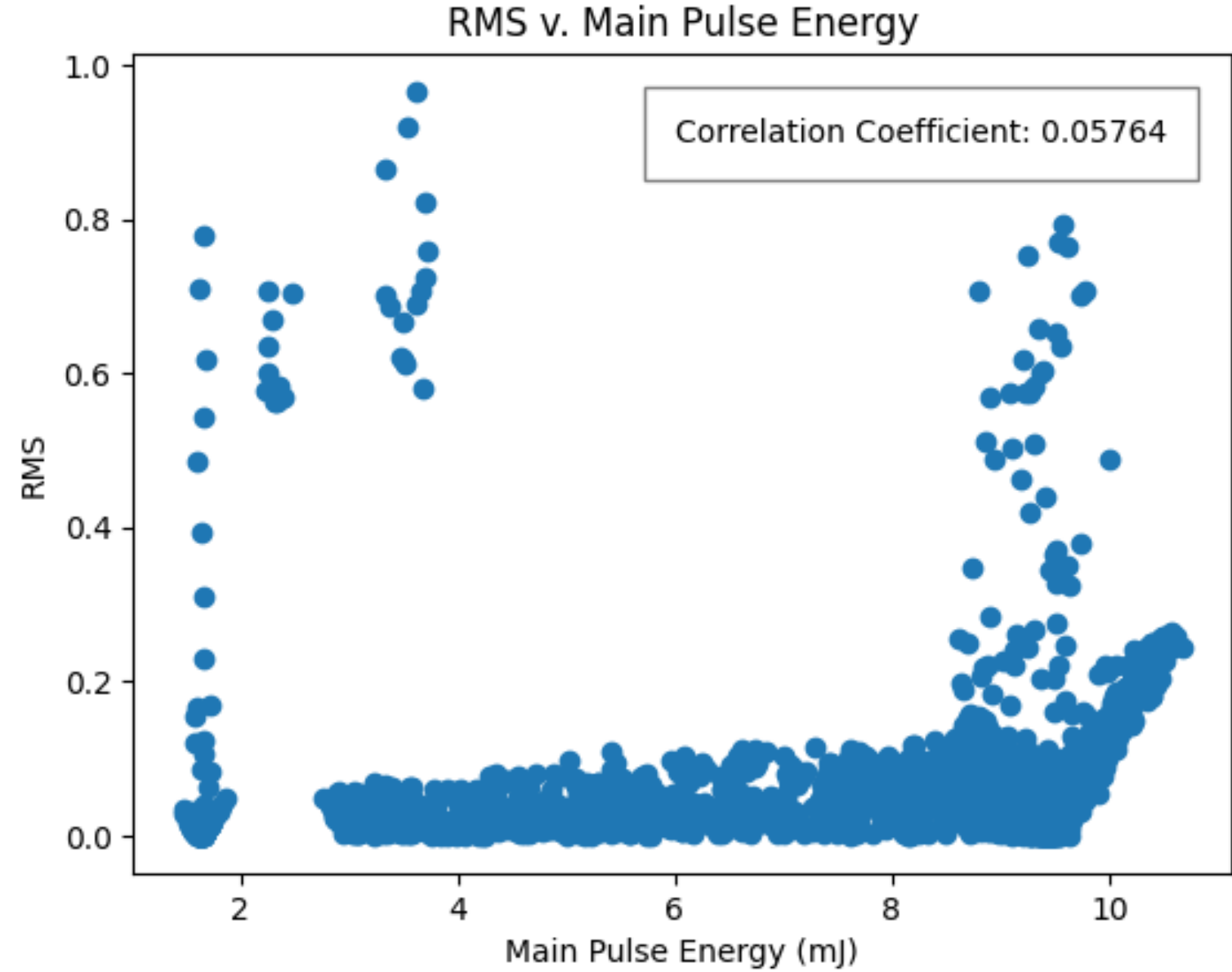
References

1. Morrison, J. *et al* (2018). MeV proton acceleration at kHz repetition rate from ultra-intense laser liquid interaction. *New J. Phys.* **20** 022001
2. George, K. *et al* (2019). High-repetition-rate (\geq kHz) targets and optics from liquid microjets for high-intensity laser-plasma interactions. *High Power Laser Science and Engineering*, 7, E50.

