Contribution ID: **942** Type: **Regular Poster**

Statistically Informed Physics Understanding and Design Optimization of Direct-Drive Inertial Confinement Fusion Experiments

Wednesday, 12 May 2021 18:25 (20 minutes)

Finding an optimized Inertial Confinement Fusion1–3 experimental design is a challenge due to the large number of physical parameters that can be modified from experiment to experiment, and the inability of simulations to accurately
and rapidly a priori predict experimental results when these changes are made. Recently, a novel method[4] has been developed to address this issue by statistically coupling simulation and experimental outcomes, resulting in the first truly predictive models for the observables of ICF experiments. These models have been used to design the highest performing experiments on the OMEGA laser system[5], which are predicted to result in about 500 kJ of fusion yield at
energies typical of the National Ignition Facility (NIF)[6]. Analyzing the dependencies of the models have also resulted in an improved scientific understanding of the degradation mechanisms affecting implosions on the OMEGA laser system. and has led to facility upgrades that have increased performance and reproducibility for ICF experiments.

The rather large parameter space over which design optimization takes place necessitates the existence of a rapid and accurate predictive tool to conduct any optimization scheme whose end goal is ignition[7,8], a necessity for inertial fusion energy (IFE) to become a reality. Historically, the primary tool in ICF design has been the radiation-hydrodynamic (RH) simulation[9–13]. Though recent advances in physics understanding has led to RH simulations achieving better
agreement with experimental observations[14–17], these simulations (regardless of spatial dimension) are not yet able to predict the results of a future experiment in which the initial conditions have been changed a priori.

The inability of RH codes to accurately predict the effect of changes in their designs is likely a major obstacle in achieving ignition in ICF, since it precludes any effective implementation of iterative optimization methodologies that could be use to rapidly increase performance. This predictive deficit also
severely restricts the ability of scientists to identify degradation mechanisms directly from experimental data, as the effect of a degradation mechanism cannot be easily decoupled from varying initial conditions in the absence of an accurate predictive model (statistical, or otherwise).

However, consider that if the outputs of an RH code $\mathbf{O}_{1\mathrm{D}}^{\mathrm{sim}}$ uniquely define the inputs to the code
$\mathbf{I}_{1\mathrm{D}}$ (which are also the inputs to the experiment), then it follows that the outputs of the experiment
$\mathbf{O}_{3\mathrm{D}}^{\mathrm{exp}}$ are $\mathbf{O}_{3\mathrm{D}}^{\mathrm{exp}} = \mathbf{F}_{3\mathrm{D}}^{\mathrm{exp}}\left[\mathbf{I}_{1\mathrm{D}}, \mathbf{S}_{3\mathrm{D}}^{\mathrm{sys}}, \mathbf{S}_{3\mathrm{D}}^{\mathrm{ran}}\right]$, (1)

where
$\mathbf{S}_{3\mathrm{D}}^{\mathrm{sys}}$ and $\mathbf{S}_{3\mathrm{D}}^{\mathrm{ran}}$ are systematic and random 3D perturbations in the experiment. For a repeatable experiment, $\mathbf{S}_{3\mathrm{D}}^{\mathrm{ran}} << \mathbf{S}_{3\mathrm{D}}^{\mathrm{sys}}$, and we have
$\mathbf{O}_{3\mathrm{D}}^{\mathrm{exp}} = \mathbf{F}_{3\mathrm{D}}^{\mathrm{exp}}\left[\mathbf{I}_{1\mathrm{D}}, \mathbf{S}_{3\mathrm{D}}^{\mathrm{sys}}\right] = \mathbf{F}_{3\mathrm{D}}^{\mathrm{map}}\left[\mathbf{O}_{1\mathrm{D}}^{\mathrm{sim}}\right]$ (2)

since $\mathbf{S}_{3\mathrm{D}}^{\mathrm{sys}}$ are constants. This implies that the results of an experiment can be related to the outputs of a 1D RH code by the function $\mathbf{F}_{3\mathrm{D}}^{\mathrm{map}}$. Ref. 4 approximates $\mathbf{F}_{3\mathrm{D}}^{\mathrm{map}}$ with power laws, and reconstructs it statistically by comparing a database of over 200 OMEGA direct-drive cryogenic implosions spanning a wide range of initial conditions, resulting in models for the neutron yield, areal density and hotspot radius (Fig.1). Ensemble averages of several semi-independent models constructed using this method can be taken to generate predictions. These predictions are typically accurate to within 10%, (Fig. 1) making them considerably more accurate than 1D simulation results. They are also pessimistic compared to 1D simulations, which fail to predict the rapid drop-off in yield when the adiabat decreases and convergence increases. Instead, the predictive models correctly expect low yields and areal densities for highly convergent, low adiabat implosions.

