Flow Reconstruction with Neural Network-based Reduced Order Modeling

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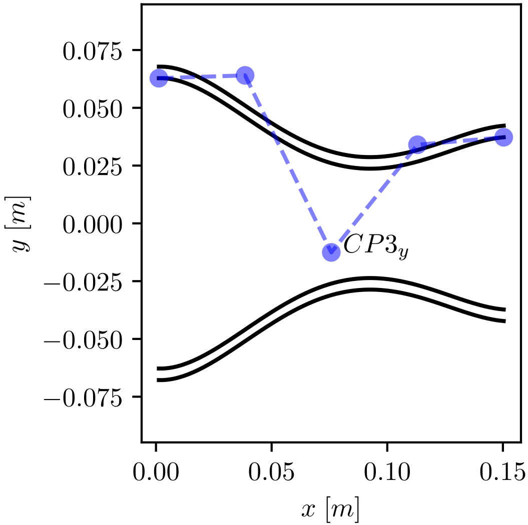
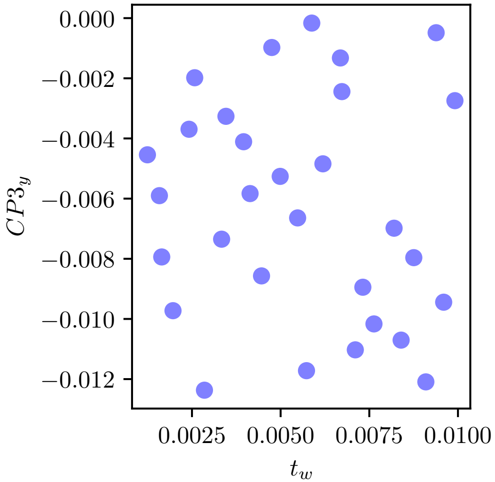
Introduction



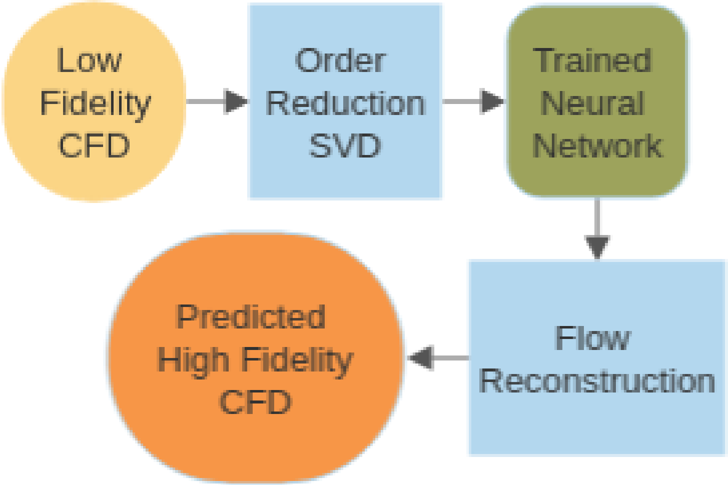
Introduction



	Minimum	**Maximum**
t_w	0.0010 m	0.0100 m
$CP3_y$	-0.0125 m	0.0000 m

Sampling ranges for the design variables.

Methodology



Step 1: Data Generation using CFD Analysis

Snapshot Matrices

$$\mathbf{A}_L = \left[\mathbf{L}^1 | \dots | \mathbf{L}^N\right]^{S_L \times N}$$

$$\mathbf{A}_H = \left[\mathbf{H}^1 | \dots | \mathbf{H}^N\right]^{S_H \times N}$$

Low fidelity model

$$\mathbf{L} = \begin{bmatrix} t_w \\ CP3_y \\ \mathbf{p}_L \\ \mathbf{T}_L \\ \mathbf{M}_L \end{bmatrix}^{1205 \times 1}$$

High fidelity model

$$\mathbf{L} = \begin{bmatrix} t_w \\ CP3_y \\ \mathbf{p}_H \\ \mathbf{T}_H \\ \mathbf{T}_\mathbf{s} \\ \mathbf{M}_H \end{bmatrix}^{252842 \times 1}$$