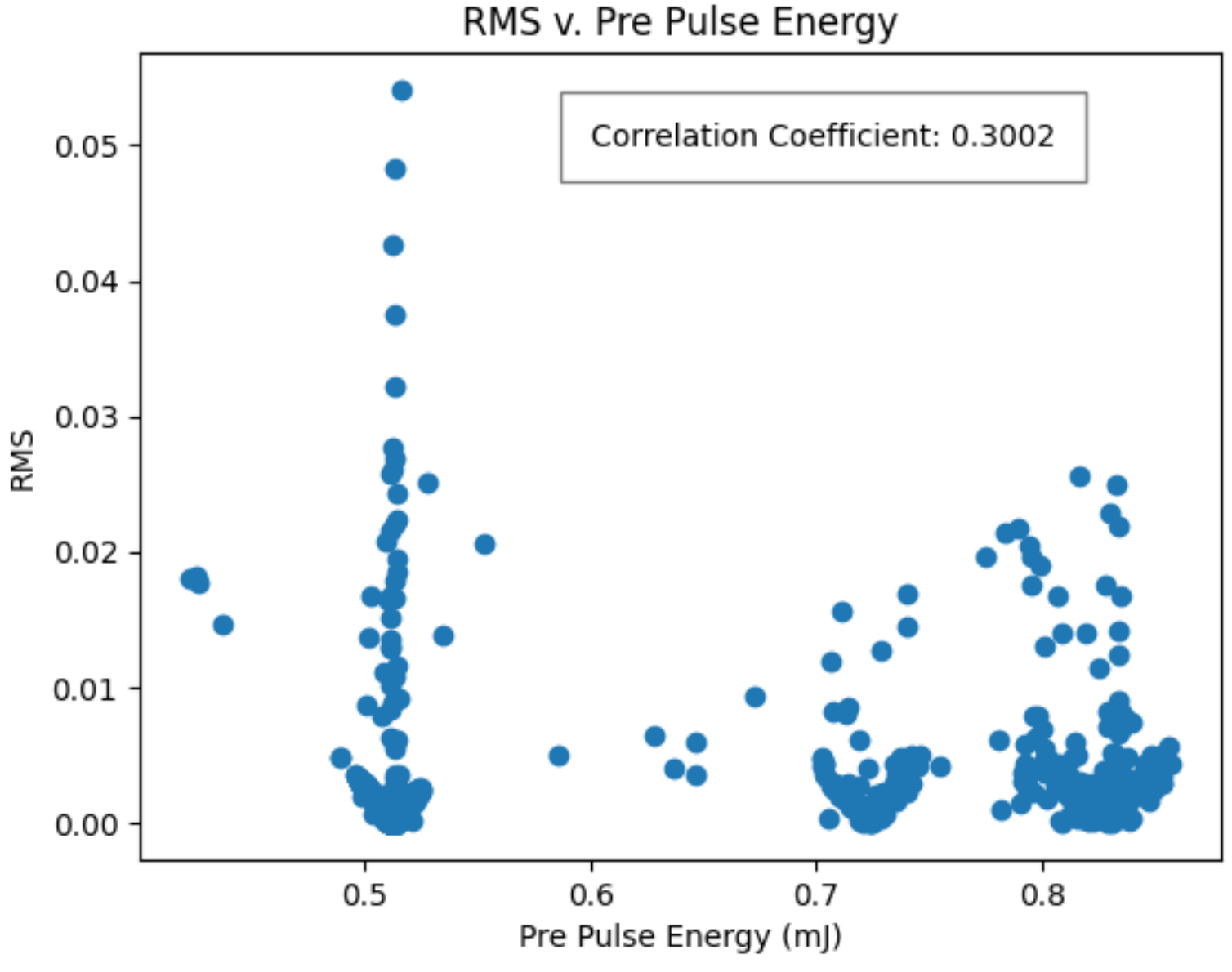
Acknowledgements

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