Towards Deep Learning Based Predictive Models for Laser Direct Drive on the Omega Laser Facility

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Summary

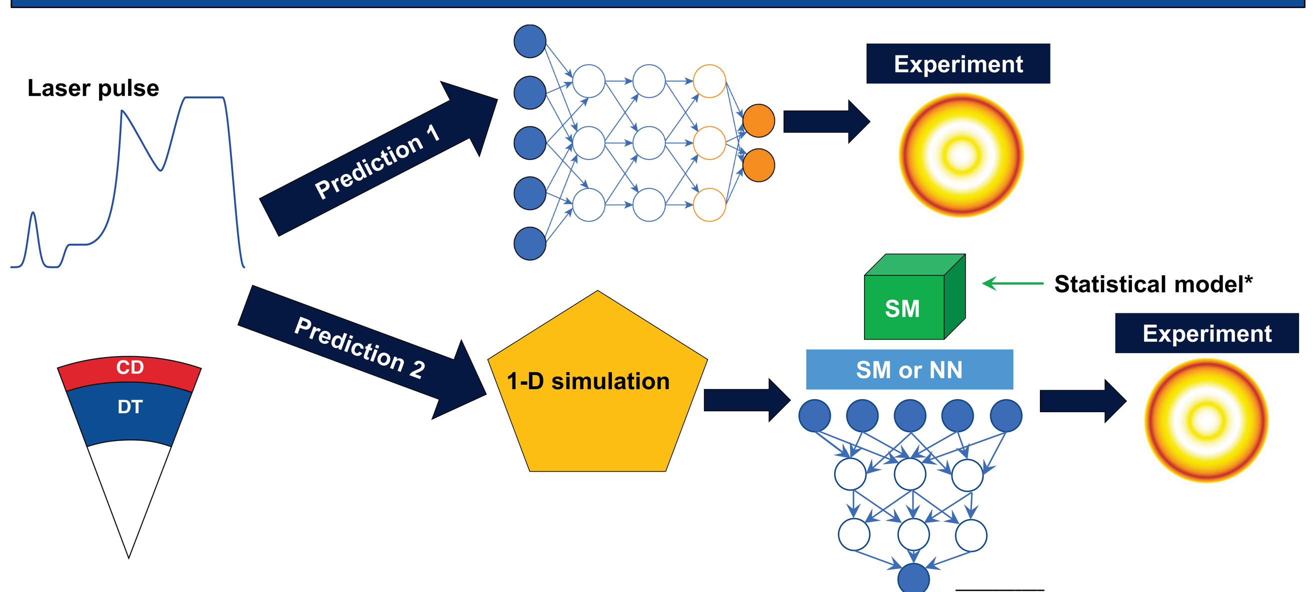
Neural network models were developed to predict the fusion yield of OMEGA direct-drive DT-layered implosions

- A deep neural network (DNN) model is developed by first building a model that emulates simulations, which is subsequently calibrated/retrained using limited experimental data*
- This enables making changes directly in input space (laser pulse shape and target specifications) and asses' effects on implosion performance
- An autoencoder is used to represent the laser pulse shape
- A second deep neural network (DNN) is developed that is trained on the measured fusion yield and uses the same parameters from 1-D simulations and experiments of the statistical mapping model** of V. Gopalaswamy *et al.*

* K. D. Humbird *et al.*, IEEE Trans. Plasma Sci. 48, 61 (2020).
** V. Gopalaswamy *et al.*, Nature 565, 581 (2019).

Motivation

We are developing deep neural net models of two kinds: (1) DNN connecting experimental input directly to experimental outcome and (2) DNN trained on *ad-hoc* simulated and experimental parameters



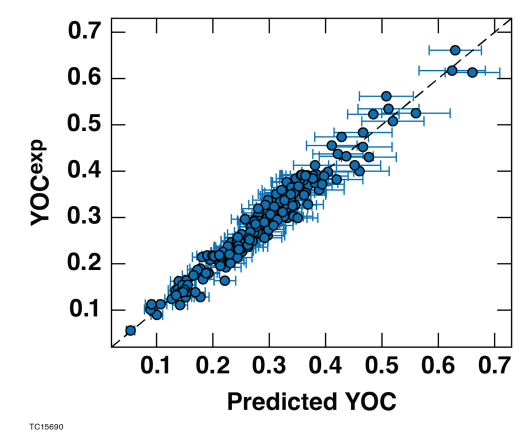
Prediction 1 has "instant" inference times