Step 2: Order Reduction using SVD

$$\mathbf{A} = \mathbf{U}\Sigma\mathbf{V}^T$$

Truncated SVD

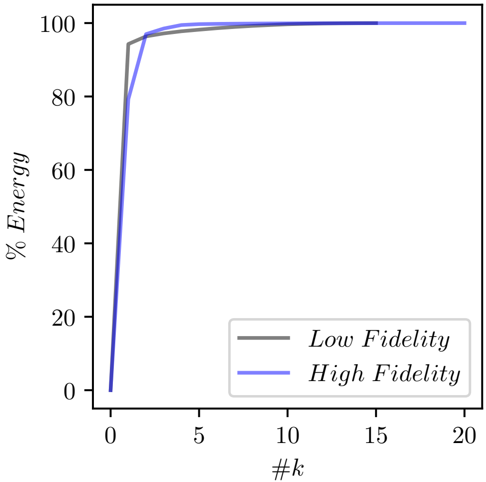
$$\mathbf{A} \approx \tilde{\mathbf{U}}\tilde{\Lambda}$$

$$\%\ Energy_i = \sum_{j=1}^{i} \frac{\Sigma_k^2}{\sum_{l=1}^{r} \Sigma_l^2} \times 100$$

$$, i = 1, 2, \ldots, r$$

$$\tilde{\Lambda}_L = \tilde{\mathbf{U}}_L^T \mathbf{A}_L$$

$$\tilde{\Lambda}_H = \tilde{\mathbf{U}}_H^T \mathbf{A}_L$$



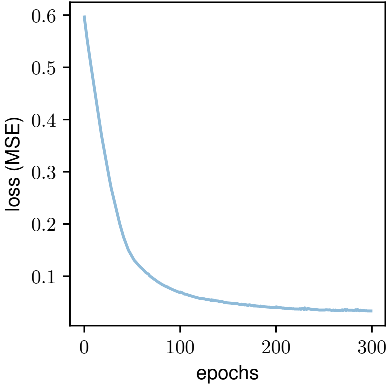
Step 3: Training the Neural Network

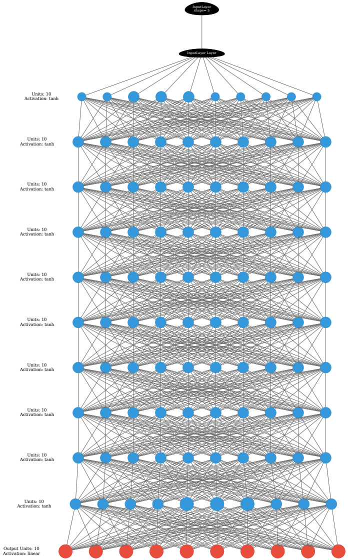
Loss

MSE $(\tilde{\Lambda}_L, \tilde{\Lambda}_H)$

Training

time 15s



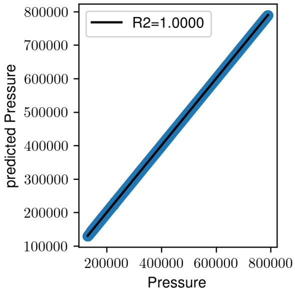


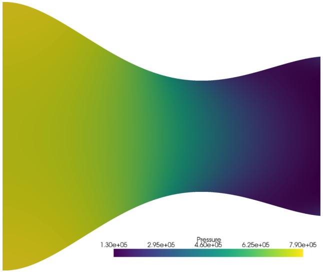
Results

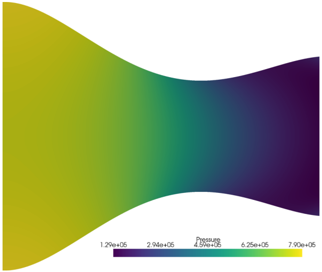
- inference time 10s
- 500-fold speedup (1h30m for full order CFD)

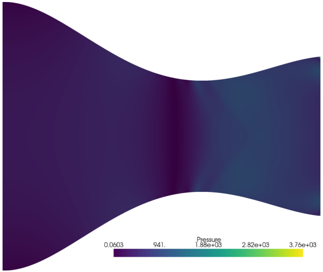
	MAE	$\mathbf{R^2}$
p	698.4111 Pa	0.9999
T	2.7631 K	0.9958
M	0.0026	0.9999
$\mathbf{T}_{\mathrm{SOLID}}$	8.3579 K	0.7179
$\mathbf{T}_{\mathrm{WALL}}$	16.757 K	0.2241
$\mathbf{q}_{\mathrm{WALL}}$	25386.4482 W/m^2	0.8093

