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The Rise of AI & ML: A Comprehensive Review of AI and Machine Learning Applications in Mechanical Engineering

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1. ABSTRACT

Emerging artificial intelligence (AI) and machine learning (ML) technologies are generating a paradigm shift in mechanical engineering, resulting in intelligent, data-driven restructuring of established mechanical engineering processes.

In this review, we discuss the various ways that AI and ML have been incorporated across key areas in mechanical engineering, specifically predictive maintenance, design optimization, quality assurance, and renewable energy systems. Intelligent engineering technologies utilize the latest advances such as deep learning, reinforcement learning, and hybrid physics-informed models to enable engineers to achieve new levels of accuracy, productivity, and sustainability.

This review successfully outlines AI's inherent capabilities of flexibility, explainability and scalability allowing it to be utilized in a ramification of mechanical systems, whilst noting a few key challenges remain; computational complexity, data quality, ethical issues, and generalization of model. By sharing recent developments in AI/ML and articulating different pathways for future research, this review serves as a reference point for the research and practitioner community adapting to intelligent mechanical engineering.

2. INTRODUCTION

Mechanical engineering, an essential pillar of technological advancement, is currently experiencing a paradigm shift due to artificial intelligence (AI) and machine learning (ML). Historically rooted in physics-based modeling and empirical design practices, mechanical engineering is starting to use data-driven approaches to make data informed decisions, enhance performance or automate the design of complex tasks.

AI and ML have a myriad of applications related to mechanical engineering; predictive maintenance of machinery, structural health monitoring; optimization of design, quality assurance and energy efficiency in renewable energy systems; to just name a few. Techniques such as deep learning, neural networks, and reinforcement learning enable engineers to identify relationships in large datasets that teach them, predict when failures will occur and aide them in designing systems faster and with higher accuracy. In addition to individual applications, AI also provides broad benefits including sustainability, lower operating costs and faster innovation timelines. With hybrid approaches that combine physics-based simulations and data-driven learning, AI provides robust solutions to the longstanding limitations of traditional approaches. While some advancements do exist, there still remain numerous challenges including interpretability, data quality, model robustness, and ethical application.

The intention of this review is to give a whole picture of what the current situation is in mechanical engineering related to AI and ML. The usefulness of it will be that, in addition to looking at the most important areas where normalized practices have developed, immediately summarizing the methodologies adopted, and collectively identifying the most common challenges, it will help all researchers, engineers and practitioners maximize the use of intelligent technologies to implement future mechanical systems.

3. Key Definitions and Concepts of AI & ML in Mechanical Engineering

3.1 Design Optimization and Simulation Improvement

As MITAOE (n.d.) underlines, design methods and processes are transforming thanks to AI tools which enhance design efforts through real-time simulation, intelligent CAD modelling, and rapid prototyping. Additionally, these AI systems reduce design cycles and enhance product design by valuing prior data on performance metrics and proposing optimized configurations.[1]

Likewise, Neural Concept (2023) highlights that simulation quality directly on CAD geometry can be achieved by using geometric deep learning, reducing computational cost and simulating fidelity of results, leading to faster design to production.[2]

2.2. Predictive Maintenance and Health Monitoring

MITAOE identified predictive maintenance as a core AI domain, which utilizes (typically) machine learning models of various types to interrogate sensor data, to predict when a failure may occur, and re-schedule maintenance accordingly. Predictive maintenance aims to minimize downtime, and maximize the equipment life.[1]

Neural Concept takes this a step further, and demonstrates how machine learning algorithms trained on historical data of mechanical systems can predict actuation fatigue, wear patterns and eventual malfunctioning behavior resulting from their fatigue and wear patterns with near 100% accuracy. Their demonstration with their tool is an example of providing "real time" monitoring and decision support.[2]