* V. Gopalaswamy *et al.*, Nature 565, 581 (2019); A. Lees *et al.*, Phys. Rev. Lett. 127, 105001 (2021).
SM: statistical model

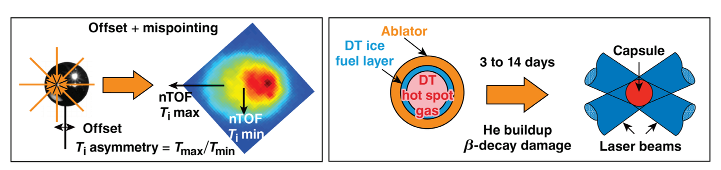
Motivation

We are investigating if DNN's can provide more-accurate predictions than the statistical mapping model of V. Gopalaswamy *et al.**

- OMEGA implosions are currently designed using a statistical model that maps experimental results into a simulation database**



- $YOC_{exp} = \frac{Y_{exp}}{Y_{1D}^{sim}}$
- $\tilde{T}_i$ is the degradation used for $l = 1$ perturbations from target offset and mispointing
- Fill age is the time between DT fill and shot time



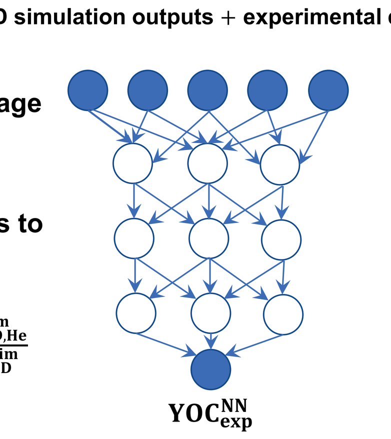
$YOC_{exp} \approx F_{SM}$ (1-D simulation inputs+outputs, $\tilde{T}_i$, fill age)

* V. Gopalaswamy *et al.*, Nature 565, 581 (2019);
**A. Lees *et al.*, Phys. Rev. Lett. 127, 105001 (2021).

DNN Model 2

The neural network (NN) model uses 1-D simulation inputs+outputs and experimental data to predict degradations on OMEGA ICF experiments

- Experimental data used are $\tilde{T}_i = \frac{T_i^{max}}{T_i^{min}}$ measurements and fill age
- Fill age is the time between DT fill and shot time
- $\tilde{T}_i$ is the degradation parameter used for shot-to-shot degradations from target offset and mispointing which leads to $l = 1$ perturbations*
- Fill age causes He^3 to accumulate in the vapor region; the degradation is represented through the parameter* $\xi_{He} = \frac{Y_{1D,He}^{sim}}{Y_{1D}^{sim}}$



$YOC_{exp} \approx F_{NN}$ (1-D simulation inputs+outputs, $\tilde{T}_i$, fill age)

*A. Lees *et al.*, Phys. Rev. Lett. 127, 105001 (2021).

The two DNN's are (1) trained on simulations and transfer learned to experiments, (2) trained on experimental outputs through selected 1-D–simulated parameters (same as SM)

Two DNN models have been developed

1. (Prediction 1) DNN is trained on a 1-D simulation database degraded according to the SM predictions that depends exclusively on 1-D simulated parameters, subsequently the model is transfer learned to experiments

   $YOC_{exp} \approx F_{NN}$ (laser pulse shape, target specs)

2. (Prediction 2) DNN is trained directly on the data and 1-D–simulated parameters

