Application of Artificial Intelligence in Computational Fluid Dynamics

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Introduction

This paper was written by Bohua Liu, Mengjiao Gou, Xiaomao Sun, and Hengyi Du from Xi'an Shiyou University, Xi'an, Shaanxi 710000, China. Computational fluid dynamics (CFD) is the science of using computers to predict liquid and gas flows based on the governing equations of conservation of mass, momentum, and energy.

The paper's purpose is to discuss how the booming AI development has affected Computational fluid dynamics algorithm and software. It shows CFD applications such as machine learning geometry model parameters, the grid generation technique, the turbulence model calculation, reducing manual intervention, improving the meshing degree, improving the predictive accuracy, and rapid turbulence data visualization analysis. Manual operation is a problem that restricts CFD applications and that is for AI to improve the efficiency of CFD meshes, reduce manual intervention, improve prediction accuracy, and realize quantitative data processing.

0.1 Key Methods and Findings

AI Database

The use of an AI database has benefited geometric parameters a lot with transforming geometric modeling form a manual, iterative process into an intelligent system greatly improving the modeling speed and reducing manpower if a feature parameter or structure size changes. Also, it stores the description of the constraint relationship and geometric structure between geometric bodies.

0.2 object recognition technology

Using this AI technology has been widely used in this aspect to construct the mesh topology of 3D computing watershed, to quickly generate high-quality mesh. Other than common grid generation softwares such as ICEM, Gridgen, and Gambit, this technology has enabled rapid grid generation which solves a huge problem of the key question facing CFD researchers that is "how many days can you shorten the overall design cycle", meeting the needs of a software like this by having simple input, convenient and flexible use, universality, reliability and high efficiency of calculation.

0.3 Neural Networks

How to break through the shortcomings of inaccurate flow field prediction in existing turbulence models, like large eddy simulation (LES), direct numerical simulation (DNS) and other methods, is still a thorny problem in the past one to two decades, which aspired Julia Lin in 2016 to use deep neural networks to build the Reynolds stress term model. Julia Lin realized the modeling based on the Reynolds stress anisotropy tensor of deep neural network and realized the prediction of channel flow through the learning of DNS/LES data, which has very good effect.

0.4 Error Analysis and AI Limitations

While AI has helped us in CFD applications, it still faces limitations particularly in the density of the multiphase flow study, considering it involves many links will have the possibility of errors, from the number of vectors, the sampling points, leakage rate and matrix decomposition method to analyze its influence on reconstruction is analyzed. Limitations as difficulty to establish an accurate mathematical model and boundary conditions of a flow process. Also, there are many turbulence phenomena in engineering practice. The difficulty of turbulence is that in the same flow field, the scale difference of fluid particles is too large, and the turbulence itself is nonlinear behavior, so the numerical simulation of turbulence in existing theories has certain limitations.

0.5 Conclusion

Artificial intelligence has a wide range of applications in computational fluid dynamics, including mesh division, turbulence model computation, geometric parameter modeling, and scientific flow field visualization. Many accomplishments have been made thus far.
The methodology is clear and well-structured showing how AI affected CFD. The paper used an example in a figure, that was quite clear in the paper, to elaborate on its methodologies. The paper shows the usages of AI clearly.

A generalized framework for integrating machine learning into computational fluid dynamics

Introduction

This paper was written by Xuxiang Sun, Wenbo Cao, Xianglin Shan, Yilang Liu, and Weiwei Zhang. presents a framework for integrating CFD with ML, while also embedding ML algorithms into CFD programs, showcasing various coupling algorithms based on this framework, encompassing stability analysis of the ML Reynolds stress model, mutual coupling between ML turbulence model and CFD solver, and online dimension reduction optimization algorithms.
These techniques are to overcome challenges such as computational cost, complexity in turbulence modeling, and accuracy in simulations.

Key Methods and Findings

The framework produced integrates ML models and algorithms to modules into the CFD simulation process, with Python programs invoked by C++ and Fortran codes. Using dynamically linked libraries, efficient and seamless communication between different components of the framework is achieved.

Neural Networks

The framework proposed in this paper overcomes these limitations by enabling the seamless embedding of both neural network and nonneural network models, such as random forests, while maintaining good compatibility with both Fortran and C++ programs. This significantly reduces the complexity of development and maintenance. To our knowledge, this is the first work in the CFD field to fully achieve these characteristics.
The primary computational workflow in the frozen coupling mode involves two data exchanges between ML and CFD: the CFD program transfers data points from grid cell centers to the ML

component for inverse distance interpolation. Subsequently, the ML component transfers optimized eddy viscosity coefficients back to the CFD solver. Afterward, these coefficients remain unchanged in the CFD solver until the completion of the computation.

0.6 Models Used

The framework uses neural network turbulence model trained using PyTorch. The training data for the ML turbulence model are derived from high-precision data obtained through data assimilation. For the purpose of enhancing computational efficiency, the neural network model has been transformed into an ONNX model, which wasn't clearly shown how would it enhance the computational efficiency exactly. The paper then shows clearly what mutual coupling is which is the data exchange between the CFD program and the ML program at each iteration step. This iterative process continues until convergence is achieved. The paper has results showing the pressure coefficient obtained using various turbulence models, showcasing a notable improvement in the computed results with the ML turbulence model compared to the SA model, which highlights the ML supremacy in this approach.
Then the Online Dimension Reduction Optimization (ODRO) method is used, aiming to improve the convergence of the traditional iterative approach for obtaining steady-state solutions of unstable problems by using Proper Orthogonal Decomposition (POD) on CFD snapshots to optimize mode coefficients, reduce residuals in the POD subspace, and iteratively refine the solution until convergence.

0.7 Limitations

While the authors state that their framework can generally for other applications, they do not show why can it be generalized when being faced with irregular complex flow scenarios.
Furthermore, while using ML is the core of the paper and it has great results, it concerns me that this ML reliance could add overhead computation on the model in the training phase which may lead to an efficiency decrease.
Also, using some more practical real-world problems or cases would fortify the impact of the paper.

Conclusion

The paper shows a creative and an adaptable framework that enhances CFD simulations, bringing it as a large contributor to the Computational Fluid Dynamics field. The suggested framework's flexibility and modularity provide a solid basis for future studies in data-driven CFD. Expanding the validation with real-world case studies, resolving computing overheads, and enhancing generalization to extremely complicated flow scenarios could be the main goals of future work. Overall, the paper is clear, well-structured and explains its methodologies well.