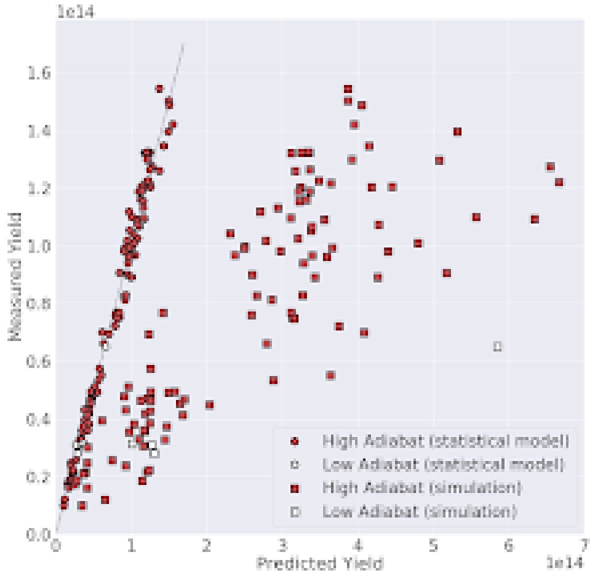

Figure 1: Fig.1, Model yield predictions (circles) vs simulations (squares).

As the statistically inferred $\mathbf{F}_{3D}^{\text{map}}$ operates on 1D simulations, a large swathe of parameter space can be rapidly scanned for viable designs, enabling rapid and iterative design. Using these models, a performance improvement campaign was conducted on OMEGA, as reported in Ref. 4. By following the recommendations of the models, the neutron yield on OMEGA was tripled, and the areal density was increased by 60%. Due to OMEGA's energy constraints, the ignition-relevant performance of these implosions was assessed by the theory of hydrodynamic scaling[18], and were predicted to produce fusion yields of about 500 kJ, with a normalized Lawson parameter[19] of about 0.7 when scaled to 1.9 MJ of symmetric drive (Fig. 2). Previous results on OMEGA[20] were expected produce approximately 100 kJ of fusion energy when scaled to 1.9 MJ of symmetric drive[21], and recent indirect-drive experiments at the NIF have demonstrated 56 kJ of fusion energy[22].

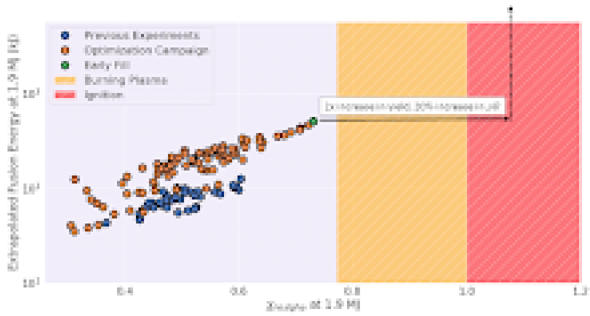

Figure 2: Fig.2, Extrapolated fusion energy vs Lawson parameter[19].

Inspecting the exact form of a predictive model has also led to physics insight regarding the degradation mechanisms active on OMEGA. In particular, it was observed[23] that targets filled with tritium close to the shot date tended to be underpredicted, while targets filled well before the shot tended to be overpredicted (Fig. 3). Accounting for this improved the prediction accuracy, including for a number of 'outlier' implosions, prompting an investigation for the underlying physical mechanism. One hypothesis was the build-up of Helium-3
from the beta decay of tritium, which considerably increases the initial vapor pressure of the target. A new database of simulations that accounted for the initial vapor pressure of He3 was constructed, and it was found that the quality of prediction remained high even in the absence of ad-hoc variables to account for the age of the fill. As this is a relatively small (10-20% for moderate adiabats) effect relative to changes in design, the statistical model was essential in providing a baseline expectation from which deviations could be identified. Recent controlled experiments have confirmed this dependence (Fig. 2), and changes to the OMEGA facility to minimize the fill age are underway to maximize future

performance.