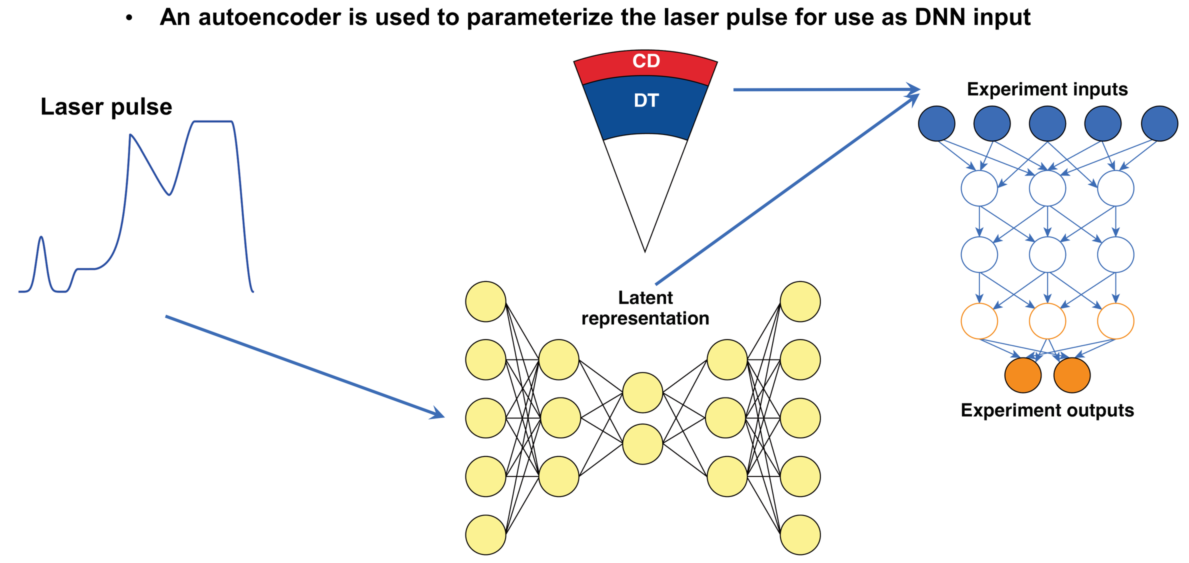
   $YOC_{exp} \approx F_{NN}$ (1-D simulation inputs+outputs, $\tilde{T}_i$, fill age)

* V. Gopalaswamy *et al.*, Nature 565, 581 (2019); A. Lees *et al.*, Phys. Rev. Lett. 127, 105001 (2021).

DNN Model 1

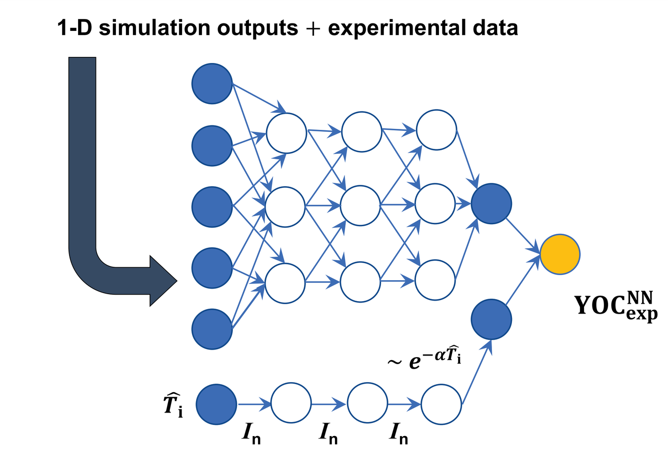
The NN model uses experimental inputs (laser pulse and target specifications)

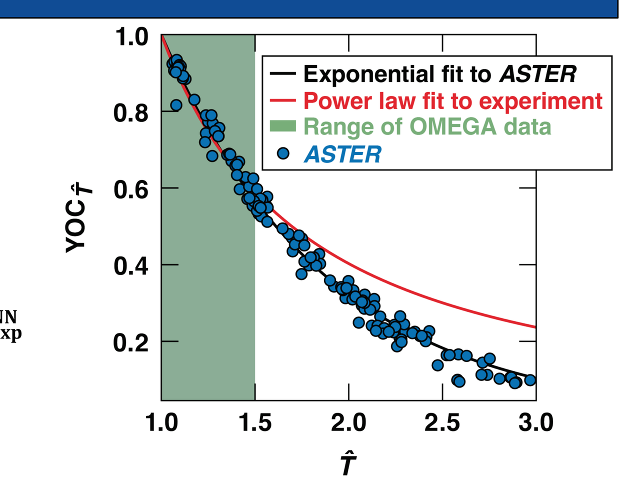
- An autoencoder is used to parameterize the laser pulse for use as DNN input



DNN Model 2

The architecture of the NN is informed by synthetic experiments done to understand degradation dependencies*





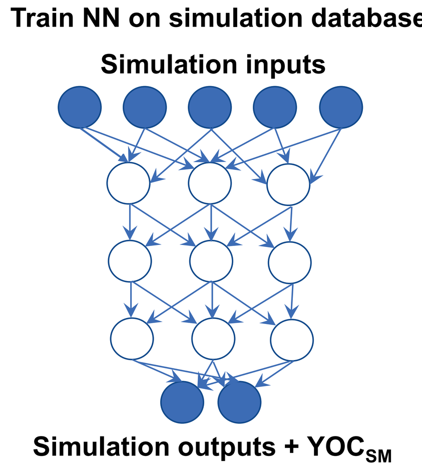
Synthetic experiments show that degradations due to $\ell = 1$ modes have an exponential dependence on $\tilde{T}_i$, this "physics" informs DNN architecture.

