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Work in Progress - Beyond LLMs: Introducing AI and ML engineering tools in the curriculum

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Introduction

Artificial Intelligence (AI) and Machine Learning (ML) have rapidly evolved from theoretical concepts to practical tools that are fundamentally transforming engineering disciplines in research and industry. Over the past decade, advancements in computational power, algorithmic sophistication, and data accessibility have enabled AI and ML technologies to address complex engineering challenges, optimize design processes, and accelerate innovation. These tools now play a pivotal role in automating routine tasks, uncovering patterns in large datasets, and guiding decision-making in areas such as circuit design, materials science, and systems engineering [1-3].

The interest in using AI tools in engineering education has spiked in recent years since the release of openAI's ChatGPT tool in 2023 [1]**,** plus other generative Large Language Models (LLMs) which have followed. These tools process language in a way that provides both opportunities and risks for student learning, which is the subject of much ongoing research and publication. For example, just over 10% of the published proceedings of American Society of Engineering Education Annual Meeting in 2025 mention ChatGPT by name - it is a subject of intense interest in the community. Themes around AI and ML such as personalized learning, virtual labs, ethics, and AI integration in the curriculum are just a few that can be found when searching the literature [5-10].

However, the AI tools available to engineers in industry are not just LLMs, they are not even all generative AI. Across various industry sectors, a range of what can be described as 'physical AI' tools, which utilize physical data (such as video or images) or operate within physical systems [11], are becoming available to engineers. These can range from simple tools based on Bayesian optimization methods through to generative tools using deep learning to shortcut traditional time-consuming computational methods and improve automation.

The benefits of integrating a wide variety of AI and ML tools into engineering workflows can be substantial. They can enhance productivity by reducing manual labor, improve accuracy through data-driven insights, and foster creativity by enabling exploration of vast design spaces. As engineering problems grow in complexity, the need for intelligent, adaptive solutions becomes more pressing, making AI and ML indispensable assets for both academia and industry [12, 13], which students will need the ability to apply in their future careers.

In many ways, engineering AI tools can be seen by the engineering education community as an extension of computational methods such as simulation. While it has taken decades for advanced computational methods to be fully embedded in curriculum learning, it is now seen as critical [14] that students understand not only how to practically use numerical simulation tools but also understand their underpinning methods enough to interrogate assumptions and potentially incorrect outputs. ‘Physical’ engineering AI tools should be considered for introduction to students in the same way.

Engineering educators are beginning to appraise how these tools can also be included in curriculum [15, 16], but even a basic introduction to their existence and their complexities is a significant subject to add to existing classes. However, the simplest inclusion is to introduce AI tools into courses which focus on a methodology the tools themselves are implementing.

Physical AI and ML Tools in Engineering Curricula

Given the transformative impact of physical, design-based AI and ML on engineering practice, it is imperative that engineering curricula evolve to include these technologies. Early exposure to AI and ML tools equips students with the skills required to thrive in a modern workforce. Integrating these topics into coursework ensures that graduates are proficient not only in foundational engineering principles but also in leveraging advanced computational techniques to solve real-world problems [17-21].

Curriculum Materials Development from Industry

This need for Physical AI skills is an ideal place for industry-academia collaboration, with industry providing technical knowledge and academics providing pedagogical insights for best integration in existing curriculum.

Synopsys stands at the forefront of AI and ML innovation within the engineering domain. As a leading provider of electronic design automation (EDA) solutions, Synopsys has developed a number of AI-powered tools, leveraging sophisticated algorithms to automate design tasks, optimizing workflows, and assisting engineers in navigating the ever-expanding complexity of modern systems [21-23]. The usage of AI to improve engineering software tools expanded in 2025 when Synopsys acquired Ansys, the leader in engineering simulation software.

Both companies have a longstanding history of working with academic institutions to support the usage of industrial tools in the classroom through the Synopsys Academic and Research Alliance Program and the Ansys Academic Program respectively. The work in this paper highlights various initiatives by both programs to support the inclusion of AI in academia via industrial software usage.