Pressure Flow Field Reconstructions

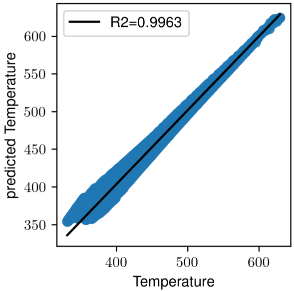


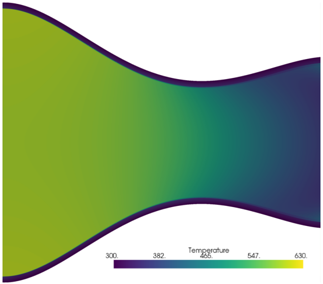


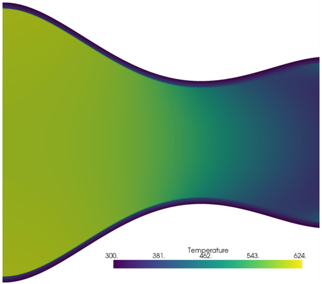


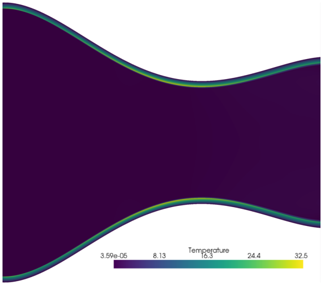


Temperature Flow Field Reconstructions

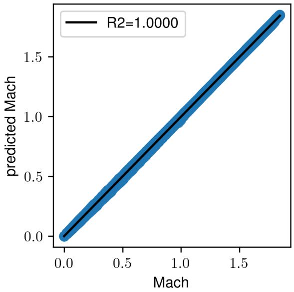


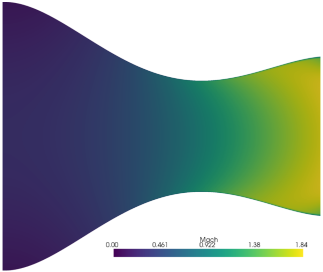


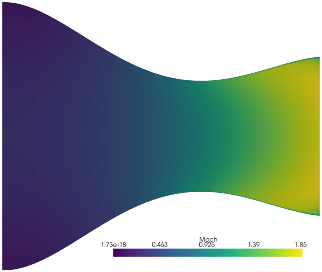


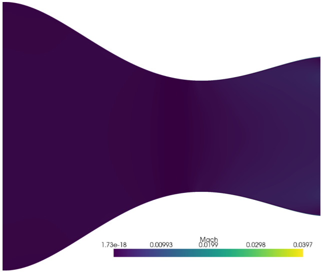


Mach Flow Field Reconstruction









Wall Heat Flux

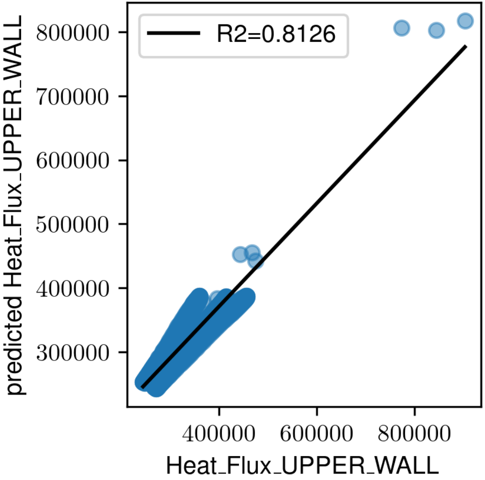


Figure 1: Surrogate model prediction of heat flux $[W/m^2]$ distributions over test dataset.

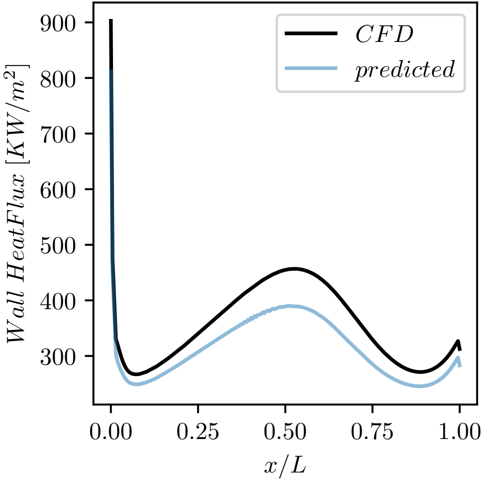


Figure 2: Surrogate model prediction of a heat flux $[W/m^2]$ distribution.

