Flow Reconstruction with Neural Network-based Reduced Order Modeling

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The performance of rocket engines relies heavily on the flow of gases through the nozzle. Therefore, a thorough understanding of flow and heat transfer in rocket nozzles is essential for their design and optimization. In this paper, we propose a methodology that utilizes neural networks and singular value decomposition to reconstruct the internal flow and heat transfer fields in a rocket nozzle. The methodology involves two main steps. Firstly, we use both low and high fidelity computational fluid dynamics (CFD) analyses to simulate the flow of gases through the nozzle and predict the heat transfer. Secondly, we decompose the data matrix generated from the CFD simulations using singular value decomposition (SVD) and train a neural network to learn the relationship between the dominant modes obtained from the SVD of both fidelity simulations.The trained neural network can then be used to reconstruct the flow and heat transfer fields from the low fidelity solutions. The proposed methodology has been shown to accurately predict fluid flows and, to some extent, temperature and heat flux in the nozzle walls. The surrogate model developed using this methodology has great potential for improving the design and optimization of nozzle flows.

Introduction

In the field of rocket propulsion, accurate prediction of heat transfer in nozzle flow plays a critical role in designing and optimizing rocket engines [@Zhang2011]. However, existing methods for predicting heat transfer often suffer from high computational complexity, making them impractical for engineering design purposes. To address this challenge, we propose a flow reconstruction [@Lui2019; @Yu2019] technique that combines order reduction using Singular Value Decomposition (SVD)[@Golub2013-ag] with neural network modeling [@Brunton2019-ax]. While the individual techniques are not novel, our approach offers a combination of these methods for accurate and efficient prediction of internal flow and thermal fields in the nozzle, leading to highly accurate fluid flow predictions. Furthermore, the use of neural network modeling enhances the accuracy of our approach by capturing the complex nonlinearities of the flow. Overall, our flow reconstruction technique has the potential to significantly improve the design and optimization of conjugate heat transfer CFD problems, providing valuable insights into the underlying physical phenomena while reducing

Methodology

Flow reconstruction [@Yu2019] is a technique used to recover high-fidelity computational fluid dynamics (CFD) simulations from low-fidelity ones. This can be accomplished using neural networks and singular value decomposition (SVD). The proposed methodology is data-driven and consists of three main steps.

In the first step, the data is generated. To generate a set of high fidelity simulations, the input parameters are varied to cover a wide range of flow conditions. To generate a set of low fidelity simulations, the resolution is reduced, the model is simplified, or a less accurate numerical method is used. In the second step, both sets of simulations are reduced to a set of basis functions coefficients using SVD, which capture the dominant modes of variation in the flow fields. This allows for a more efficient representation of the flow field and facilitates the use of neural networks for flow reconstruction.

The final step of the proposed flow reconstruction technique involves training a neural network to map the low-fidelity reduced

Results

The proposed methodology for flow reconstruction of the internal flow and heat transfer on a rocket nozzle using neural network and singular value decomposition was evaluated by comparing the reconstructed results with the CFD simulation results. The performance of the proposed methodology was assessed using two metrics: the mean absolute error (MAE) and the coefficient of determination (R^2). The MAE measures the average magnitude of the errors between the reconstructed and CFD simulation results, while R^2 measures the proportion of the variance in the predictions. The MAE and R^2 were calculated for both fluid and solid flow fields, and the results are presented in Table 2.

Table 2: Mean absolute error and coefficient of determination for surrogate model predictions.

	MAE	$\mathbf{R^2}$
p	698.4111 Pa	0.9999
T	2.7631 K	0.9958

Conclusion and Future Work

In conclusion, although our methodology did not introduce any novel techniques, it proved to be effective in accurately reconstructing the fluid flow in a rocket nozzle using neural network and singular value decomposition. However, we acknowledged that the methodology's performance was limited in reconstructing the heat flux and wall temperature fields. We provided suggestions for improving the methodology and suggested increasing the sample size in the dataset and comparing our model with other surrogate models as future work. Despite these limitations, the proposed methodology has the potential to enhance the design and optimization cycle by offering a more precise understanding of flow and heat transfer while reducing computational cost.

Code Repository

The code utilized and developed for this project can be found in its entirety on the corresponding GitHub repository [@Carvalho_A_Flow_Reconstruction_2023].