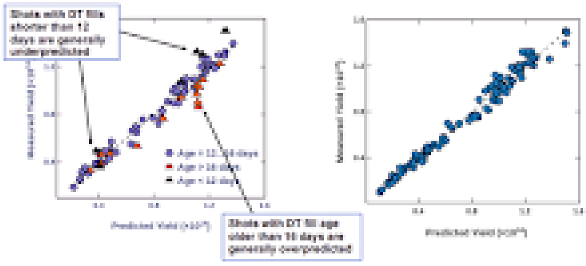

Figure 3: Fig.3, Left: Short fills (black triangles) are under-predicted; long fills (orange triangles) are over-predicted. Right: He3 buildup is incorporated into simulations; all shots (including those with large fill time deviations) are predicted accurately.

Though the US ICF program has not yet achieved ignition, steady progress over the last few decades means that only comparatively modest improvements are required to demonstrate ignition (Fig. 2), which is necessary for the realization of IFE. While we cannot know the exact magnitude of the improvements the statistical model can provide, it is clear that applying the statistical model to generating new designs, and to investigate and eliminate degradation sources has the potential to push the ICF program to the high yields necessary for IFE.

1. J. Nuckolls, et. al, Nature 239 (1972)
2. S. Atzeni et. al,(Oxford Univ. Press, Oxford, 2004).
3. S. Craxton, Phys. Plasmas 22 (2015)
4. V. Gopalaswamy, et al. Nature 565, 581–586 (2019).
5. R. Boehly, Opt.Commun. 133 (1997)
6. E. M. Campbell and W. J. Hogan, Plasma Phys. Contr. Fusion 41 (1999)
7. A. R. Christopherson, Phys. Plasmas 25 (2018),
8. R. Betti, Phys. Rev. Lett. 114 (2015)
9. J. Delettrez, et. al, Phys. Rev. A 36 (1987),
10. P. B. Radha, Phys. Plasmas 12 (2005),
11. G. Zimmerman, et. al, J. Opt. Soc. Am. 68 (1978).
12. M. M. Marinak, Phys. Plasmas 8 (2001),
13. S. Atzeni, Comput. Phys. Commun. 169 (2005)
14. I. V. Igumenshchev, Phys. Plasmas 17 (2010),
15. D. T. Michel, High Power Laser Sci. Eng. 3 (2015)
16. V. N. Goncharov, Phys. Plasmas 13 (2006)
17. S. X. Hu, Phys. Rev. E 92 (2015)
18. R. Nora, Phys. Plasmas 21(2014),
19. R. Betti, Phys. Plasmas 17 (2010)
20. S. Regan, Phys.Rev. Lett. 117 (2016)
21. A. Bose, Phys. Rev. E 94 (2016)
22. S. Pape, Phys. Rev. Lett. 120 (2018)
23. A. Lees, et. al, Bull. Am. Phys. Soc. 64 (2019).

Affiliation

University of Rochester/Laboratory for Laser Energetics

Country or International Organization

United States

Primary authors: Mr GOPALASWAMY, Varchas (University of Rochester/Laboratory for Laser Energetics); Dr BETTI, Riccardo (University of Rochester/Laboratory for Laser Energetics); Dr KNAUER, James (University of Rochester/Laboratory for Laser Energetics); Mr LEES, Aarne (University of Rochester/Laboratory for Laser Energetics); Mr PATEL, Dhrumir (University of Rochester/Laboratory for Laser Energetics); Dr WOO, Ka Ming (University of Rochester/Laboratory for Laser Energetics)

Presenter: Mr GOPALASWAMY, Varchas (University of Rochester/Laboratory for Laser Energetics)

Session Classification: P4 Posters 4

Track Classification: Inertial Fusion Energy