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# Efficient Sampling Methods for Machine Learning Error Models with application to Surrogates of Steady Hypersonic Flows

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January 5, 2022

AIAA SciTech Forum, San Diego, CA



# Goal: Develop Error Models of Surrogates Faster

QOI Error

$$\text{---} \quad \delta_s(\boldsymbol{\mu}) := s(\boldsymbol{\mu}) - \tilde{s}(\boldsymbol{\mu})$$

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# Reducing Sampling Size

- Problem: FOM is computationally expensive
  - Necessary FOM training points for ROM and error model
- Solution:
  1. Sampling types
  2. Sampling strategies





# Sampling Types

1. Latin Hypercube Sampling (LHS)
2. LHS with maximin criterion
  - Adds constraint on distance between sampling points
3. D-Optimal design
  - Maximizes determinant of information matrix
  - Reduces variance in results
  - Contains replicates not useful for computational experiments
  - Replace replicates with random LHS points
  - End result may not be a true D-Optimal design



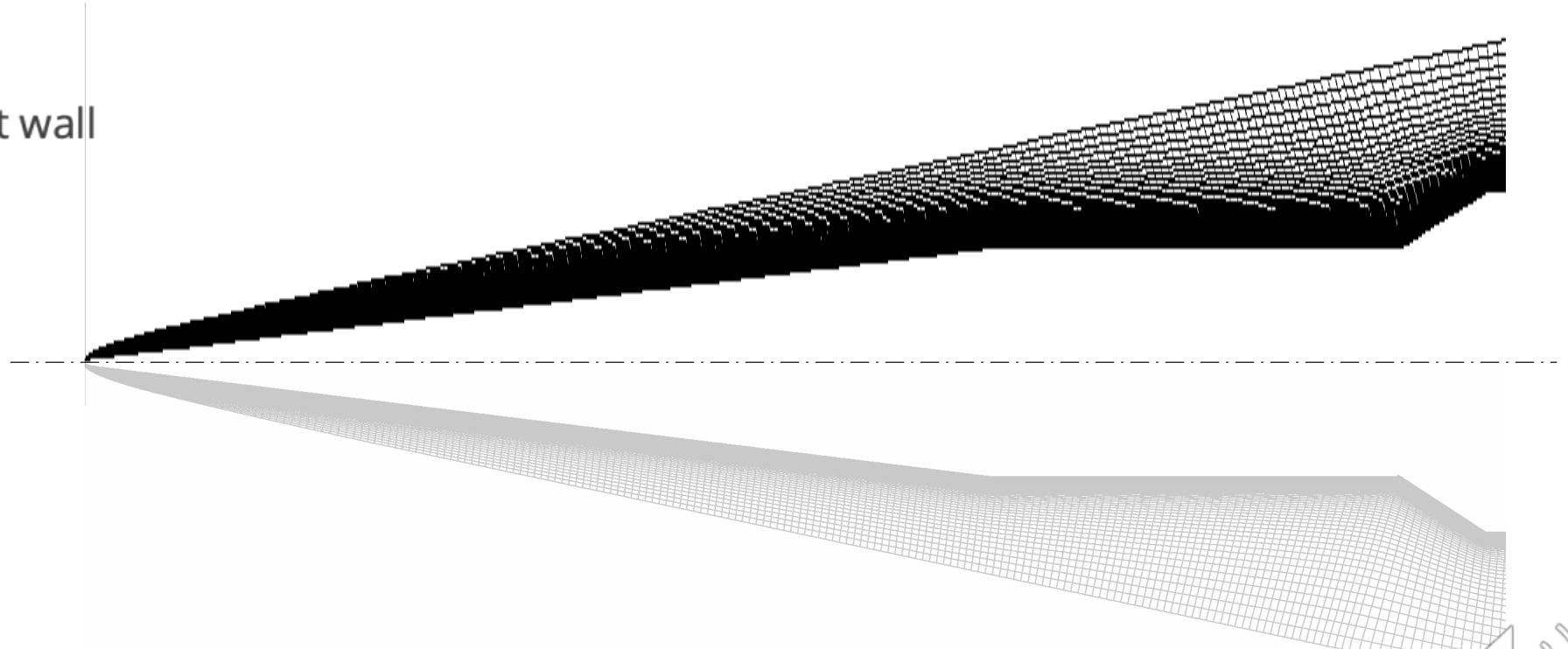
# Sampling Strategies

- Distinct training set
- Augmented training set
- Single training set



# HIFiRE-1

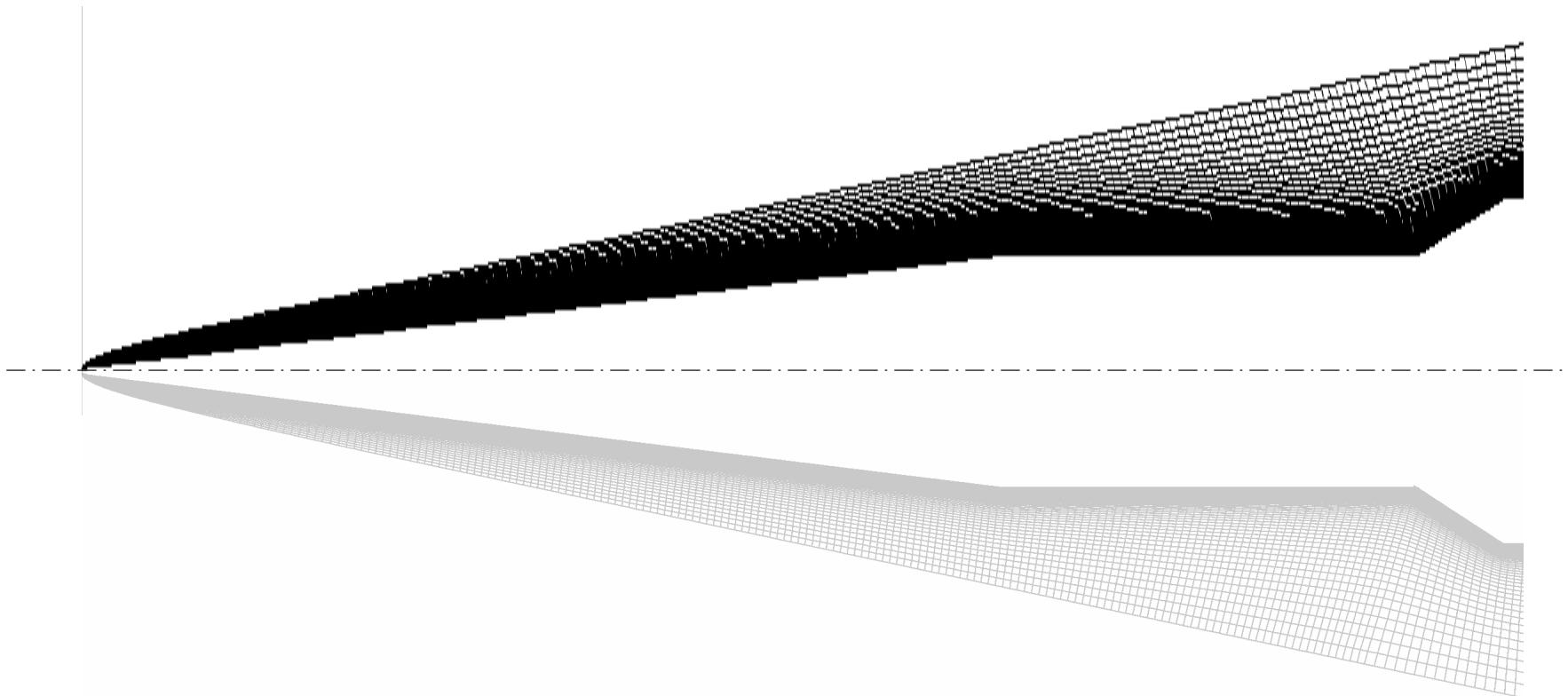
- Run 30 of CALSPAN University of Buffalo HIFiRE-1 wind tunnel tests [1]
- $N = 32,768$  cells
- Boundary conditions:
  - Supersonic inlet
  - Supersonic outlet
  - No-slip enforced at wall
  - Fixed temperature



[1] Wadhams, T. P., Mundy, E., MacLean, M. G., and Holden, M. S., "Ground Test Studies of the HIFiRE-1 Transition Experiment Part 1: Experimental Results," *Journal of Spacecraft and Rockets*, Vol. 45, No. 6, 2008, pp. 1134–1148. <https://doi.org/10.2514/1.38338>.



