First Paper : AI Applications in CFD: Feed-Forward Neural Network for Convergence Prediction

This summary focuses on a recent study that explores the integration of Artificial Intelligence (AI) techniques into Computational Fluid Dynamics (CFD) workflows to enhance simulation efficiency. The paper presents a Feed-Forward Neural Network (FNN) approach combined with OpenFOAM's CFD solver (SimpleFoam) to predict convergence states and accelerate the solution process.

Objective and Motivation

The primary goal of the study is to address the high computational cost associated with CFD simulations, particularly for complex flows. By leveraging AI, the authors aim to reduce the time required to achieve convergence without compromising the accuracy of results. This approach is especially relevant for industrial applications where rapid simulations are crucial.

Methodology

The methodology involves training an FNN to predict key parameters, such as residual norms, at intermediate stages of the simulation. The network is trained using a dataset generated from multiple CFD runs involving different geometries and boundary conditions. Key steps include:

- **Data Collection**: Generation of CFD results using SimpleFoam for training and validation.
- **Neural Network Design**: Development of an FNN architecture with optimized hyperparameters.
- **Integration**: The trained model is integrated into the CFD workflow to predict convergence states dynamically.

Key Findings

The study demonstrates that the AI-enhanced CFD solver achieves significant reductions in computational time while maintaining high accuracy in predicted flow fields. Key results include:

- **Efficiency**: Up to a 10x reduction in time-to-solution.
- **Accuracy**: Over 99% accuracy in velocity and pressure field predictions compared to full CFD simulations.
- **Scalability**: The method is adaptable to various flow configurations and boundary conditions.

Conclusion

The integration of neural networks into CFD represents a significant step forward in reducing computational costs and enhancing efficiency. This study provides a robust framework for applying AI in CFD and opens avenues for further exploration of machine learning techniques in engineering simulations.

Second Paper: Summary of SAU-Net for Closure Modeling in CFD Applications

Introduction

This paper introduces SAU-Net, a specialized neural network architecture, for improving turbulence closure modeling in computational fluid dynamics (CFD). Turbulence modeling, particularly in Reynolds-averaged Navier-Stokes (RANS) equations, presents significant challenges due to the inherent nonlinearity and multiscale behavior of turbulent flows. The study aims to leverage AI techniques, specifically deep learning, to address these challenges effectively.

Methods

The authors propose SAU-Net, a modified U-Net architecture tailored for closure modeling in RANS equations. Key components of the methodology include:

- **Network Design:** The SAU-Net architecture features skip connections and attention mechanisms to capture multiscale features and ensure efficient learning.
- **Loss Functions:** The training process incorporates custom loss functions, including physics-informed constraints, to ensure physical consistency in the predictions.
- **Data Augmentation:** Extensive data augmentation techniques are employed to improve generalization and robustness across different flow scenarios.
- **Training and Validation:** The model is trained on high-fidelity DNS (Direct Numerical Simulation) data and validated across multiple RANS test cases to ensure reliability.

Key Findings

The study demonstrates the effectiveness of SAU-Net in turbulence closure modeling, highlighting the following results:

- The model significantly outperforms traditional turbulence models, including Spalart-Allmaras and k-ϵ, in terms of accuracy and robustness.
- SAU-Net's attention mechanism enables it to adapt to varying flow regimes and capture critical flow structures.
- Cross-domain validation shows the model's capability to generalize to unseen flow configurations.

Conclusion

The SAU-Net architecture represents a significant step forward in the application of AI to CFD. By combining physics-informed design with advanced deep learning techniques, the model provides a robust and generalizable solution for turbulence closure modeling. This work highlights the growing role of AI in enhancing the accuracy and efficiency of CFD simulations.