1 Reference

- Shape optimization of airfoils by machine learning-based surrogate models

This article, in my perspective, has the strong connection with our project. Chapter 6 and Chapter 7 are the most related part with our project. It illustrates the ANN model establish and the optimization process.

Key Point: The thesis focuses on optimizing airfoil shapes using machine learning-based surrogate models integrated with computational fluid dynamics (CFD).

Concept: It explores the use of artificial neural networks (ANNs) to develop surrogate models that link airfoil design parameters to aerodynamic force coefficients, thus facilitating efficient shape optimization.

Main Theme: Integration of machine learning and CFD for airfoil shape optimization.

New Insights & Primary Research Method: Zanichelli provides insights into using ANNs for surrogate model creation, a significant shift from traditional CFD methods, which is the primary research methodology.

Data-Supported Points: Data in the thesis support the effectiveness of surrogate models in accurately and efficiently predicting aerodynamic forces, reducing computational costs and time.

Significant Arguments: The thesis argues for the superiority of machine learning-based surrogate models over conventional CFD simulations in airfoil optimization, highlighting efficiency and accuracy.

Main Conclusion: The conclusion emphasizes the potential of machine learning-based surrogate models in revolutionizing airfoil shape optimization, offering significant computational benefits.

Author's Perspective: Zanichelli views the integration of machine learning with CFD as a transformative approach in aerodynamic design, offering a more efficient alternative to traditional methods.

- Bishop C M. Pattern recognition and machine learning[M]. Springer, 2006.225-311

The 'Neural Network' section in Bishop's "Pattern Recognition and Machine Learning" covers the fundamentals of neural networks, including their architecture and learning algorithms. It delves into feed-forward networks, the backpropagation method for training, and the importance of the Hessian matrix in understanding network dynamics. The section also explores regularization techniques to combat overfitting and introduces Bayesian approaches to neural networks. These concepts are crucial for understanding how neural networks learn and generalize from data.

The 'Neural Network' part describes the theory of neural network in detail and helps a lot for understanding the neural network theory.

- High Reynolds number airfoil turbulence modeling method based on machine learning technique

the development of a turbulence model for turbulent flow around airfoils at high Reynolds numbers using deep neural networks. This model, which is based on data from the Spalart-Allmaras turbulence model, aims to improve the accuracy and stability of airfoil simulations by effectively mapping flow features to eddy viscosity and integrating them with computational fluid dynamics solvers. The article discusses the methodology, feature selection, neural network design, and results of this approach.

- Machine learning methods for turbulence modeling in subsonic flows around airfoils

the application of machine learning techniques to improve turbulence modeling in fluid mechanics, particularly focusing on high Reynolds number turbulent flows around airfoils. The paper explores the use of neural networks to reconstruct a mapping function between turbulent eddy viscosity and mean flow variables, entirely replacing traditional partial differential equation models. This novel approach aims to enhance the accuracy and generalization capability of turbulence models, especially in the context of complex subsonic flow fields around airfoils.

- Machine-Learning-Enabled Foil Design Assistant

Key Point: The article emphasizes the use of supervised ML techniques for real-time prediction and design optimization of foil's aerodynamic/hydrodynamic performance, using a parametric model and geometric moments for enhanced ML training.

Concept Explanation: ML techniques are employed to solve forward (predicting performance from design) and inverse (determining design from desired performance) problems in foil design. A parametric model and geometric moments are key components in this approach, offering a novel way to improve ML model training and effectiveness.

Main Theme: Integration of ML in foil design for efficient prediction and optimization, leveraging parametric models and geometric moments.

New Insights: The study introduces a unique approach combining a high-level parametric model with geometric moments in the context of ML, enhancing the prediction accuracy and training process for foil design.

Primary Research Method: The research primarily involves supervised ML techniques, with a focus on artificial neural networks, for developing predictive models in foil design.

Data-Supported Points: The effectiveness of the proposed ML models, particularly in enhancing prediction accuracy and reducing computational time compared to traditional methods, is supported by the data.

Significant Arguments: The authors argue for the superiority of their ML approach in addressing the complexity of foil design problems, demonstrating improved efficiency and accuracy over traditional methods.

Main Conclusion: The study concludes that the proposed ML method, incorporating a parametric model and geometric moments, significantly enhances the design and optimization process in foil design.

Author's Perspective: The authors advocate for the adoption of advanced ML techniques in foil design, emphasizing their potential to revolutionize traditional approaches in this field.

- Airfoil Analysis and Optimization Using a Petrov–Galerkin Finite Element and Machine Learning

Key Point: It focuses on optimizing airfoil designs using a combination of Petrov–Galerkin finite element methods and machine learning.

Concept: The concept involves integrating machine learning with finite element analysis for efficient and accurate airfoil optimization.

Main Theme: Integration of advanced finite element methods and machine learning for airfoil optimization.

New Insights: The article offers insights into combining computational fluid dynamics with machine learning for airfoil design.

Primary Research Method: Uses a mix of computational methods and machine learning algorithms for optimization.

Data-Supported Points: Data supports the effectiveness of this integrated approach in enhancing airfoil design efficiency.

Significant Arguments: The paper argues for the benefits of combining machine learning with traditional computational methods for airfoil optimization.

Main Conclusion: Concludes that this integrated approach significantly improves airfoil design processes.

Author's Perspective: The author advocates for the synergy of computational methods and machine learning in aerospace design.

- A Reinforcement Learning Approach to Airfoil Shape Optimization

Key Point: It focuses on optimizing airfoil shapes using Deep Reinforcement Learning (DRL), formulated as a Markov Decision Process.

Concept: The concept involves using DRL to iteratively modify airfoil shapes, aiming to optimize specific aerodynamic metrics like lift-to-drag ratio.

Main Theme: Applying DRL for efficient and innovative airfoil shape optimization in aerodynamics.

New Insights: The article offers insights into how DRL can surpass traditional optimization methods in airfoil design.

Primary Research Method: The method involves DRL algorithms interacting with a custom environment for airfoil shape modifications.

Data-Supported Points: The data supports DRL's ability to efficiently explore high-dimensional design spaces and generate optimized airfoil shapes.

Significant Arguments: The authors argue the effectiveness of DRL in handling complex, non-linear optimization problems in airfoil design.

Main Conclusion: The study concludes that DRL is a promising tool for airfoil shape optimization, showing potential for broad applications in aerodynamics.

Author's Perspective: The authors view DRL as a transformative approach in aerodynamics, offering significant improvements over traditional methods.