# Modeling HIFiRE-1



Full-Order Model



Reduced-Order Model

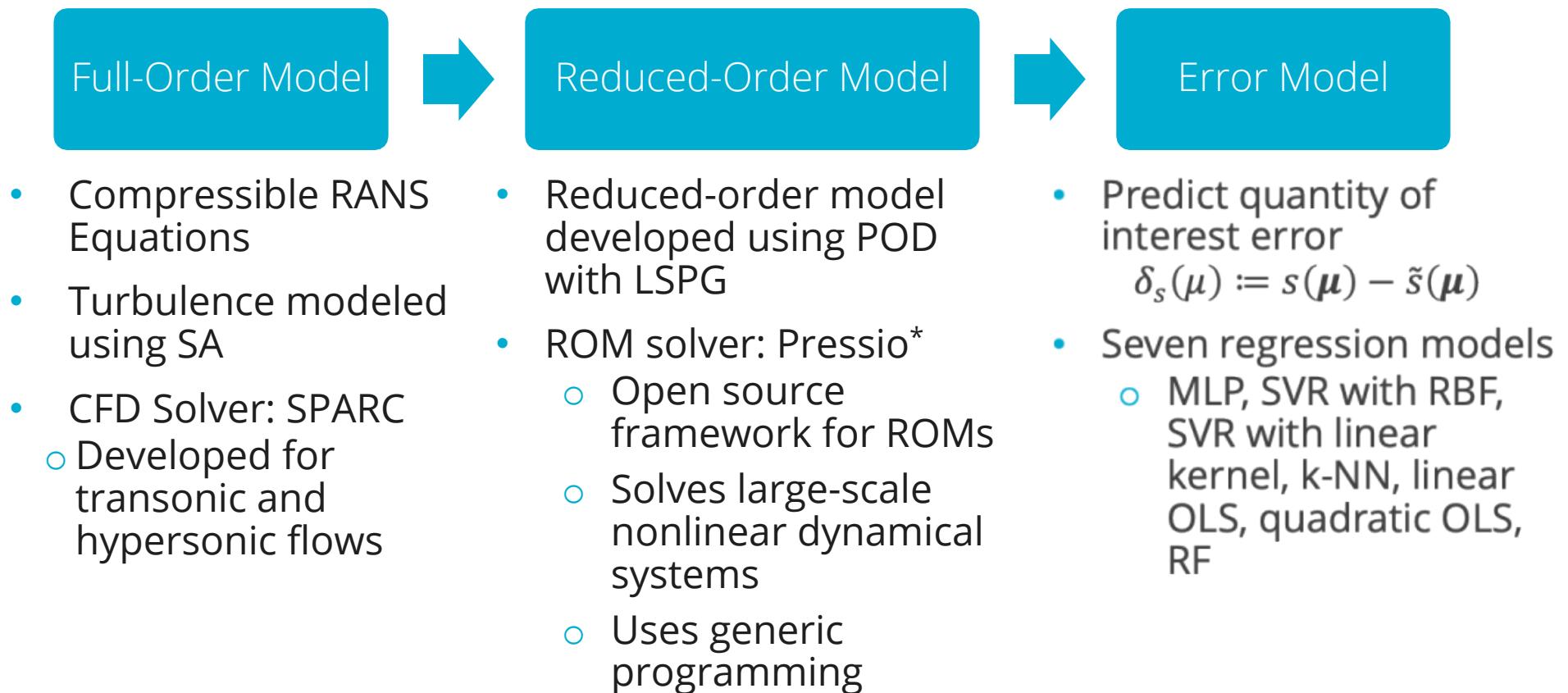


Error Model





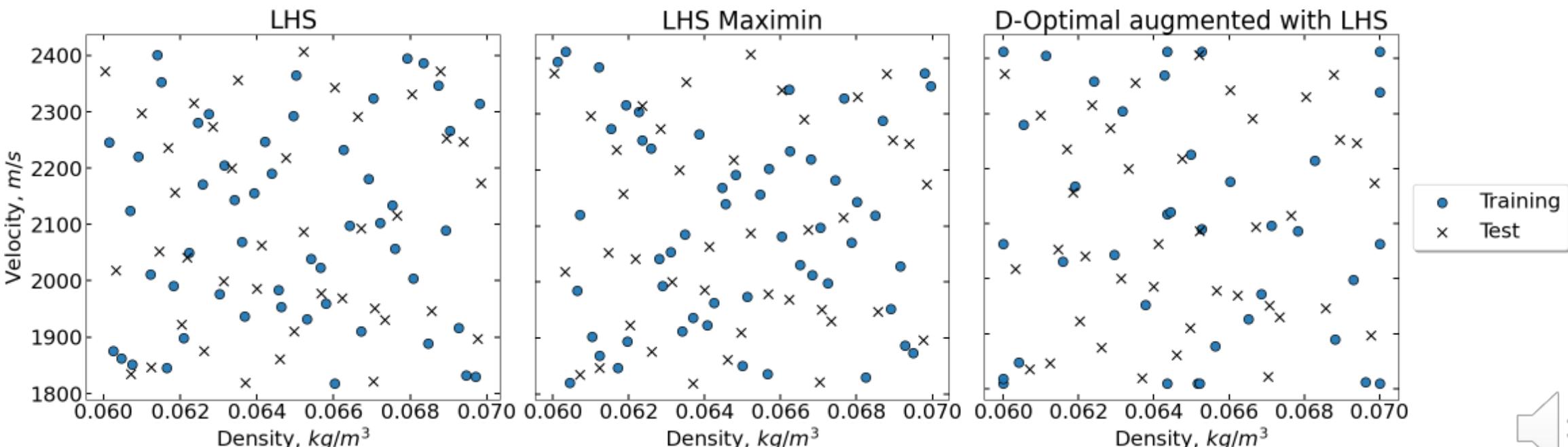
# Modeling HIFiRE-1



# Distinct Training Sets

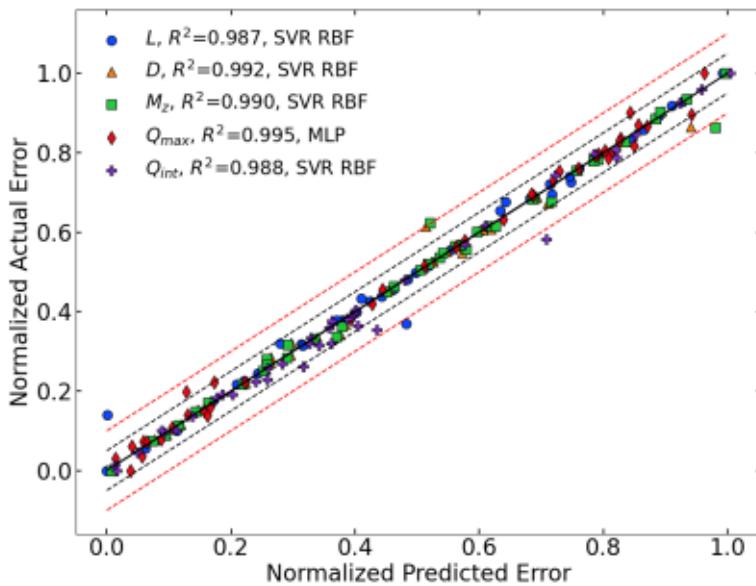
- Reduced-order model trained with 50 points
- Error model trained with 3 sampling types
  - Number of points determined by achieving statistical power of 80%

