(U) Machine Learning to Estimate Dante Response for Hohlraum Design

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Abstract

This work considers the design to hohlraums to obtain a desired temperature profiles. Our objective is to train machine learning models using simulations to predict the simulated Dante response. The machine learning method will then be used to optimize the design.

The hohlraum design and parameter variation simulations were undertaken by I.L. Tregillis as described in LA-UR 17-22657 [1]. For completeness, we repeat some of the discussion in that report.

We consider a nominal hohlraum design as shown in Figure 1. In the parlance of opacity experiments, the region in the center of the hohlraum is called the sample chamber and it is bounded by two radial baffles a distance of $Z_{\rm baf}$ from the center of hohlraum. The radial distance from the edge of a baffle to the centerline of the hohlraum is the radius of the aperture.

In our study we considered variations to this nominal hohlraum defined by four different parameters:

- A `scale` parameter where every dimension ($R_{\rm hoh}$, $R_{\rm apt}$, $R_{\rm LEH}$, $Z_{\rm hoh}$, and $Z_{\rm baf}$) is scaled by a factor. When scaling the hohlraum in this way, the wall thickness is not changed. As an example, if `scale` $= 0.5$, then every dimension would be halved.
- The `sc_length` perturbation scales $Z_{\rm baf}$ by a factor *while keeping the ratio* $R_{\rm apt}/Z_{\rm baf}$ a constant.
- An $R_{\rm apt}$ perturbation where the dimension of the aperture to the sample chamber is scaled *independently* of $Z_{\rm baf}$.
- `pulse_length` is the length of the laser pulse drive, scaled to deliver the same amount of energy, 250 kJ.

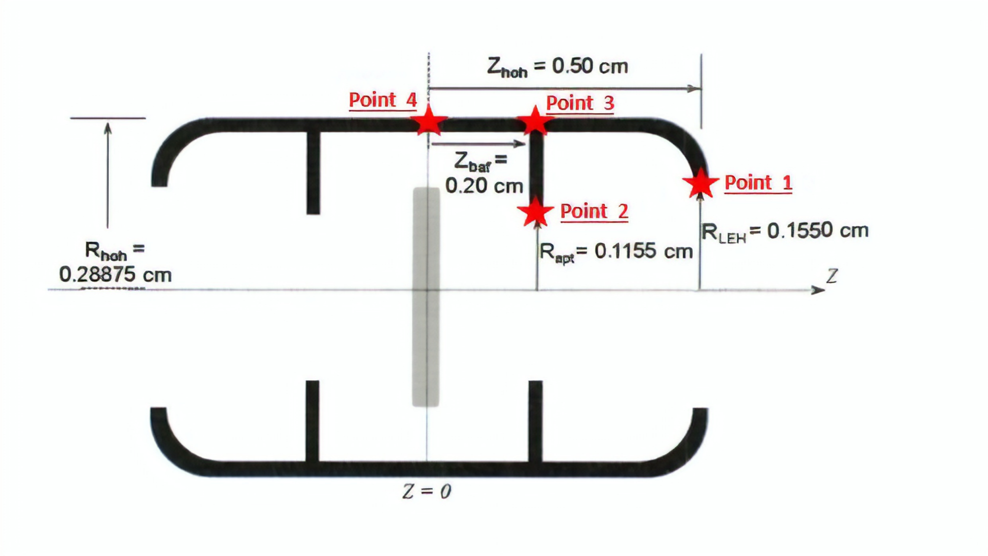

Figure 1: The nominal hohlraum design used in this study. In the terminology of this report this hohlraum has $\texttt{scale} = \texttt{sc\_length} = R_{\text{apt}} = 1$**. The** (r, z) **values of the 4 indicated points are used as inputs to the machine learning model.**

The parameter variations can be mapped to eight input variables: the (r, z) values of four points that determine the hohlraum shape as shown in Fig. 1.The parameters and their corresponding effects on the points were as follows:

