Inverse Modeling of Laser Pulse Shapes in Inertial Confinement Fusion with Auto-Regressive Models

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Motivation

Nuclear Fusion offers the potential for limitless, clean energy. Inertial Confinement Fusion (ICF) achieves nuclear fusion by compressing a tiny fuel pellet to extreme temperatures and pressures using a precisely controlled laser pulse.

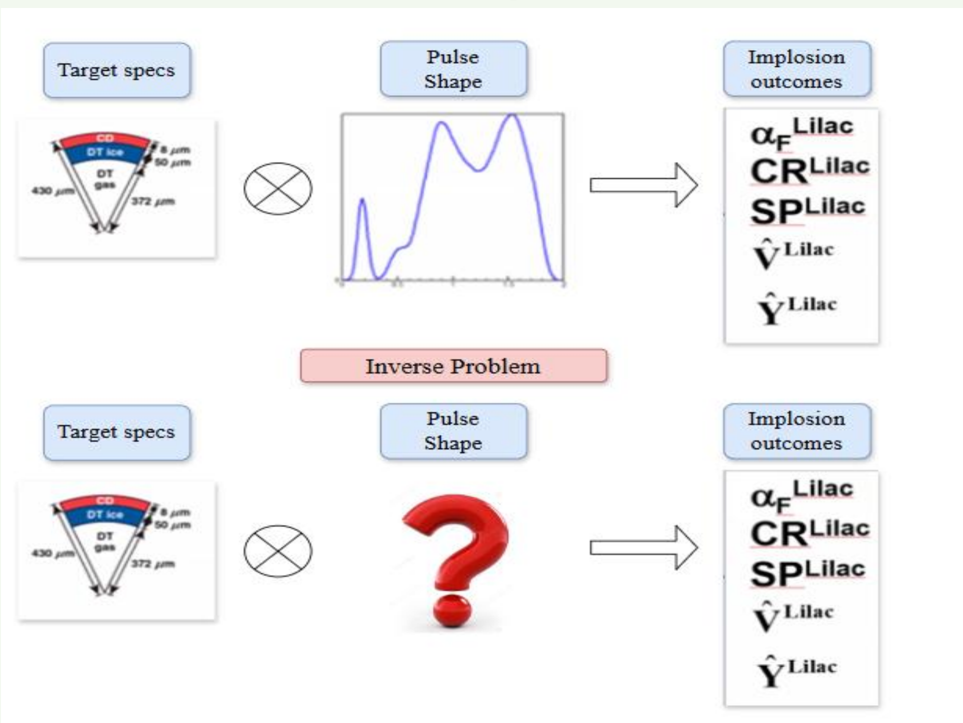
Challenges:

The right laser pulse shape is critical to achieve desired fusion outcomes.

Designing it is currently a manual and cumbersome process

Goal:

Use generative modeling to get the desired pulse shape ***by inverting the outcomes***



Training Setup

Multi-objective loss:

- *Reconstruction error:* To ensure the model generates pulse shapes that are in-distribution