Sampling Type	Number of Points
LHS	52
LHS Maximin	53
D-Optimal	37

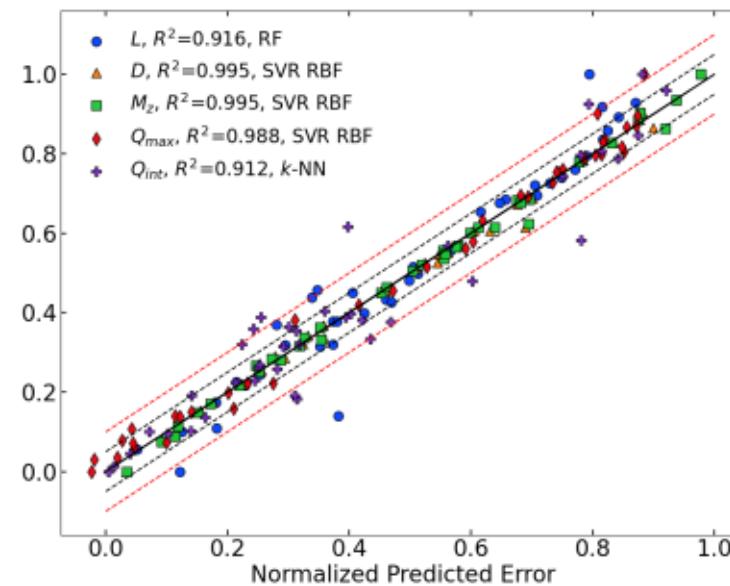


# Distinct Training Set Normalized Error

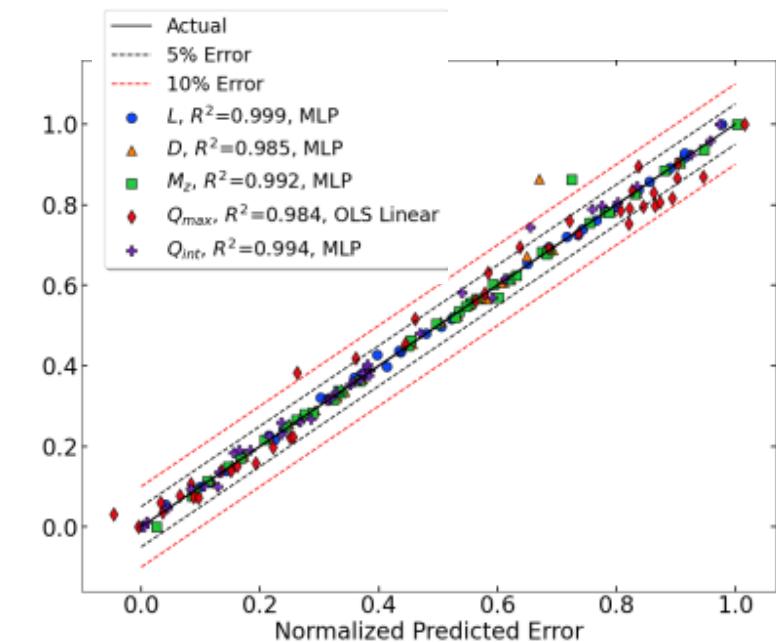
- D-Optimal and LHS sampling types produced best results
