Developing neural-network surrogate models for predicting laser-accelerated proton characteristics

L. Buckleton[1], E.J. Dolier[1], C.J.G McQueen[1,2], R. Wilson[1,2], J. Goodman[3], M. King[1,2], P. McKenna[1,2].

[1]SUPA Department of Physics, University of Strathclyde, Glasgow, UK.

[2]The Cockcroft Institute, Sci-Tech Daresbury, Warrington, UK.

[3]AWE plc., Aldermaston, Reading, Berkshire, UK.,

lana.buckleton@strath.ac.uk

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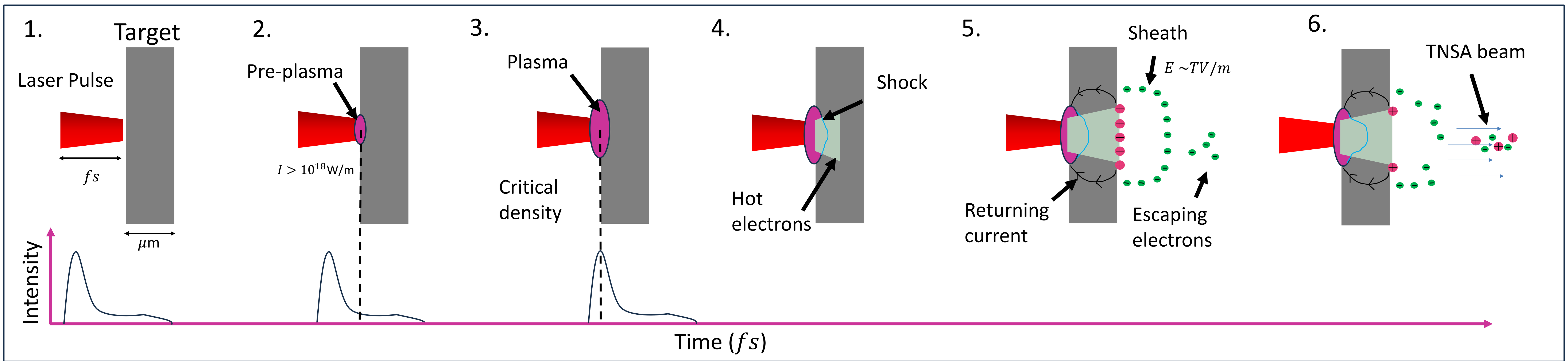
Introduction

- Reliable, well-characterised laser-accelerated proton beams are essential for practical deployment in industry [1] and medical physics [2].
- However, shot-to-shot variability and real-time characterisation remain major challenges; existing diagnostics are typically invasive, preventing simultaneous beam use.
- Machine learning approaches [3] offer a promising route to overcome these limitations by enabling non-invasive prediction of proton beam parameters directly from experimental inputs.
- Here, we extend the synthetic diagnostic framework of McQueen et al. [4], demonstrating that proton energy spectra can be predicted using only laser parameters, without explicit modelling of the laser-target interaction.