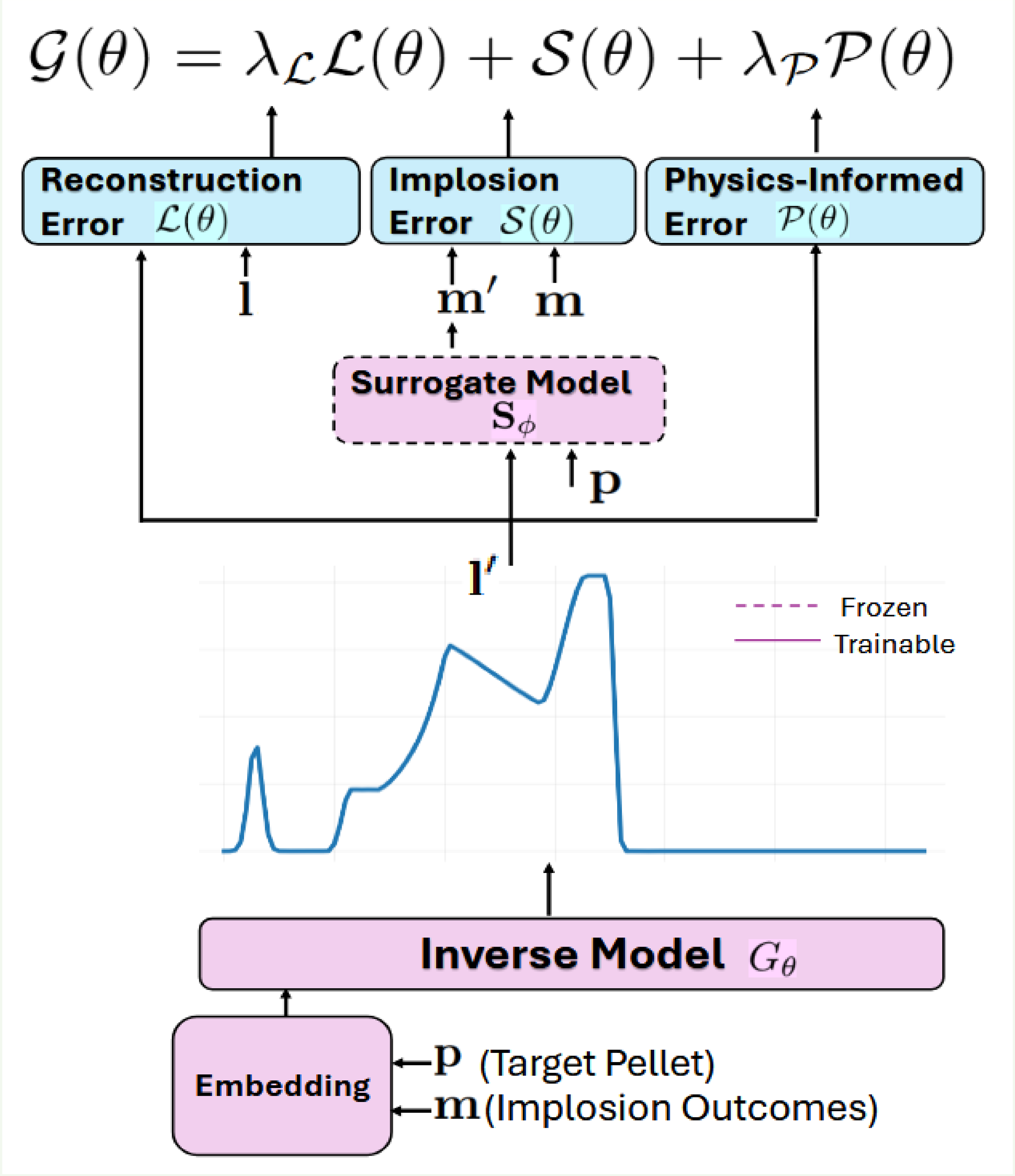
- *Implosion error*: To ensure the generated pulse shapes produce the desired fusion outcomes

- *Physics-informed error*: To ensure the generated pulse shaped adhere to physical constraints