  - D-Optimal little bit better than LHS ( $\bar{R}_D^2 = 0.991 > \bar{R}_{LHS}^2 = 0.990$ )



LHS



LHS Maximin

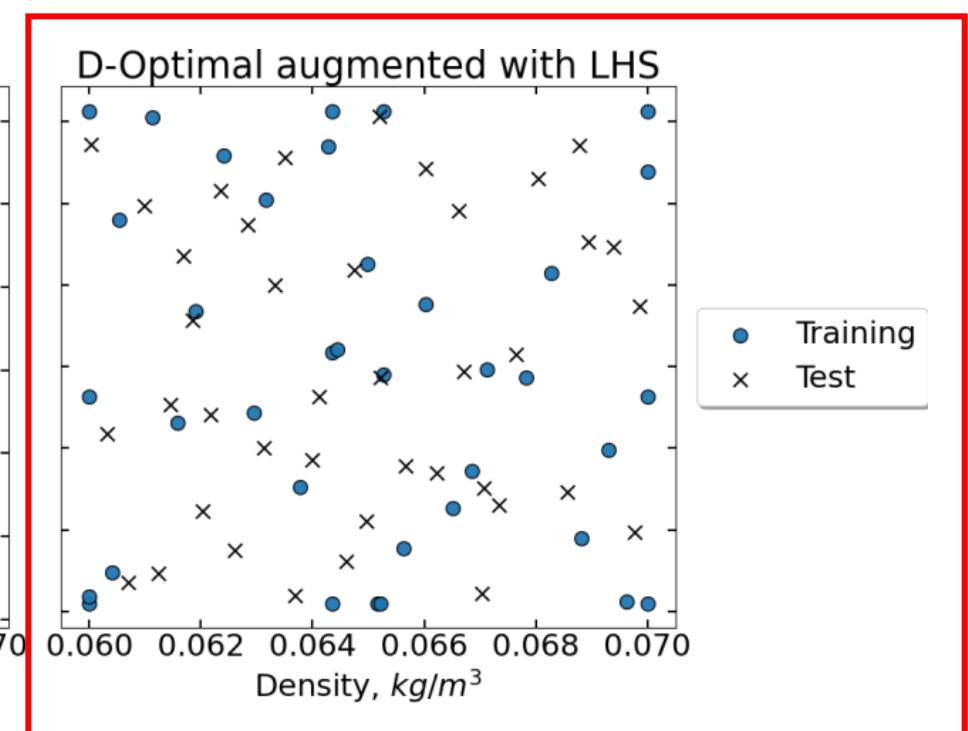
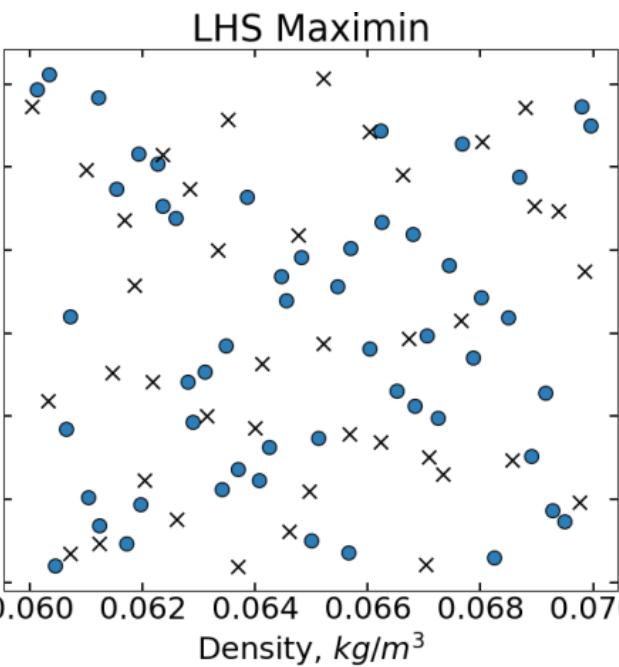
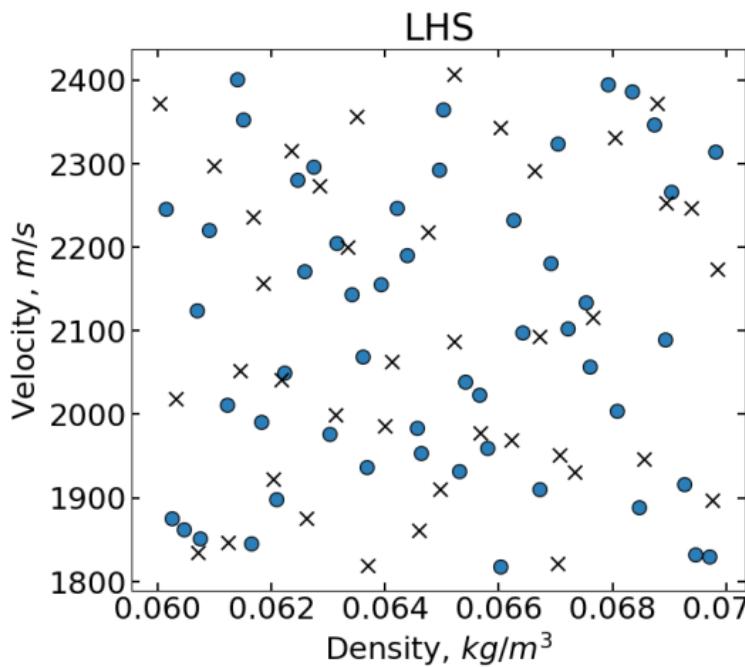