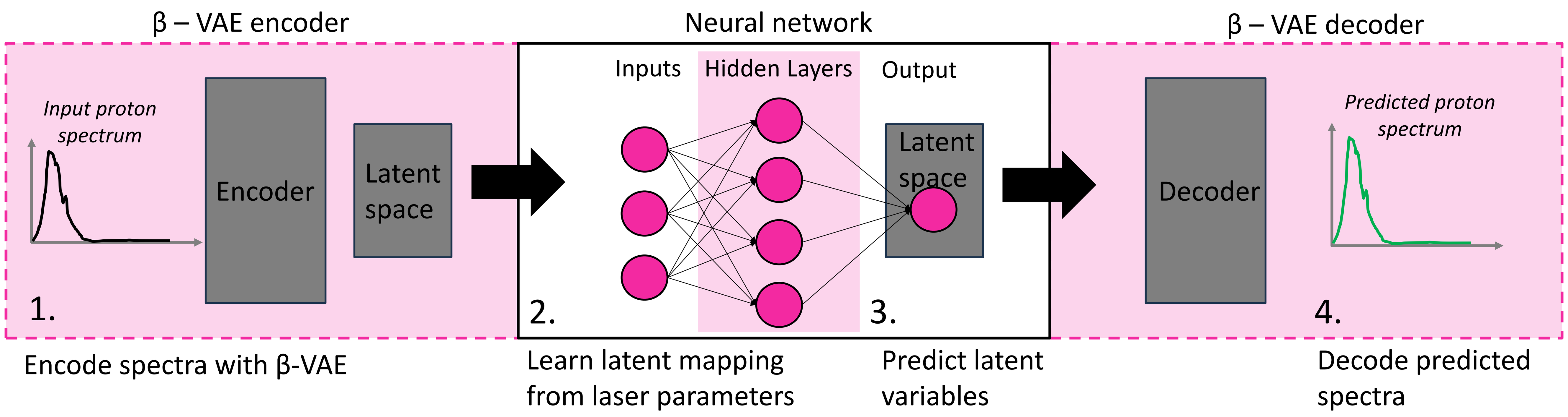
Laser-driven proton acceleration

One of the most widely researched mechanisms for laser-driven proton acceleration to date is Target Normal Sheath Acceleration (TNSA) [5]. A high-power laser (TW-PW) irradiates a thin µm-scale target forming a plasma. Plasma electrons absorb laser energy then setup an electric sheath field at the target rear, accelerating rear surface protons up to ~90 MeV [6]. TNSA produces high-energy proton beams but with significant shot-to-shot variability.

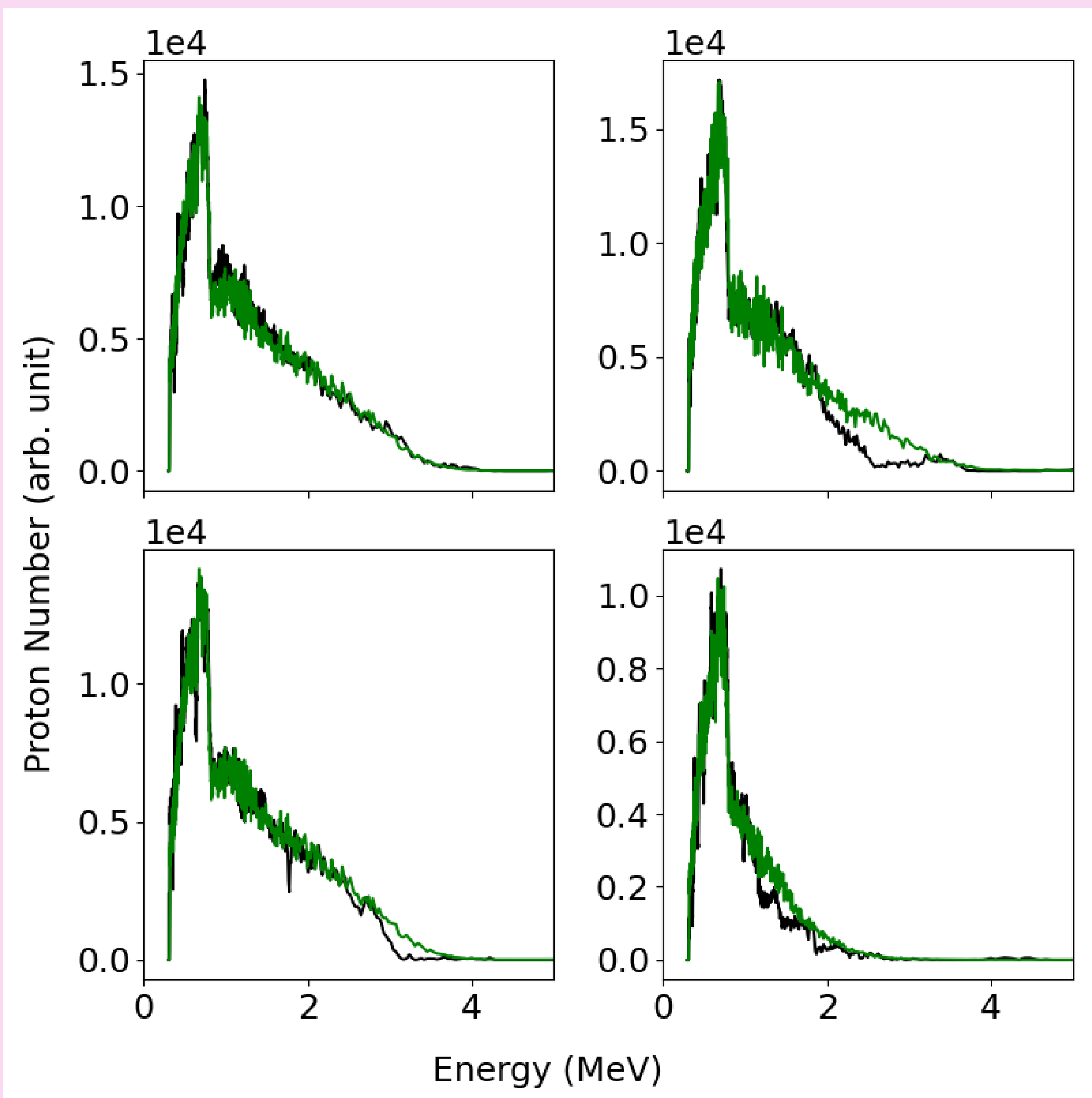


Model pipeline

- Proton energy spectra are compressed into a latent space using a Beta Variational Autoencoder (β-VAE), this compresses spectra while enforcing physically meaningful latent structure.
- A predictor neural network learns the relationship between the input parameters and the latent variables.
- The predicted latent variables are decoded to reconstruct the proton energy spectra.