2.3. Smart Manufacturing and Process Control

The use of intelligent system decisions is enabled by the use of AI modeled systems. According to MITAOE, smart manufacturing refers to the application of AI in the manufacturing field, to realize automated production flows, as well as automated adjustments based on machine learning data for real-time production, resulting in higher output, lower human intervention, and reduced wastage.[1]

Notably, Neural Concept similarly supports AI in manufacturing, in a different sense, by maximizing mechanical performance of the numerical models or simulations they develop based on the influences of AI, while significantly simplifying the computational task by using machine learning-based model reduction approaches to complex, and high-fidelity simulation approximations. These model reduction approaches are very useful and can be integrated with other approaches to allow real-time operational performance adjustments on the shop floor.[2]

4. Real-World Applications of AI and ML in Mechanical Engineering

4.1. AI-Based Design & Prototyping

AI expedites the design process through algorithms to recommend the optimal shape and material, and ML models, which predict structure performance using simulation data, provide design reliability and creativity across major areas of industry, including automotive and aerospace [4].

4.2. Predictive Maintenance

Machine Learning leverages real-time sensor data to identify wear patterns and operational anomalies. This allows for advanced intervention in manufacturing plants and transportation systems, improving equipment lifespan and reducing downtime [3],[4].

4.3. Simulation and FEA Acceleration

Surrogate ML models and methods are now increasingly being put in place of slow running FEA solvers as part of iterative workflows. AI-based approaches have significantly improved the speed of validation for a design, while maintaining tolerated accuracy [3].

4.4. Robotics and Automation

AI-integrated robots can adaptively work with humans to accomplish complex tasks. They use vision and learning algorithms to recognize objects, track movement and provide safety in factories [4].

4.5. Smart Energy Systems

AI allows the modeling and optimization of thermal and fluid systems, using knowledge of energy usage patterns. Reduction of emissions and improvement of energy efficiency from HVAC to turbine design is made possible by AI, which is critically important and applicable to sustainable mechanical designs [3].

5. Challenges of AI and ML in Mechanical Engineering

Despite the promising applications of Artificial Intelligence (AI) and Machine Learning (ML) in mechanical engineering, several challenges hinder their widespread adoption and effective deployment in practical scenarios.

5.1. Data Availability and Quality

Good quality datasets will always need to be on multiple scales to train robust ML models. Many mechanical engineering systems will struggle to find or generate sufficient data that is structured and clean, thus skimming the potential of an effective ML model with a generalizable model of acceptable accuracy [5]. Collecting labeled data can also be expensive, complex, and time reliant, especially if trying to create data for high-dimensional mechanical behavior.

5.2. Trust and Model Interpretability

ML models, or more generally DL techniques, are inherently "black boxes". This creates challenges in interpreting the decision-making process, especially in systems requiring safety-critical judgement. Engineers need to trust the AI's outputs, which must be explainable and interpretable with verifiable performance before challenging uncertainty limits using AI-aided actions [6].

5.3. Integration with Physics-Based Models

In certain circumstances fully data-driven ML models may be considered, at least in their initial design phase. However, most ML models are not representing true mechanical behavior consistent with the laws of mechanics or thermodynamics. It is unlikely pure data driven ML models will provide this behavior without integrating some form of physics modelling [5]. The integration methods, along with computational costs, may not be trivial, but combining AI modelling with physics-based modelling produces an expected mechanical or physical behavior model.

5.4. Computational Complexity and Resource Demands

Complex AI models, and subsequently dependent on how they are implemented/modelled, will naturally incur layer upon layers of computational demand and resources for training bespoke models. This leaves the question open, can every engineering firm afford the level of computational real estate? Will AI-aided systems ever reach a level of real-time operation? It further leaves an open question; Can AI processes be executed using efficient collective-layered modelling on repeatable scalable models, especially if real-time computations must weigh up speed vs level of accuracy with fast approaches available? [7].