* V. Gopalaswamy *et al.*, Phys. Plasmas 28, 122705 (2021).

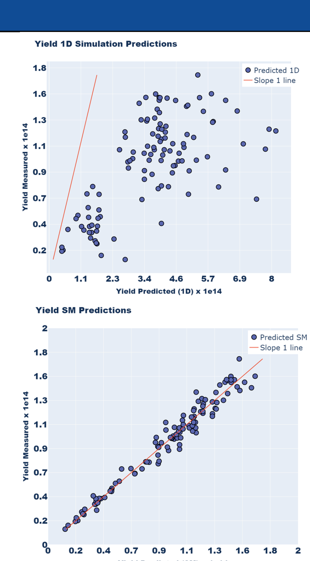
DNN Model 1

A 1-D simulation database is used for training; a degradation term calculated from the SM* is also included since it brings simulations closer to "reality"

Train NN on simulation database



DNN model hyperparameters	
Hidden layers	10
Hidden layer units	27-150-500 × 5-150-50-15
Learning rate	0.001
Batch size	7000
Epochs	1022

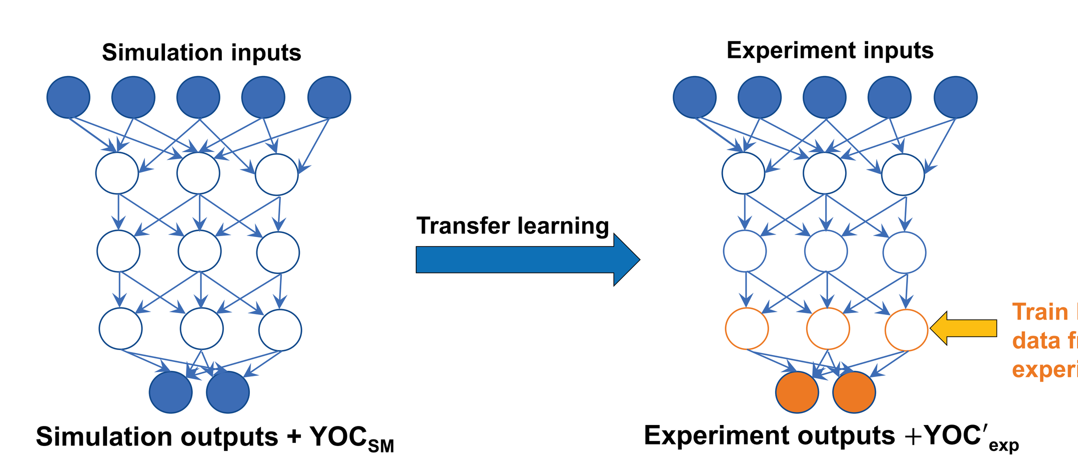


$YOC_{exp} \approx YOC_{SM} = YOC_{\tau} YOC_{h} YOC_{l} YOC_{\ell=1} YOC_{res}$

*A. Lees *et al.*, Phys. Rev. Lett. 127, 105001 (2021).

DNN Model 1

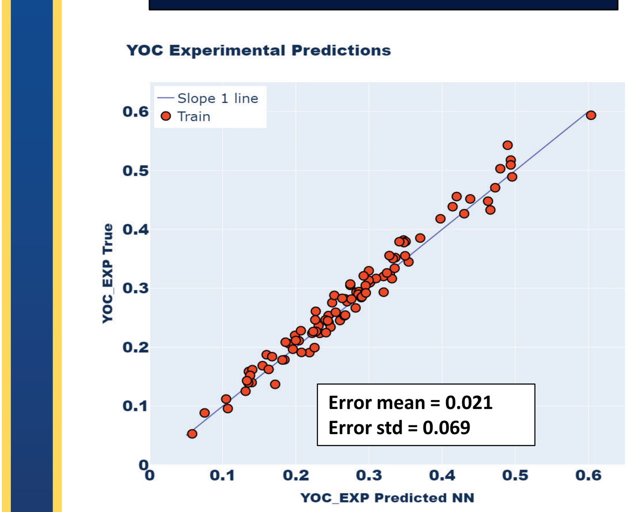
Transfer learning is used to integrate the NN model with experiments