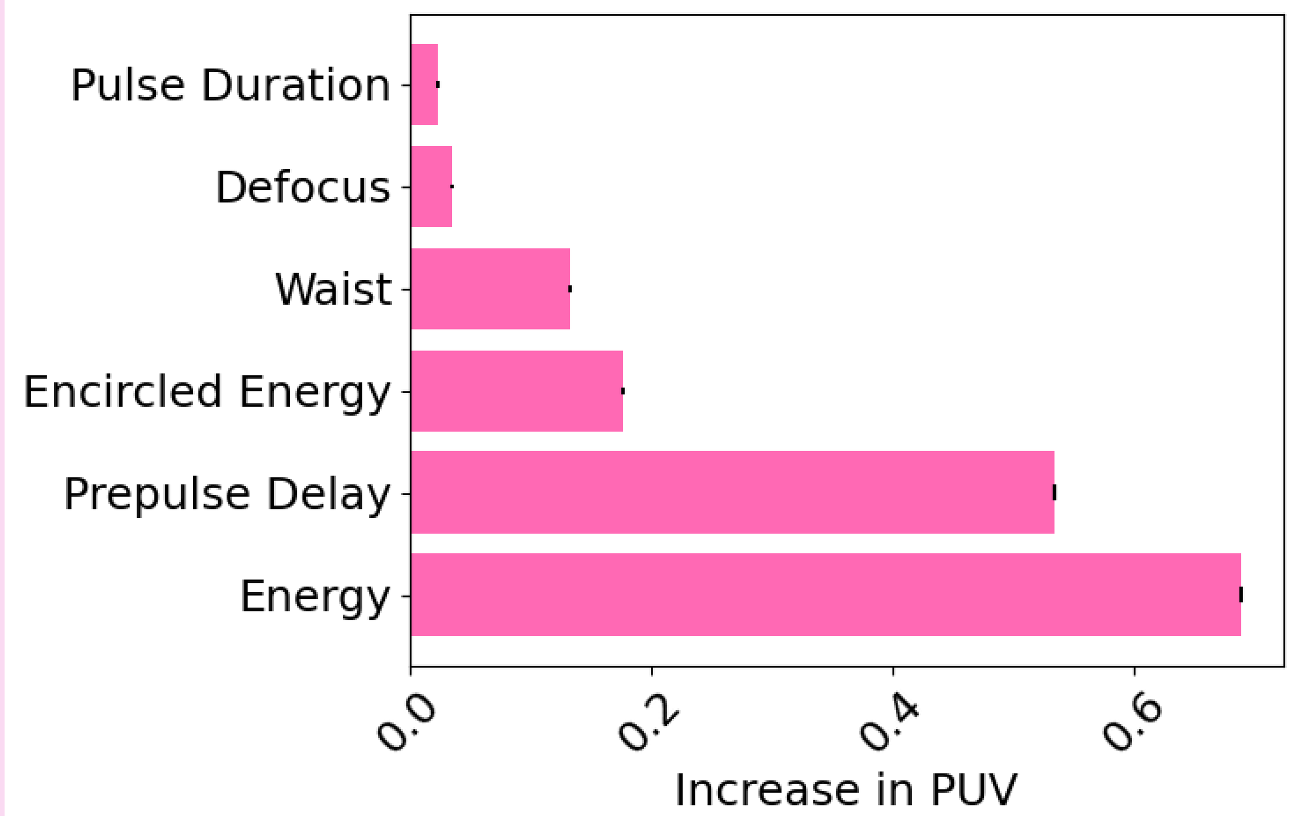


Results



Example comparisons of the surrogate model–predicted and reconstructed proton energy spectra (green) with the original proton energy spectra (black).

Preliminary results showing Percentage Unexplained Variance (PUV) metrics:
β-VAE ~9%
Latent prediction~24%
Reconstructed spectra ~36%



Permutation feature importance shows which parameters are the most important when predicting the proton energy spectrum. Laser energy and pre-pulse delay dominate spectral prediction, consistent with TNSA physics.

Future work

To address some of the limitations currently within the model;

- Evaluate model generalisation across datasets from different laser facilities to test robustness and cross-facility applicability.
- Increase the β-VAE latent space dimensionality to improve the surrogate model's ability to accurately predict encoded beam features.
- Apply weighting to the proton energy bins so that each MeV range contributes equally during training, reducing bias toward high-count regions.
- Perform extended hyperparameter optimisation for both the β-VAE and surrogate models to improve overall performance and stability.

This paves the way for real-time, non-invasive proton beam diagnostics during experiments.

References

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