Challenges of Teaching with AI

Before diving into the details of physical AI applications in engineering education, particularly in the Design of Experiments (DoE) space, it is imperative to comment on the challenges of teaching with AI. A common and highly relevant concern for this work is students relying too much on the outcomes of AI tools like the ones mentioned above, without checking for accuracy.

One can look at how simulation software can successfully be integrated across curriculum as an example. For a student to be able to competently run a computational fluid dynamics (CFD) simulation, they must understand the foundational theory and mathematics being used to solve the simulation itself. Properly scaffolding simulation alongside theory can strengthen understanding of both, leading to more experienced engineers upon graduation.

The two different tools and their related resources mentioned in this work endeavor to do the same; supporting coursework that is grounded in the foundations of DoE and allows AI tools to be introduced in a way that reinforces the benefits and limitations of such technology. Emphasis on how to use foundational knowledge to perform critical evaluation of AI results needs to be included.

Importance of Design of Experiments in Engineering Education

A critical component of engineering education is the mastery of systematic design methodologies. DoE courses are focused on introducing students to the methodologies to plan, conduct, and analyze experiments to optimize product and process designs. DoE principles enable engineers to make data-driven decisions, identify key variables, and maximize performance within resource constraints. As engineering challenges grow in scale and complexity, proficiency in experimental design becomes increasingly valuable. Integrating DoE into the curriculum not only enhances technical competence but also cultivates analytical thinking and problem-solving skills essential for innovation.

DoE is an area where AI/ML tools have been deployed for several years in industry, to help reduce the number of either computational or physical tests which need to be run to optimize a design.

Ansys optiSLang software and Synopsys Design Space Optimization AI (DSO.ai) software are both AI/ML tools which have been developed to help engineering with DoE tasks, and which have the potential to be introduced into relevant courses which cover DoE topics, either as an introductory example of industry software, or applied in students' coursework as a core tool.

Teaching Mechanical Engineering with Ansys optiSLang Software

Ansys optiSLang is a software which works alongside Ansys's simulation tool chains, offering process integration and design optimization tools to pair with engineering simulation, facilitating sensitivity analysis, optimization, and robustness evaluation across multidisciplinary engineering problems. As multidisciplinary engineering challenges increase, exposure to the optimization concepts included in tools such as Ansys optiSLang software is invaluable for preparing engineers to tackle complex challenges in areas such as automotive, aerospace, and electronics, where design space exploration is essential for innovation.

The integration of Ansys optiSLang software with other simulation tools which may already be embedded in curriculum, such as Ansys Mechanical, allows easy routes to explore the benefits of deploying its metamodeling and machine learning techniques within the design process. This is ideal in disciplines such as Mechanical Engineering where limited time may be available in the curriculum to address these topics.

Two education resource have been developed to introduce Ansys optiSLang software to students in Mechanical Engineering courses, and these have been made available online. One is a more fundamental case, which highlights machine learning as a technique to further improve on designs without going into much detail, making it appropriate for maybe 2nd or 3rd year, while the second shows fundamentals of DoE sampling and methods, making it more appropriate for 4th year or graduate studies.

The first, more fundamental resource includes Ansys optiSLang software as a small, final optimization step in a design case study focusing mostly on the appropriate material selection and mechanical simulation of a truck suspension arm. In this case study, students are advised simply to use the 'one click' optimization wizard in Ansys optiSLang software once they have completed their initial design stages. This treats Ansys optiSLang software as a black box but demonstrates the use of machine learning algorithms to explore design space and enable optimization. Figure 1 shows the post-processing results of c.700 designs generated and evaluated by Ansys optiSLang software for this problem, allowing students to see the Pareto fronts of results for each of three different material options.