D-Optimal



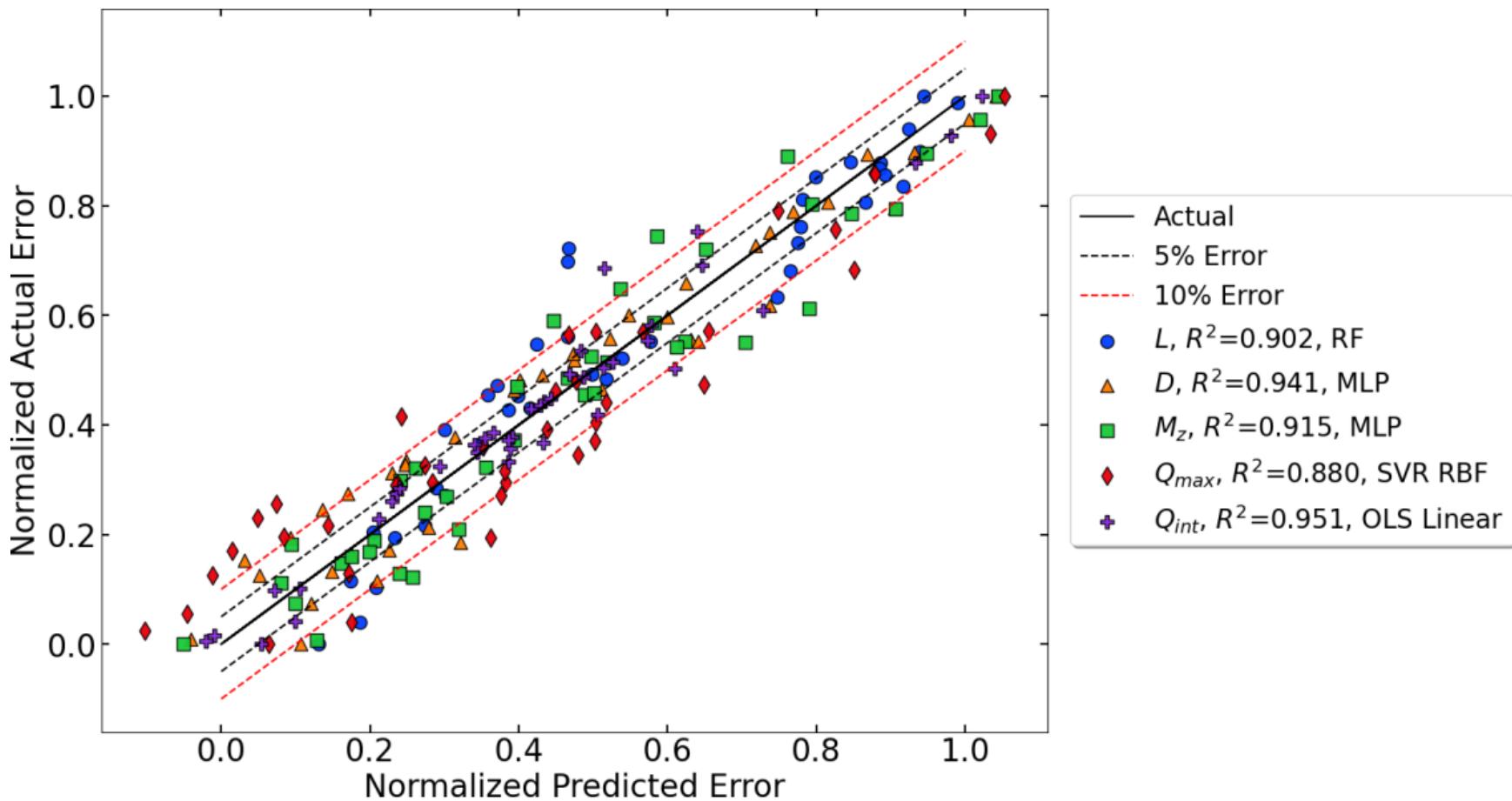
# Single Training Set

- Leave-one-out cross validation (LOOCV)
  - Same training set for reduced-order model and error model