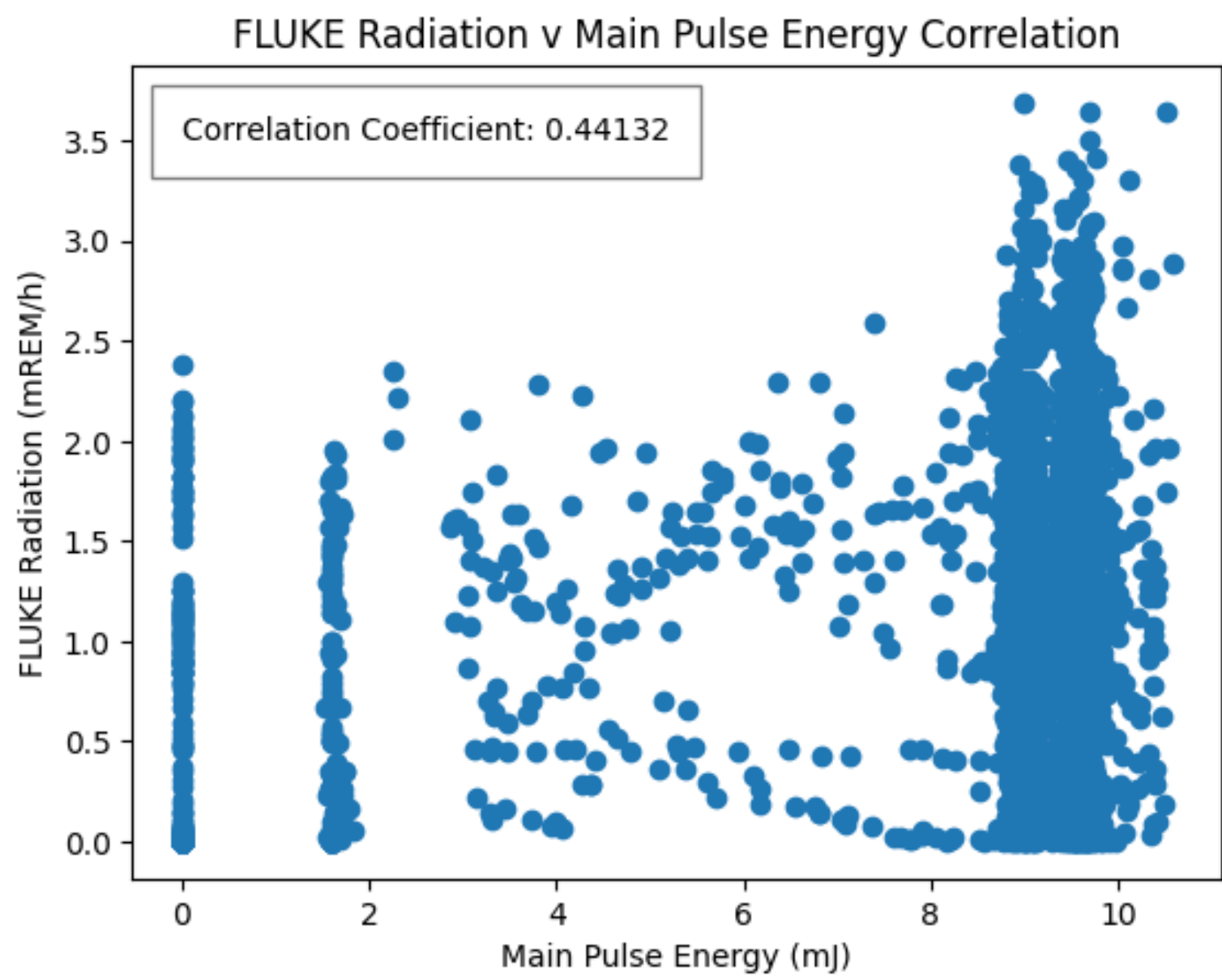
Data Correlation