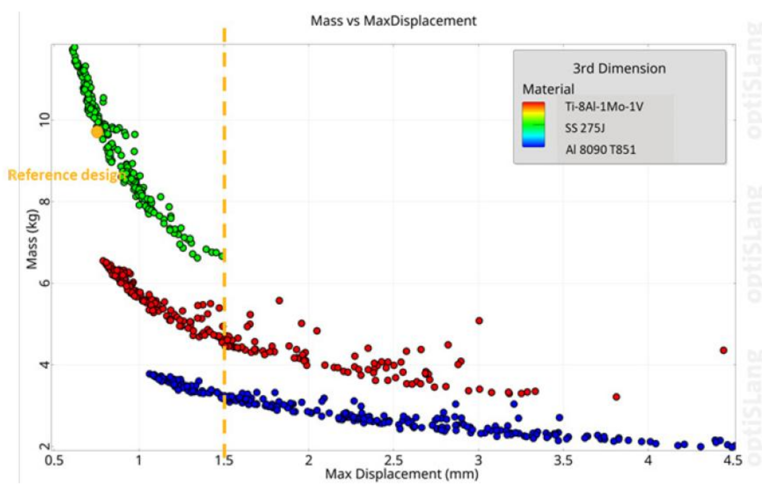

Figure 1: Ansys optiSLang software results from Truck Suspension Arm resource

The second resource would be more appropriate for an in-depth or advanced course, possibly teaching DoE or related concepts. It considers the design of a hook on a crane, starting from an initial existing design and looking to optimize the design to reduce the volume of material needed while still sustaining the design load. This resource leads students through a full design process using Ansys Mechanical and Ansys optiSLang software, and explains the process of DoE sampling, regression methods, sensitivity analysis and metamodels of optimal prognosis used by the software, thus providing real examples of concepts encountered in DoE and related courses.

Figure 2 shows an illustration used in this resource to show the concepts and connections between the different techniques being used.

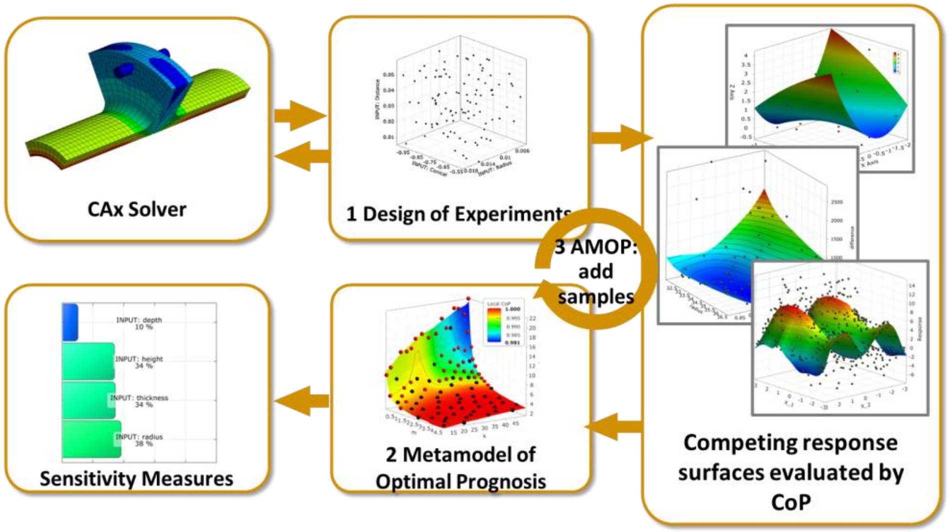

Figure 2: Schematic of Sensitivity Analysis Flow using Ansys optiSLang Software

With these two resources, it is hoped that educators can start to introduce a tool such as Ansys optiSLang software to their existing curriculum, in either a simple or more advanced way, to support student understanding of machine learning algorithms in DoE contexts in Mechanical Engineering and other disciplines.