Wall Surface Temperature

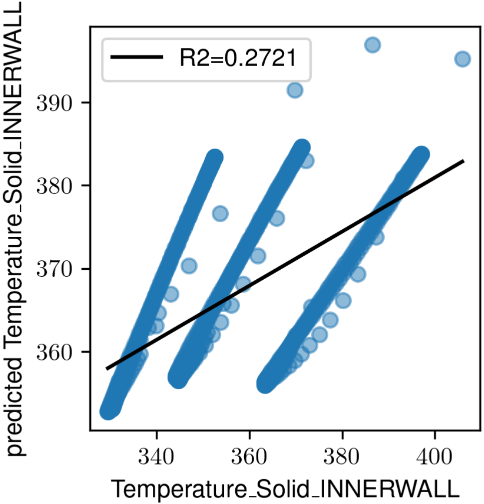


Figure 3: Surrogate model prediction of nozzle wall surface temperature [K] distributions over

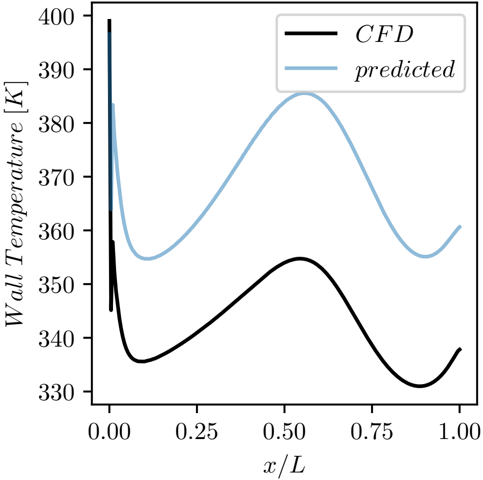
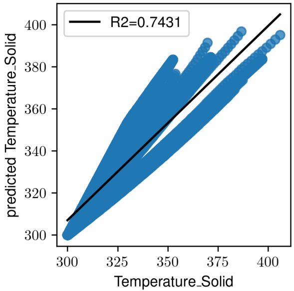
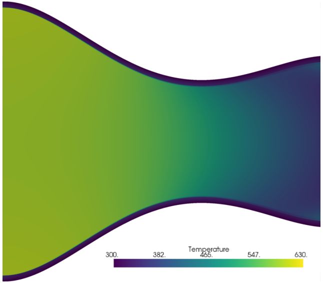
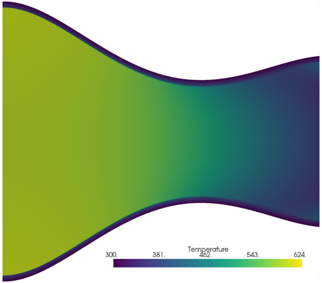


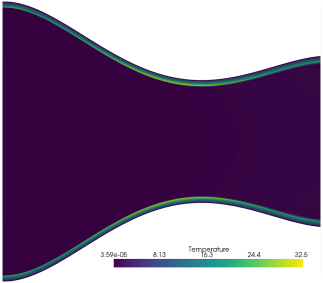
Figure 4: Surrogate model prediction of a nozzle wall surface temperature [K] distribution.

Wall Solid Temperature









Model Limitations and Improvements Suggestions

- the need for a large amount of data for training.
- adding more snapshots is expected to improve model accuracy.
- using individual normalization techniques for each variable.
- perform hyperparameter optimization.
- try more advanced loss functions.
- trye other optimization algorithms.
- redesigning the snapshot variables selection

Conclusion and Future Work

- it effectively reconstructed the fluid flow variables
- performance was limited in reconstructing solid variables
- suggestions for improving the methodology and suggested
- increasing the sample size in the dataset
- comparing our model with other surrogate models as future work
- the proposed methodology has the potential to enhance the design and optimization cycle while reducing computational cost.

Code Repository

GitHub repository https://github.com/properallan/ihtc_repository

THANK YOU!