- Changing the $scale$ parameter resulted in both the z and r values of each point to be multiplied by the scaling factor
- Changing the `sc_length` parameter resulted in the z value of point 2 and 3, as well as the r value of point 2, to be multiplied by the `sc_length` parameter. This was in order to scale Z_{baf} while also maintaining the nominal ratio of $R_{\text{apt}}/Z_{\text{baf}}$
- Changing the R_{apt} parameter resulted in the r value of point 2 to be multiplied by the R_{apt} parameter so that R_{apt} was scaled independently of Z_{baf}

For the simulations we fit a range of supervised learning models to the available simulation data, (61 simulations). To predict the time series, we interpolate the Dante outputs to a common time grid, and take the SVD of the output. The dependent variable in our models is the coefficient for the dominant singular components. To date we have used linear regression models, regularized regression, and Gaussian process regression. Future work will be based on recurrent neural networks.

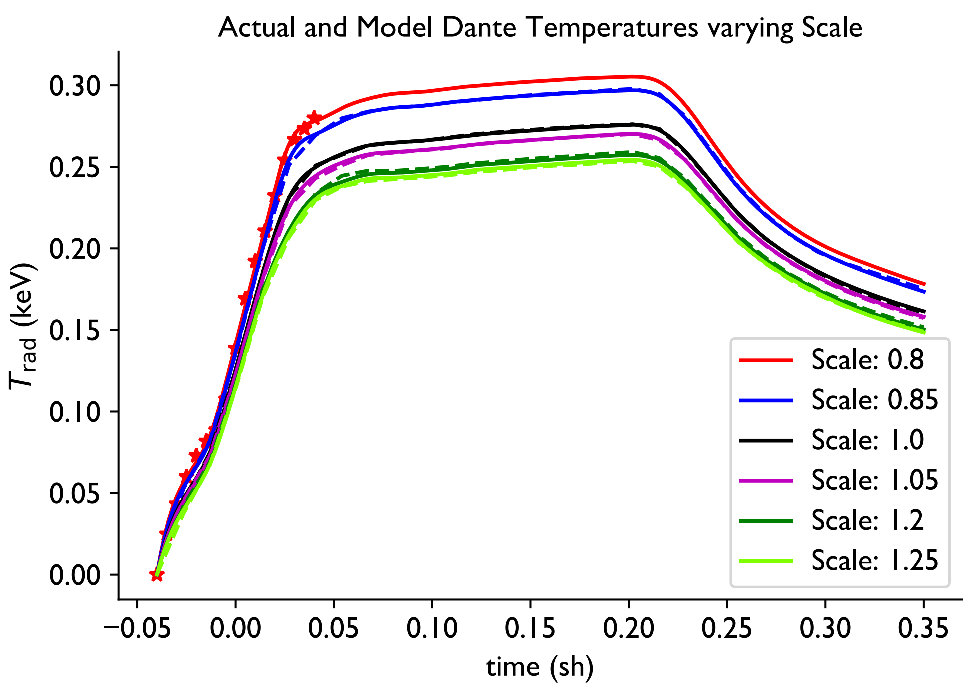

Figure 2: Comparison of the model predictions (solid lines) with the simulated profiles (dashed lines) for various values of the `scale` parameter. The symbols indicate the simulation values for the `scale` $= 0.8$ simulation that crashed.

Typical results from our model are shown in Fig. 2 where the time series for variations in the scale parameter. The time series predicted by a linear regression model (solid lines) and the actual Dante temperatures from the simulation code (dashed lines) are depicted. The predictions from the machine learning model perform well. The model also is able to predict the time history of a simulation that crashed.

We have used the model to consider other holhraum designs by adjusting the baffle in the hohlraum so that it is not at a right angle. We are currently producing simulation results to train models for this wider array of hohlraum designs.

References

[1] I. L. Tregillis. Synthetic Dante-1 temperatures from parameter variations of NIF hohlraums (phase 01). Technical Report LA-UR-17-22657, Los Alamos National Laboratory, (2017).