6. Recommendations for Advancing AI and ML in Mechanical Engineering

To effectively address these challenges and harness the potential of AI and ML applications in mechanical engineering, we propose the following recommendations:

6.1. Data quality and availability.

Develop data collection and management protocols, and promote data sharing for academia and industry to develop complete datasets that support AI model development and validation [1],[8].

6.2. Interpretable and trustable AI.

The focus should be on making interpretable AI systems that have accessible reasoning that is transparent to users, to build trust and enhance user acceptance for instance in safety-critical mechanical engineering systems [2], [8].

6.3. Use of AI informed by physics-based models.

We should advocate for hybrid models that take advantage of machine Learning, while following fundamental principles of mechanical engineering so that model outputs remain physically valid and meaningful [3],[8].

6.4. Development of computationally efficient and scalable AI algorithms.

We should develop relatively light AI algorithms and maximally optimize them, and leverage cloud or edge computing to enable real-time inference and integration into engineering workflows [2], [4].

6.5. Invest in the education and collaboration of AI and mechanical engineers.

Support education and training for AI and the promotion of collaborations between AI researchers or practitioners and mechanical engineers to fill skill gaps and facilitate the transition of AI from research to application [3], [8].

7. Conclusion

The application of artificial intelligence (AI) and machine learning (ML) in mechanical engineering indicate a revolutionary change in the way complex engineering problems are solved. They have shown significant benefits in predictive analytics, designing techniques, structural health monitoring, and automated quality assurance, having helped improve operational efficiency, reduce costs, and become more proactive with maintenance decision-making.

This review has identified the importance of hybrid modelling approaches involving physics-based principles and data-driven algorithms for improving model accuracy and generalizability. At the same time, limitations such as lack of high-fidelity datasets, a lack of interpretability, high computational resources, and ethical implications remain challenges to many organizations to employ and use this technology in practice.

Moving forward, research should prioritize the development of explainable AI, efficient algorithm implementations, and effective data management solutions to address the current challenges.

AI and ML have the potential to transform the future of mechanical engineering as well as the profession. If the underlying technologies continue to advance, and the research focuses on addressing current challenges, we are looking forward to a future where more intelligent, adaptive, and sustainable mechanical systems exist that will change the future of engineering design and manufacturing.

REFERENCES

[1] MITAOE. (n.d.). *Impact of Artificial Intelligence in Mechanical Engineering*. MIT Academy of Engineering. Retrieved from https://mitaoe.ac.in/blog/Impact-of-Artificial-Intelligence-in-Mechanical-Engineering.php

[2] Neural Concept. (2023, January 25). *Applications of Machine Learning in Mechanical Engineering*. Neural Concept Blog. Retrieved from https://www.neuralconcept.com/post/applications-of-machine-learning-in-mechanical-engineering

[3] Skill-Lync. (n.d.). *Design Applications of Machine Learning and AI in Mechanical Engineering*. Retrieved from https://skill-lync.com/blogs/technical-blogs/design-applications-of-machine-learning-and-ai-in-mechanical-engineering

[4] CAE Assistant. (n.d.). *AI in Mechanical Engineering*. Retrieved from https://caeassistant.com/blog/ai-in-mechanical-engineering-video/

[5] Carnegie Mellon University. (n.d.). *Machine Learning in Mechanical Engineering*. Retrieved from https://www.meche.engineering.cmu.edu/research/machine-learning.html

[6] Neural Concept. (2023). *Will AI Replace Engineers?* Retrieved from https://www.neuralconcept.com/post/will-ai-replace-engineers

[7] Thriam Technologies. (2022). *Impact of Artificial Intelligence on Mechanical Engineering*. Retrieved from https://thriam.com/impact-of-artificial-intelligence-on-mechanical-engineering

[8] Jain, S., & Arola, D. (2020). *Artificial Intelligence and Machine Learning in Design of Mechanical Materials*. Retrieved from https://www.researchgate.net/publication/347890941_Artificial_Intelligence_and_Machine_Learning_in_Design_of_Mechanical_Materials