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AI ENHANCED CFD

MING-JYH CHERN[*], CHING-YAO CHEN[†]
AND JUDY P. YANG[†]

[*] National Taiwan University of Science and Technology
43 Sec. 4 Keelung Road, Taipei 106335, Taiwan
E-mail mjchern@ntust.edu.tw and www.ntust.edu.tw

[†] National Yang Ming Chiao Tung University
300093 1001 Ta Hsueh Road, Hsin Chu 300093, Taiwan
E-mail chingyao@nycu.edu.tw ; jpyang@nycu.edu.tw and www.nycu.edu.tw

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ABSTRACT

In recent years, the integration of artificial intelligence (AI) with computational fluid dynamics (CFD) has revolutionized the field by enhancing simulation accuracy, reducing computational costs, and accelerating design processes. This minisymposium aims to explore the transformative impact of AI on CFD methodologies and applications across various industries, including aerospace, automotive, and biomedical engineering.

AI techniques, particularly machine learning, deep learning, and physics-informed neural networks (PINNs)[1], have shown remarkable potential in improving turbulence modeling, optimizing mesh generation, and predicting complex flow phenomena. PINNs, in particular, leverage the underlying physical laws governing fluid dynamics, allowing for the incorporation of governing equations directly into the learning process.[2] This approach not only enhances the predictive capabilities of CFD models but also ensures that the solutions remain consistent with the fundamental principles of physics.

The symposium will feature presentations that highlight cutting-edge research on AI-driven CFD applications, including advancements in neural network-based solvers, data-driven turbulence closures, and surrogate modeling techniques. Furthermore, we will discuss the challenges and limitations of integrating AI with CFD, such as data scarcity, model interpretability, and the need for robust validation frameworks.

REFERENCES

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