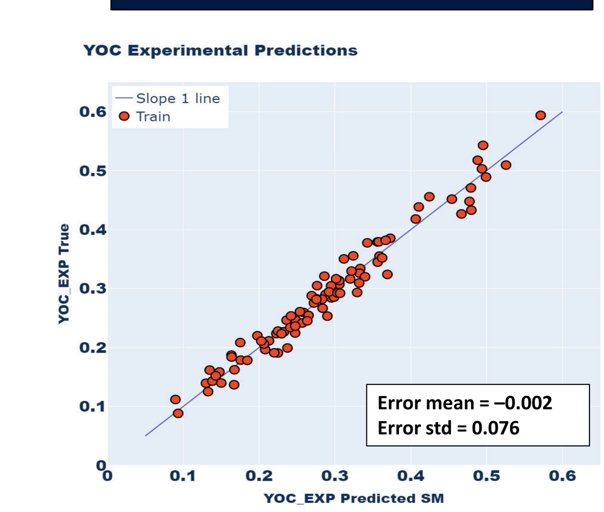
$YOC'_{exp} = \frac{YOC_{exp}}{YOC_{\tau}^{SM} YOC_{\ell=1}^{SM}}$

The DNN model and SM model are both able to fit the training data

DNN model

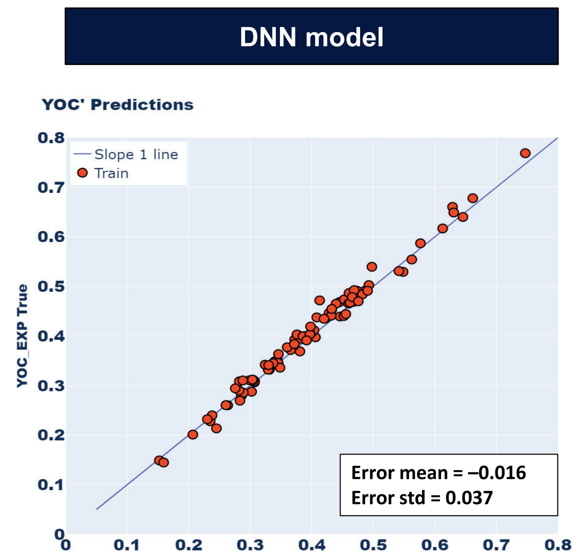


SM model

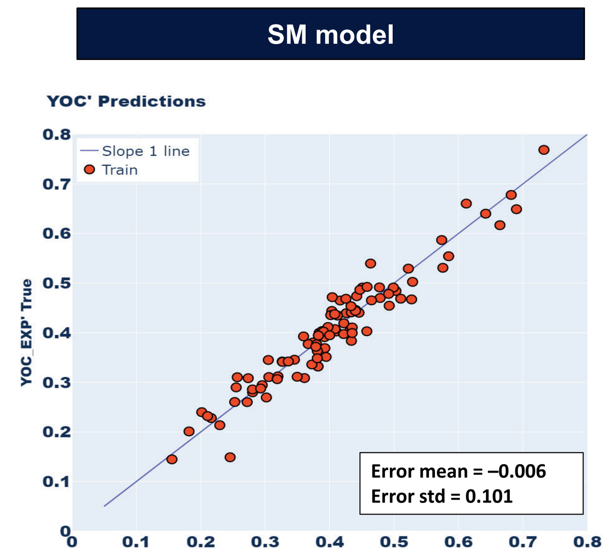


The NN model and SM model are both able to fit the training data

DNN model

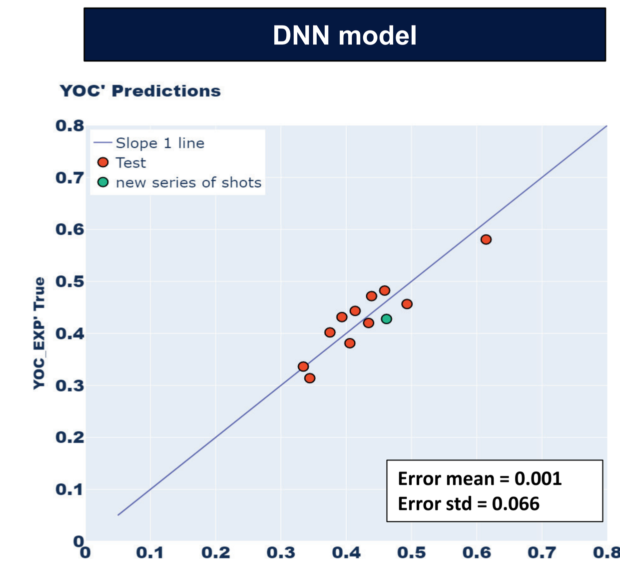


SM model