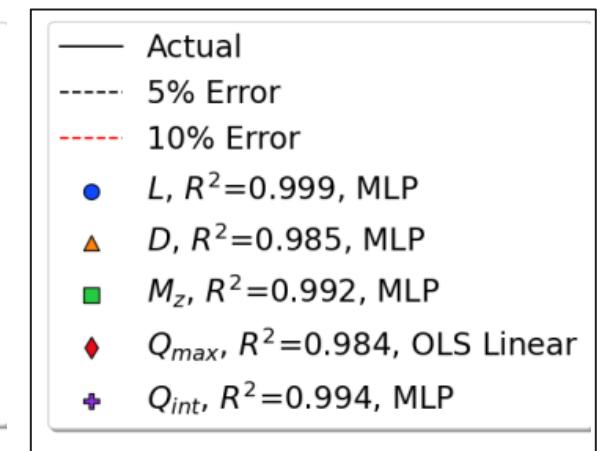




# Single Training Set Normalized Error

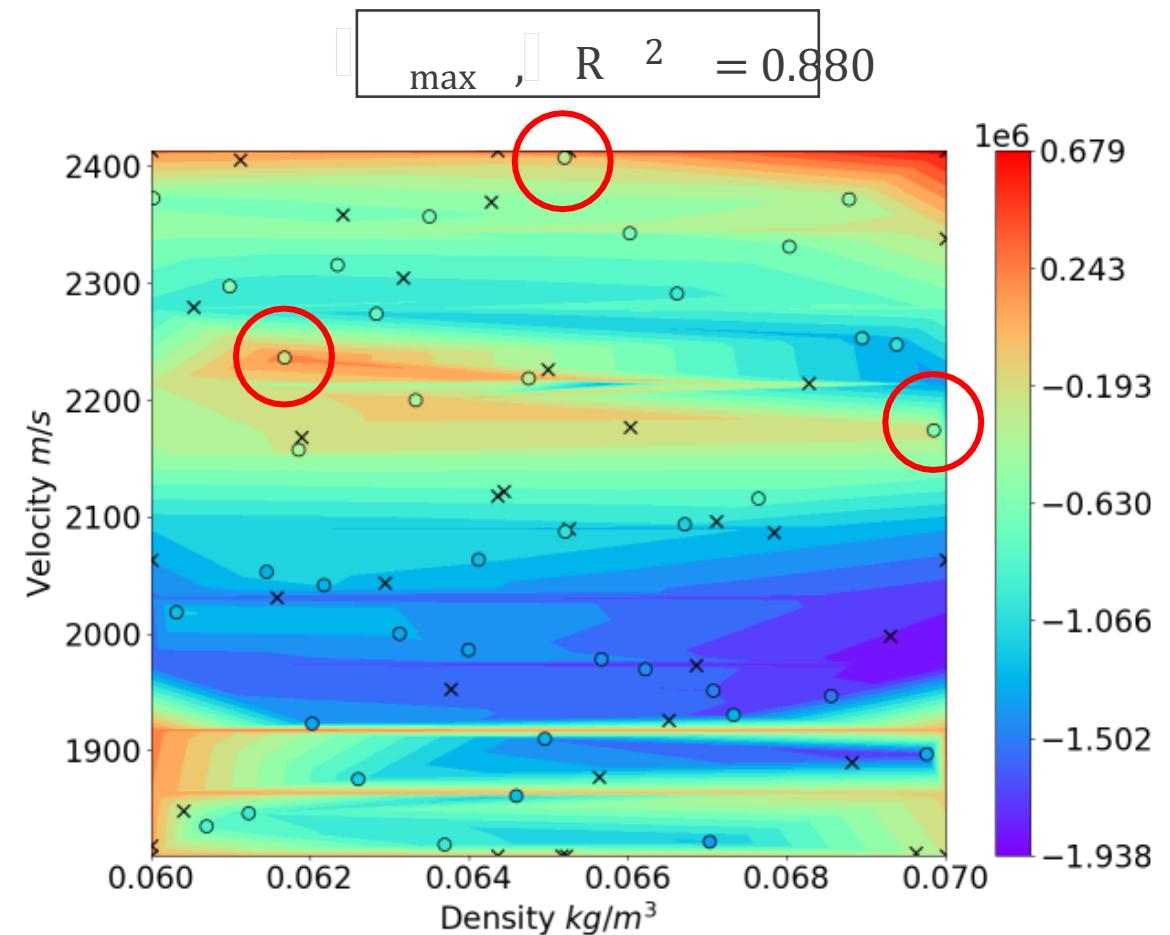


Distinct Training Set



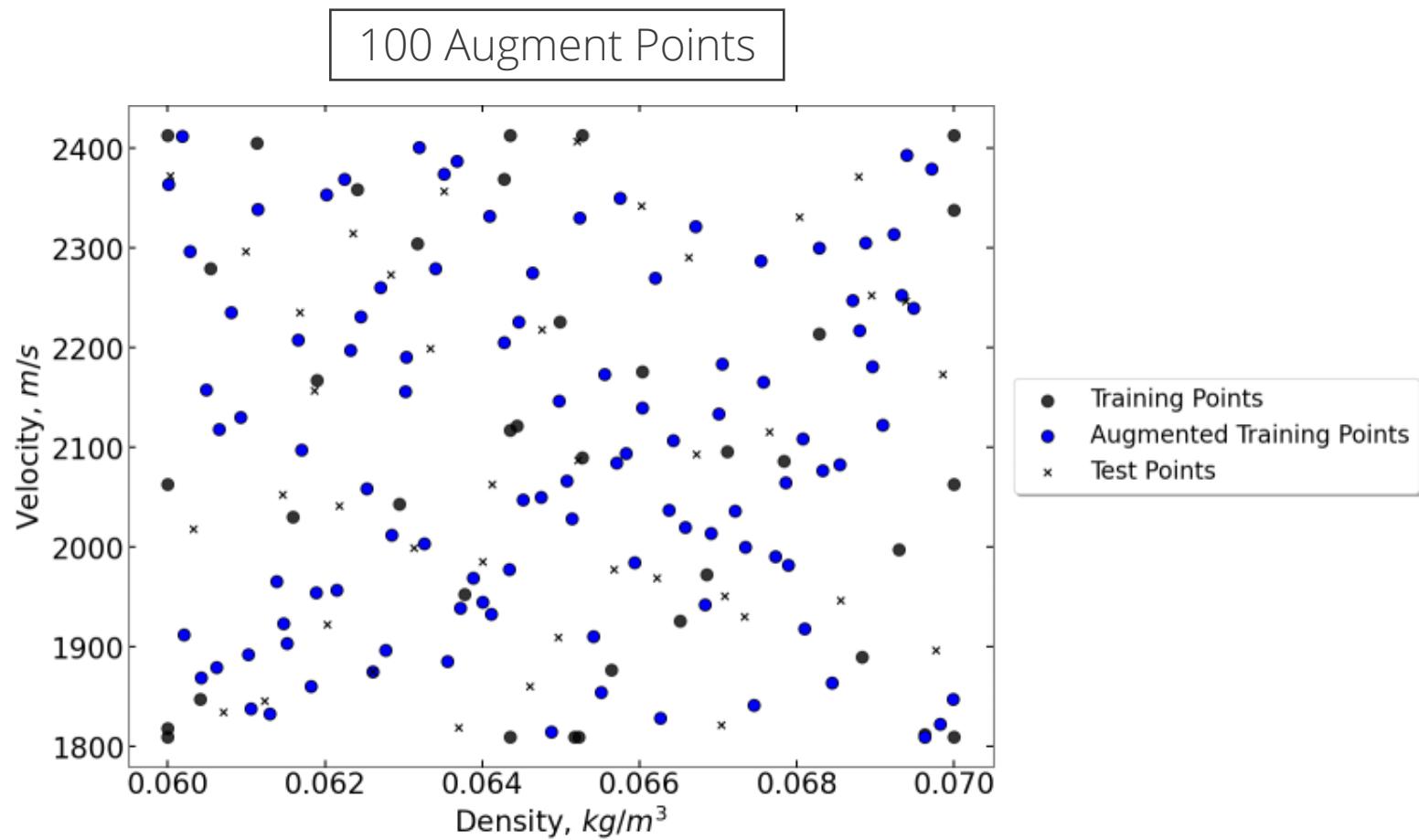
# Single Training Set Error Contours

- Highly nonlinear error surface
- Large errors occur where
  - Few training points placed
  - Highly nonlinear areas
- Improve error model by improving spread of training points
  - D-Optimal design augmented with LHS
  - No distance constraint on augmented LHS points