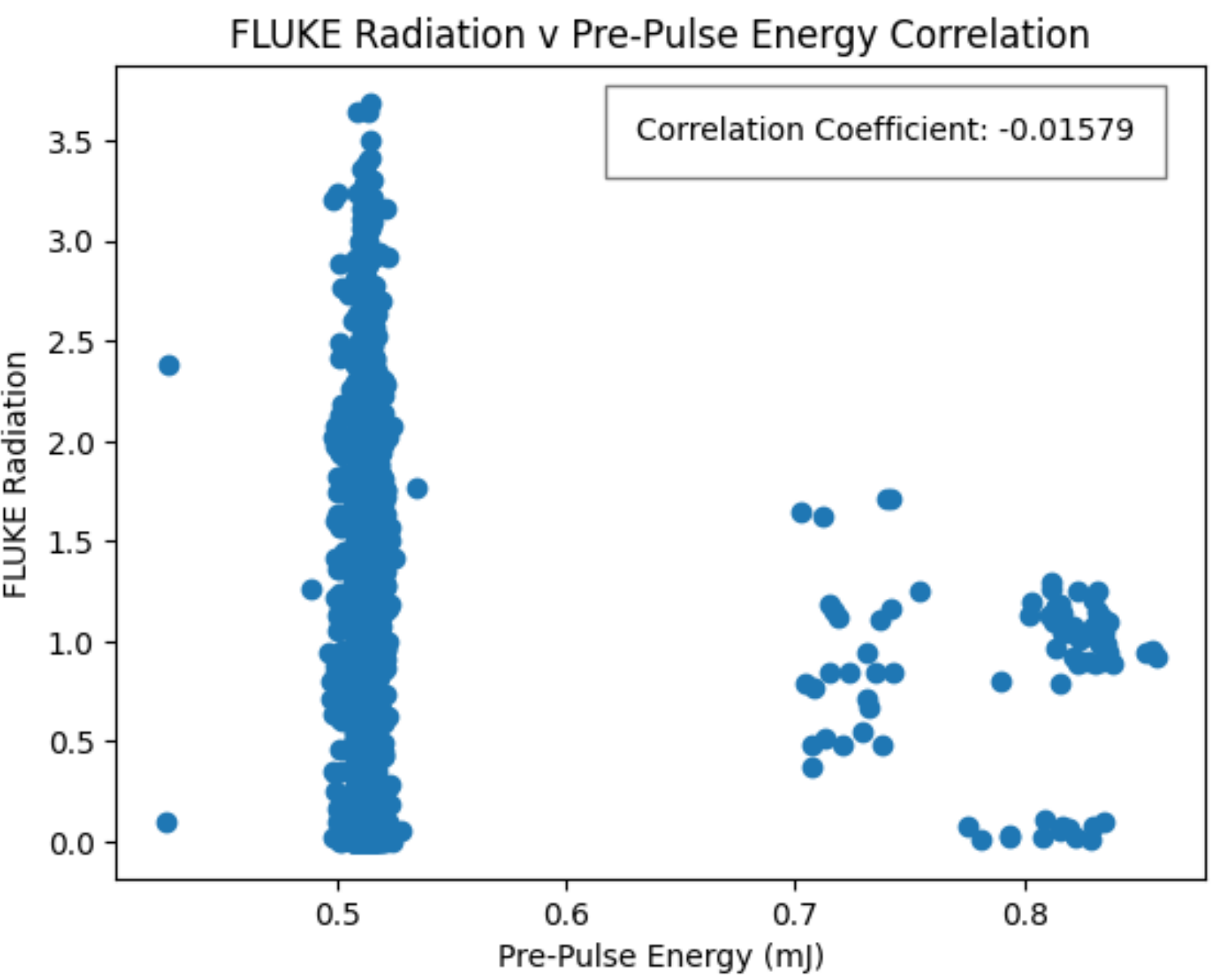
There is almost no correlation between the main pulse energy and the RMS observed.



There is a small correlation between the pre-pulse intensity and the RMS observed.