Teaching Integrated Circuit (IC) Design with Synopsys DSO.ai Software

In the field of IC design, AI and ML tools significantly streamline the development of integrated circuits and electronic systems. By automating time-consuming processes—such as layout generation, error checking, and parameter optimization—these technologies reduce manual intervention and enhance design accuracy. Machine learning models can rapidly analyze vast amounts of circuit data, identify inefficiencies, and suggest improvements, leading to faster prototyping and higher-performing products [1-2, 25-27].

In response to the growing need for advanced design methodologies in engineering education, Synopsys has developed a comprehensive DoE course in partnership with Purdue University. This advanced course, new in the 2025-2026 school year, offers a comprehensive exploration of systematic experimental design methodologies within an engineering context. The curriculum is structured to provide students with foundational knowledge in experimental design, statistical analysis, and advanced optimization techniques. Key topics include the principles of factorial and fractional factorial designs, response surface methodology, robust parameter design, and real-world applications of data-driven decision making. The course further delves into the integration and practical use of AI-driven optimization tools such as Synopsys DSO.ai (Design Space Optimization AI) software, enabling students to efficiently navigate complex design spaces and identify optimal solutions through reinforcement learning and advanced search algorithms.

Synopsys DSO.ai software is an advanced artificial intelligence platform developed to address the increasing complexity of semiconductor and electronic system design. At its core, DSO.ai leverages state-of-the-art machine learning algorithms, including reinforcement learning and advanced search strategies, to autonomously explore vast design spaces and optimize multiple objectives such as power, performance, and area. The tool can evaluate millions of possible design configurations, identifying optimal solutions that would be difficult or time-consuming for human designers to find manually.

In the context of engineering education, Synopsys DSO.ai software provides students with hands-on experience in utilizing AI-driven optimization within real-world design scenarios. By interacting with the tool, learners develop a deep understanding of how AI can be harnessed to address complex engineering challenges, equipping them with valuable skills for the modern workforce.

A distinguishing feature of the course is its emphasis on hands-on laboratory work, where students engage directly with industry-standard platforms and solve genuine engineering problems through a series of interactive exercises and case studies. These labs provide invaluable opportunities to experiment with real data, set up optimization studies, analyze experimental outcomes, and synthesize findings into actionable engineering solutions. This practical component is vital in bridging the gap between theoretical concepts and their implementation, equipping students with critical thinking skills, technical competency, and agility needed to become highly skilled and innovative engineers. This course setup also allows students to compare experimental and AI-generated data, helping build awareness of limitations of AI tools and the vital importance of AI and simulation tool validation. By fostering this experiential learning environment, the course ensures graduates are thoroughly prepared to contribute meaningfully to the advancement of engineering practice in dynamic, real-world settings.

This hands-on approach not only deepens students’ understanding of experimental design but also familiarizes them with the sophisticated tools shaping contemporary engineering workflows. As students progress through the curriculum, they gain practical proficiency in using AI-powered design optimization platforms, positioning them to excel in environments where the ability to navigate complex design spaces is increasingly essential. This educational model underscores the evolving synergy between academia and industry, empowering students to become agile, innovative problem-solvers ready to contribute to the advancement of engineering in diverse sectors.

Limitations and Next Steps

There are some inherent limitations to this work related to collecting feedback on both curriculum materials explained above. The Ansys optiSLang software resources are free to download with no record of who accesses the document, which makes it difficult to carry out robust implementation studies. Authors are currently looking for specific courses to test the materials above for more critical feedback from both instructors and students. In the case of the Purdue course, it has only recently been implemented, and a complete feedback and improvement cycle is underway. We hope to continue sharing the outcomes of these resources and courses after additional review and testing.

Summary

AI and ML are here to stay and it's important that engineering students are familiar with them when entering the workforce and understand the wide variety of applications for these technologies. The growing number of tools utilizing physical AI to optimize systems is increasing, leading to a need for inclusion in engineering curriculum. In this paper, we have introduced two example tools in which educational content has been developed to help support integration of AI in courses focused on Design of Experiments, a common engineering topic. We hope that this work showcases how AI can go beyond ChatGPT and fit into more spaces within the curriculum.

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