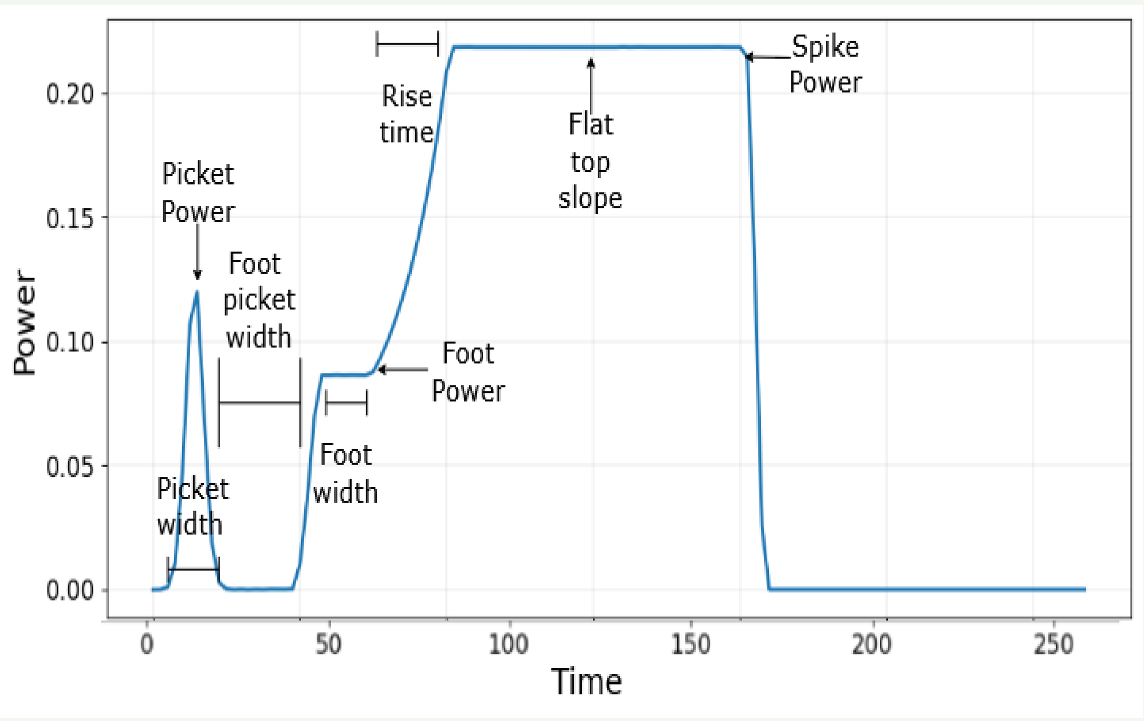
The three terms are weighted according the priority

Surrogate model*:*

The generated pulse shapes are passed through a surrogate to test if they produce the desired outcomes



The Laser Pulse



Results

Approach	Diversity ↑	m Error ↓	Reconstruction Error ↓	Energy Conservation ↓
$\mathbf{LPDS}_{\text{LSTM}}$	–	1.65%	0.0001	0.66%
$\mathbf{LPDS}_{\text{Transformer}}$	–	1.94%	0.0008	0.95%
$\mathbf{LPDS}_{\text{GaussianAR}}$	0.42	$1.89\% \pm 0.01$	$0.0005 \pm 2e^{-5}$	$0.58\% \pm 0.004$
$\mathbf{LPDS}_{\text{MixtureOfGaussianAR}}$	0.56	$1.95\% \pm 0.09$	$0.0006 \pm 8e^{-5}$	$1.58\% \pm 0.006$
$\mathbf{LPDS}_{\text{CategoricalAR}}$	0.39	$2.01\% \pm 0.04$	$0.0009 \pm 5e^{-5}$	$1.18\% \pm 0.08$
$\mathbf{LPDS}_{\text{LSTM, w/o }\mathcal{S}}$	–	3.9%	0.0004	0.69%
$\mathbf{LPDS}_{\text{Transformer, w/o }\mathcal{S}}$	–	4.4%	0.001	1.23%
$\mathbf{LPDS}_{\text{LSTM, w/o }\mathcal{P}}$	–	1.85%	0.0001	0.95%
$\mathbf{LPDS}_{\text{Transformer, w/o }\mathcal{P}}$	–	2.1%	0.0009	1.3%

Table 1: LPDS model performance. ± denotes standard deviation over seeds. For the predictive auto-regressive models ($\mathbf{LPDS}_{\text{LSTM}}$, $\mathbf{LPDS}_{\text{Transformer}}$), diversity is not defined since they are deterministic.

- ➢ Implosion loss is critical to reduce the implosion error
- ➢ LSTM gives the lowest reconstruction error and implosion error (m-error)

Approach

Auto-regressive:

- We approach the pulse shape generation as an auto-regressive task where we "prompt" the model with the desired outcomes and the target specs.
- The pulse shape is generated auto-regressively using sequence generation model like a Transformer or LSTM

Generative modeling:

- The inverse problem can have multiple solutions since different pulse shapes can result in similar outcomes.
- However, some pulse shapes are more physically plausible than others and hence multiple options are desirable.
- We approach this as a generative modeling task where the model produces a distribution over pulse shapes

Experiments:

- We experiment with different model architectures and output probability distributions – both continuous and discrete.

Example Pulse Shapes

Multiple samples generated by LSTM Gaussian model for 4 cases