Artificial Intelligence in Computational Mechanics

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Unlocking the Transformative Potential of Artificial Intelligence in Computational Mechanics

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ABSTRACT: Integrating artificial intelligence into computational mechanics represents a transformative paradigm shift in modelling, simulation, analysis, and design methodologies. By harnessing AI's power while ensuring its explainability to the users, we can enhance predictive capabilities, optimize design and performance, accelerate research and development efforts, and empower our engineers to address longstanding challenges. Let us embrace this transformative technology and work together to unlock its full potential in advancing the frontiers of computational mechanics.

KEYWORDS: Artificial intelligence; computational mechanics; explainable AI; optimization; prediction; ethical considerations

1. Introduction

Artificial intelligence (AI) has revolutionized countless fields, and its impact on computational mechanics is no exception. Navigating the complexities of material behaviour, structural analysis, and fluid dynamics, AI presents unparalleled opportunities for refining predictive models, necessitating explainable models, optimizing designs, and accelerating research endeavours [1]. This editorial explores the transformative potential of AI in computational mechanics and advocates for its widespread integration into both research and practice.

2. Enhancing Predictive Capabilities

One of the most compelling aspects of AI in computational mechanics is its ability to enhance predictive capabilities [2, 3]. Traditional modelling approaches, which often rely on simplifications and assumptions, may fall short of capturing the full complexity of real-world phenomena [4]. In contrast, AI excels in identifying patterns and relationships within data [5], allowing for not only more accurate forward predictions of material behaviour, structural responses, and fluid flows [3, 6] but also the resolution of inverse problems to deduce unknown characteristics [7]. In addition, AI-enabled predictive models often achieve processing speeds orders of magnitude faster than those of traditional approaches [8, 9]. By integrating AI-driven techniques with traditional methods, researchers can develop accurate and efficient models on a large scale, thereby leading to more reliable simulations and analyses [10].

3. Necessitating Explainable AI

As we further integrate AI within computational mechanics, the call for explainable AI (XAI) becomes increasingly imperative. While beneficial for handling intricate computations, the complexity of AI-driven models introduces a layer of opacity that can hinder trust and reliability. Comprehending the rationale behind AI predictions is paramount in fields as critical as computational mechanics, where decisions directly impact safety and functionality. For instance, AI algorithms can optimize the design based on safety criteria, such as load capacities and structural stability defined by structural engineers, but without a good understanding of the reasoning behind the AI predictions, engineers might not be able to detect bias and prevent the failure of AI-generated design solution in maintaining safety requirements in practice.

XAI facilitates the inclusion of domain knowledge into physics-informed hybrid models, thereby enhancing transparency, reducing training data requirements, and improving prediction accuracy. XAI emerges not merely as a beneficial addition but as a fundamental necessity for navigating the complexities of modern technology. It ensures the protection of human well-being and propels the advancement of science and engineering [11, 12].

4. Optimizing Design and Performance

The transformative role of AI in enhancing design and performance optimization is increasingly evident. [13]. By leveraging developed algorithms and techniques, such as meta-heuristic optimization [14, 15, 16], XAI [17], reinforcement learning [18], and surrogate modelling [19], AI facilitates the exploration of vast design spaces, identifying solutions that optimize performance while adhering to constraints such as material properties, environmental factors, and cost. This optimization extends beyond mere efficiency, enabling the development of innovative designs that push the boundaries of what is physically and creatively possible. One example of this capacity is the attempt to minimize the structural weight while maintaining the strength [20]. A practical approach for addressing complex problems is to use a hybrid algorithm that combines optimization and machine learning techniques, leveraging the benefits of both methodologies to create a robust framework. Integrating optimization techniques into the machine learning process significantly enhances decision-making capabilities. A hybrid algorithm can leverage these optimization capabilities to guide the learning process and improve decision-making accuracy and efficiency [21]. Furthermore, AI-driven tools can significantly reduce the time and resources required for design iteration cycles, allowing for a more agile and experimental approach to engineering challenges [22].

5. Accelerating Research and Development

Integrating AI into computational mechanics also has the potential to accelerate research and development efforts across a wide range of applications. By automating labour-intensive and repetitive tasks, such as mesh generation [23], model calibration [24, 25], and post-processing analysis [26], AI frees researchers to focus on more creative and intellectually challenging work aspects. Moreover, AI can accelerate computationally demanding techniques such as peridynamics [27, 28]. AI's ability to quickly process and analyze vast datasets enables the discovery of new patterns and relationships that might elude traditional approaches. This acceleration speeds up the research cycle and enhances the quality of outcomes, fostering a faster transition from theoretical models to practical applications. However, automation has several potential limitations or drawbacks, especially in areas like model calibration, where human expertise traditionally plays a significant role. For example, models and calibration processes can vary greatly depending on the application and domain. Automated systems may need help to adapt to this variability or require extensive customization and tuning, reducing the overall efficiency gains. Additionally, human experts are adept at handling unforeseen scenarios or edge cases that may not have been accounted for in the automation process [29].

6. Addressing Challenges and Ethical Considerations

While the potential benefits of integrating AI into computational mechanics are substantial, it is essential to acknowledge and handle the challenges and ethical considerations associated with its adoption. These include issues related to the quality and bias of data [30], as well as the transparency and interpretability of AI models [31]. In response, initiatives such as the Fairness, Accountability, and Transparency (FAT) [32] and AI Fairness 360 [33] have been developed. These frameworks focus on establishing principles, metrics, and algorithms designed to identify and mitigate bias in machine learning data and models, preventing discrimination and ensuring equitable outcomes in AI systems.

Addressing these challenges demands a concerted effort to develop guidelines and standards that ensure the ethical use of AI. Moreover, fostering a multidisciplinary dialogue between engineers, computer scientists, ethicists, and policymakers is crucial for navigating these complexities. By proactively addressing these challenges and integrating fairness, accountability, and transparency principles, we can leverage AI's transformative power whilst minimising risks.

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