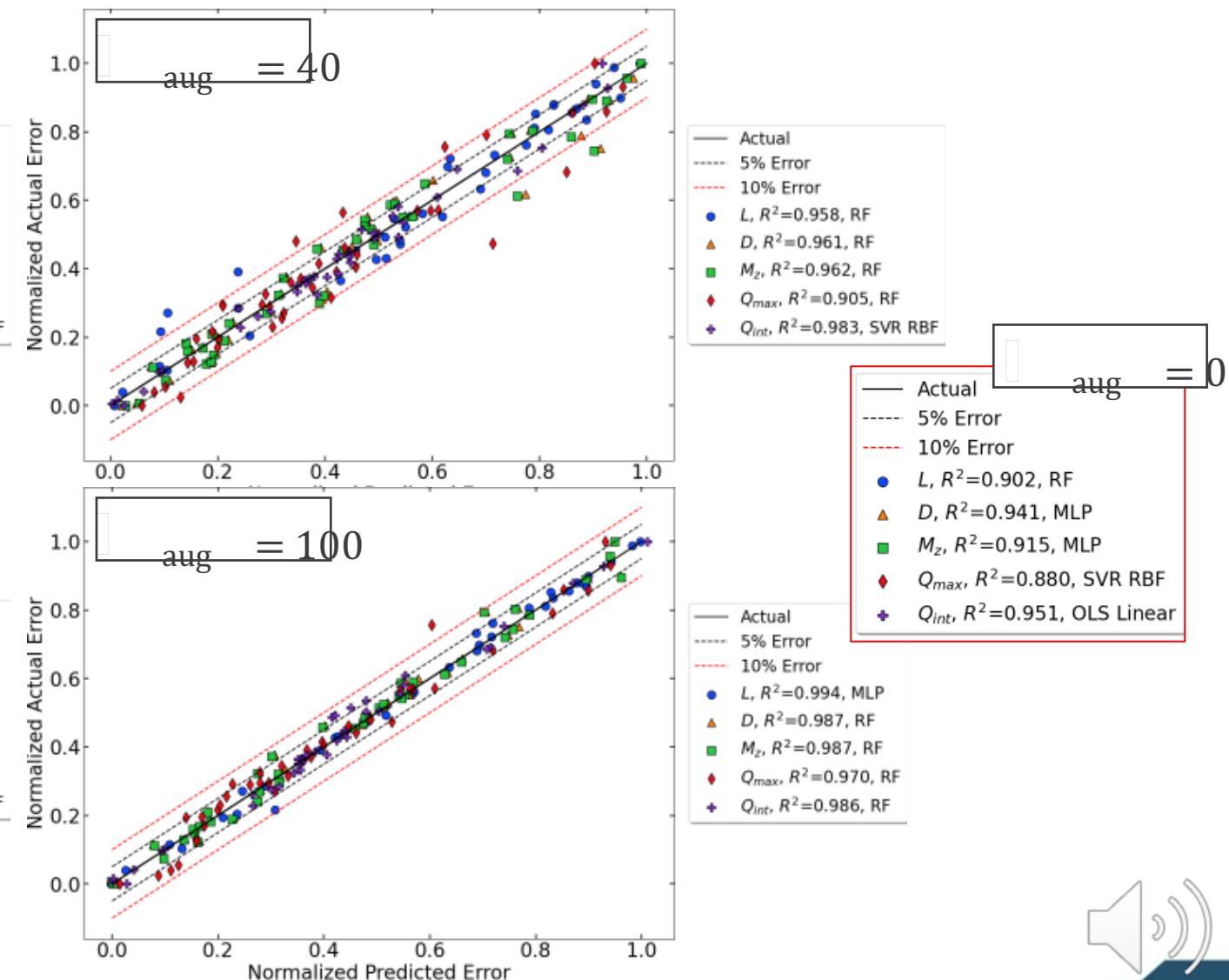
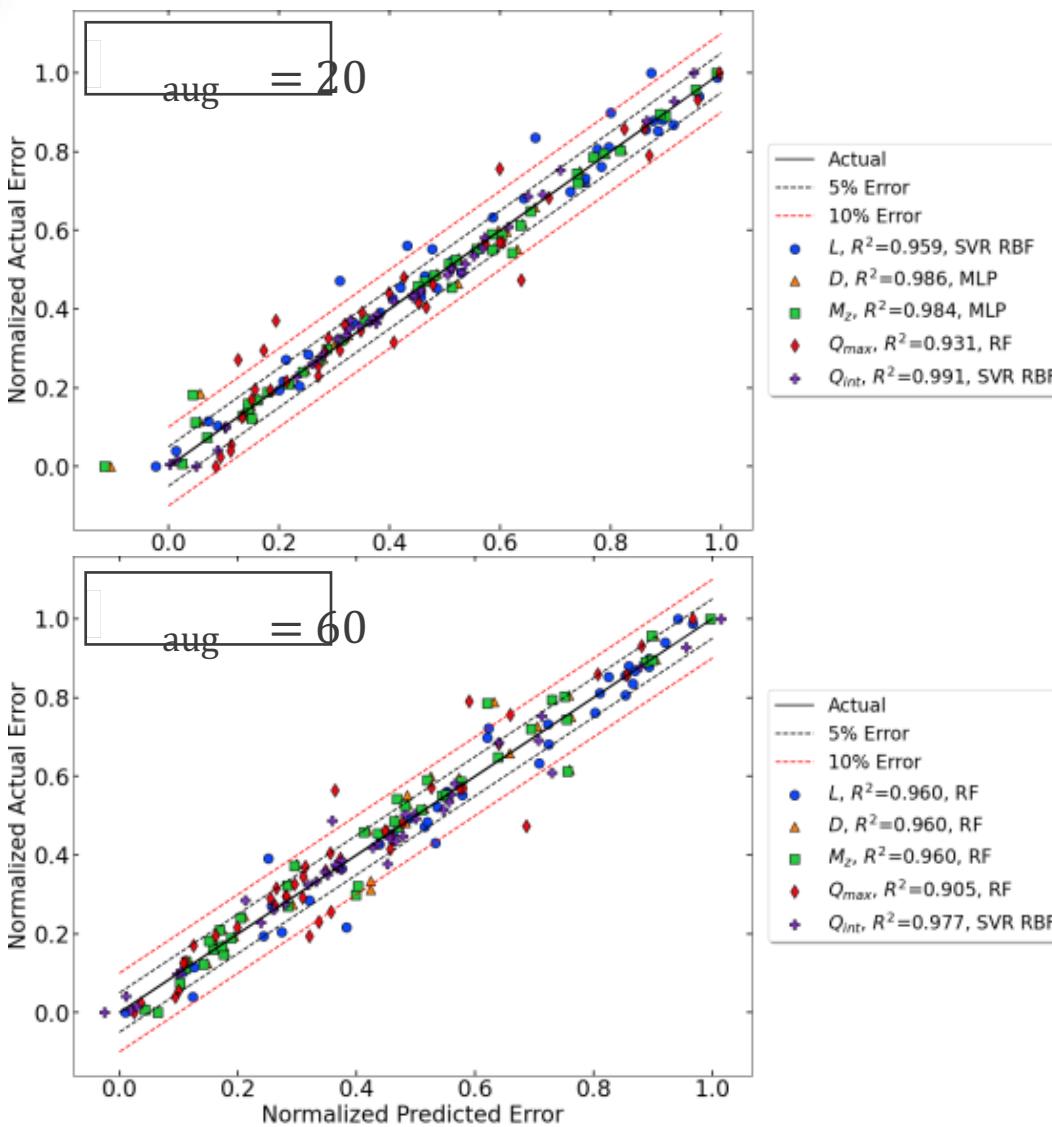


# Augmented Training Set

- Improve error model by augmenting with additional points



# Augmented Training Set Normalized Error





# Computational Runtime

- D-Optimal with LOOCV cuts computational expense by 64% compared to Distinct LHS
  - Design with 20 augmented points cuts computational expense by 44%

Category	Sampling Type	$N_{train}$	Total Time [s] $\times 10^6$	Relative Time to Distinct LHS	$\bar{R}^2$
Distinct	LHS	102	1.43	1.00	0.990
	LHS Maximin	103	1.44	1.01	0.961
	D-Optimal	87	1.22	0.85	0.991
Single Training Set	D-Optimal	37	0.52	0.36	0.918
Augmented Training Set	D-Optimal	57	0.80	0.56	0.970
		77	1.08	0.75	0.954
		97	1.36	0.95	0.952
		117	1.64	1.15	0.962
		137	1.91	1.34	0.985





## Conclusions

- D-Optimal design reduces development cost of error model by 15%
  - Reduced total number of training points from 102 to 87
- LOOCV with D-Optimal design reduces development cost of error model by 64%
  - Adding 20 augment points improves accuracy from  $\bar{R}^2 = 0.92$  to 0.97
  - Using 20 augment points reduces development cost by 44%
- May improve overall cost reduction by improving POD updates
  - Recalculating POD takes up 30% of overall cost with LOOCV
  - Possibility to use rank-1 updates to POD basis [1]

[2] Brand, M., "Fast low-rank modifications of the thin singular value decomposition," *Linear Algebra and its Applications*, Vol. 415, No. 1, 2006, pp. 20–30. <https://doi.org/10.1016/j.laa.2005.07.021>, special Issue on Large Scale Linear and Nonlinear Eigenvalue Problems.





## Acknowledgements

This presentation describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the presentation do not necessarily represent the views of the U.S. Department of Energy or the United States Government. Supported by the Laboratory Directed Research and Development program at Sandia National Laboratories, a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA-0003525.

The authors would like to thank Eric Parish for his feedback.





# Questions?