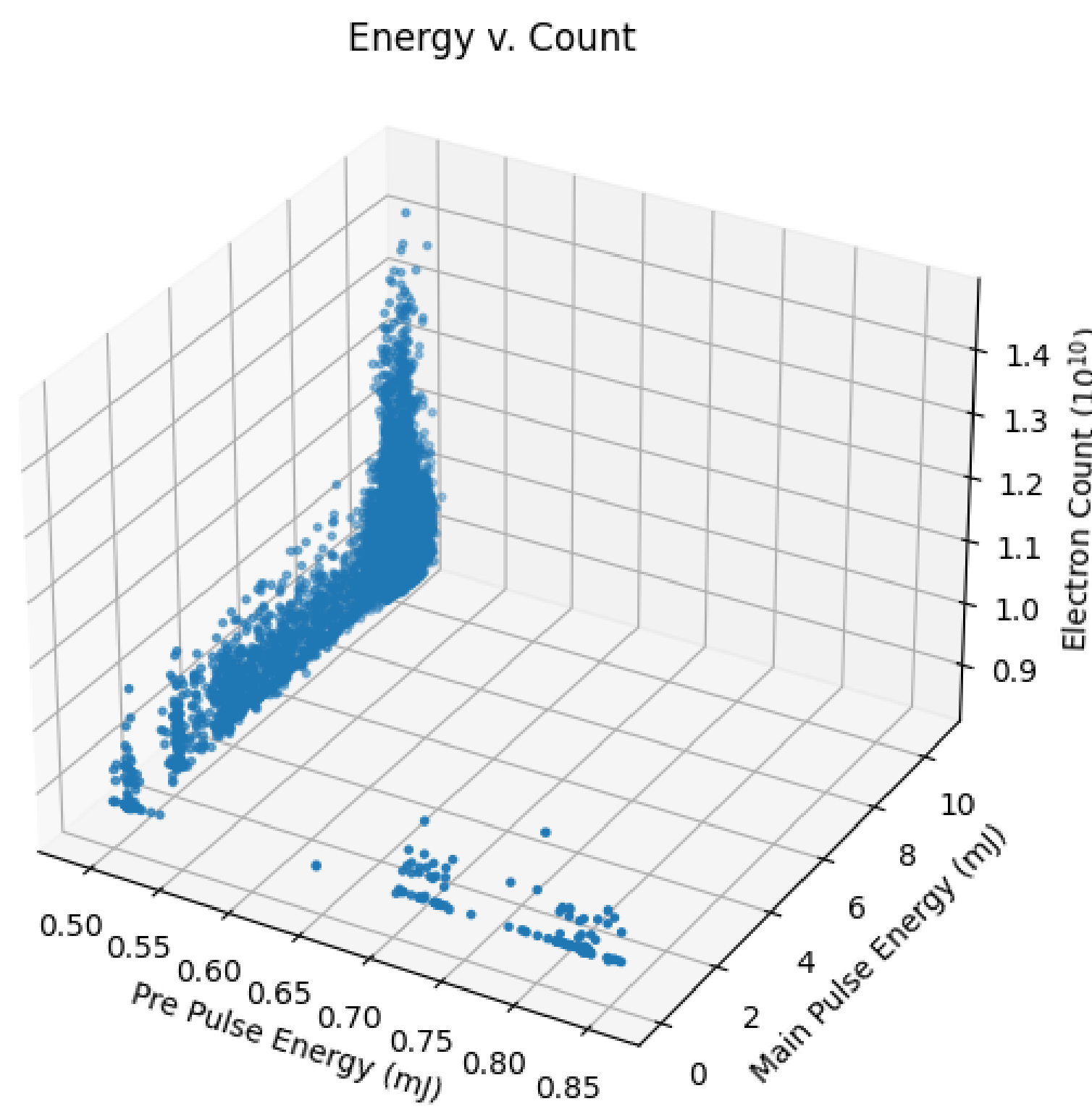
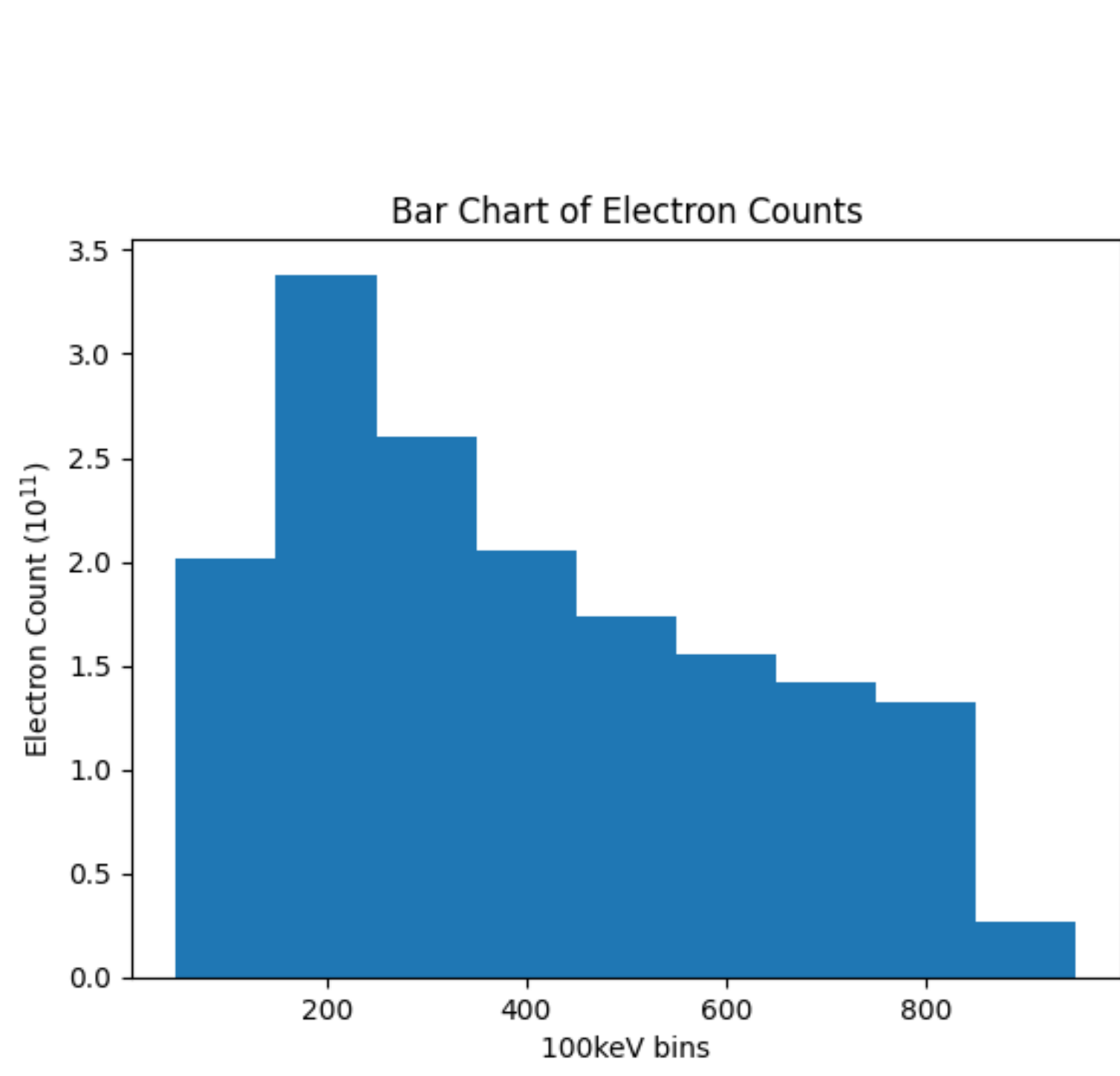
This plot shows a moderate correlation between the radiation and the energy of the main pulse.



This plot shows that there is very little correlation between the pre-pulse energy and the radiation.

We were concerned about an increase in RMS as we increased the intensity of the laser, but we did not find any significant correlation. We collected radiation information, which is collected at a rate of 1Hz. To see any correlation, we need to change the pulse energies slower.

Electron Results



Left: Electrons were measured with energies between 53keV-822keV with a majority in the 300-500keV range.
Right: Plotted electron count v. pulse intensities. Our preliminary network will input the pulse intensities and adjust them to output a desired electron energy. Future data sets will be committed to filling the intensity parameter space.

Future Work

1. Intentionally vary the laser energy through all possible combinations of main and pre-pulse, to fill the intensity space and create a training data set.
2. Training a neural network post facto to optimize the laser settings on a shot-to-shot basis.
3. Include the proton spectrometer and target position sensors



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