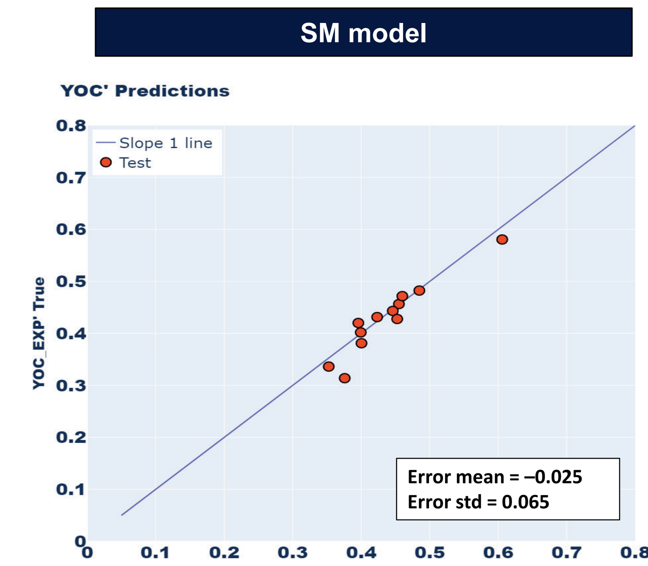


The NN Model and SM model are both able to predict the test data to within an acceptable error

DNN model

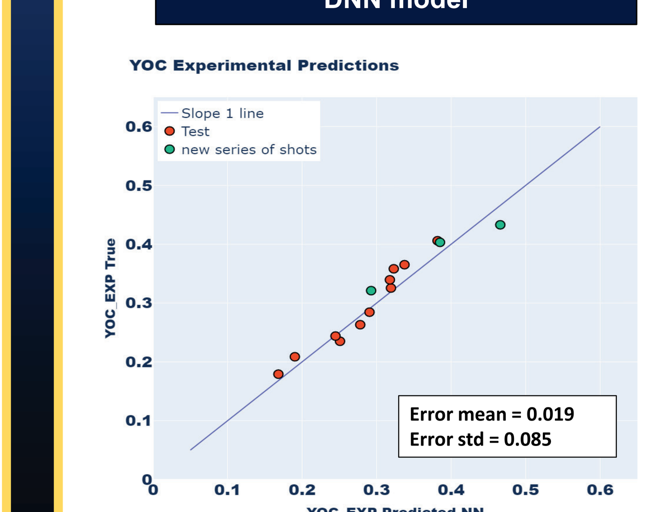


SM model

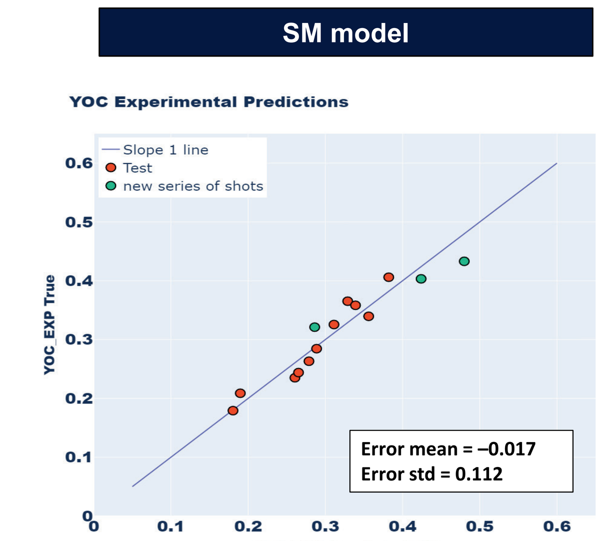


The DNN model and SM model are both able to predict the test data to within an acceptable error

DNN model



SM model



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