Infusing Data Science into Mechanical Engineering Curriculum with Course-Specific Machine Learning Modules

Prof. Yuhao Xu, Prairie View A&M University

Yuhao Xu received a Ph.D. in Mechanical Engineering from Cornell University in 2017. He is currently an Assistant Professor in the Department of Mechanical Engineering at Prairie View A and M University. He was previously employed by ASML-HMI North America Inc., where he worked on the industrial applications of focused ion beams. His current research includes experiments on high-pressure combustion of petroleum-based liquid fuels and bio-derived fuels, digital image processing of experimental data, and studies of microfluidics in energy systems.

Bo Zhao
Prof. Steve Tung, University of Arkansas

Dr. Steve Tung is currently a professor and associate department head at the Department of Mechanical Engineering of the University of Arkansas. He was a postdoctoral fellow at UCLA Mechanical and Aerospace Engineering Department from 1993-1997, and an engineer specialist at Litton Guidance and Control Systems from 1997-1999. He joined the University of Arkansas as an assistant professor in 2000. Dr. Tung's research interest is in the development of micro- and nanofluidic systems for engineering applications. His work has been funded by the National Science Foundation and National Institute of Health. He was named a Fellow of the American Society of Mechanical Engineers (ASME) in 2016.

Prof. Han Hu, University of Arkansas

Han Hu is an Assistant Professor in the Department of Mechanical Engineering at the University of Arkansas. He received his Ph.D. from Drexel University in 2016 and B.S. from the University of Science and Technology of China in 2011. Before he joined the University of Arkansas, he worked at the Cooling Technologies Research Center at Purdue University as a postdoc on two-phase electronics cooling. His current research is focused on the development of experimental and numerical tools to address research and development needs in the thermal management of IT and power electronics. The specific areas include single-phase and two-phase cooling with textured surfaces, remote sensing using acoustic emissions and optical imaging, and data-driven modeling of transport processes and multimodal data fusion. His research is supported by federal and state agencies including NSF, NASA, AEDC, and ASGC as well as industrial companies including Google and Safe Foods.

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Yuhao Xu [1], Bo Zhao [2], Steve Tung [3], and Han Hu [3]

[1]*Department of Mechanical Engineering, Prairie View A&M University, Prairie View, TX 77446*
[2]*Department of Mechanical Engineering, University of Houston, Houston, TX 77204*
[3]*Department of Mechanical Engineering, University of Arkansas, Fayetteville, AR 72701*

Abstract

Recent advances in data science algorithms and libraries have impacted approaches and strategies for research and development in the industrial sector, which necessitates the integration of data science into engineering education. Data science courses offered by programs such as mathematics, computer science, and data science in academic institutions normally lack the implementation in solving engineering problems. To fill this gap, we have developed a project-based technical elective course "Machine Learning for Mechanical Engineers" and offered it to undergraduate and graduate students at the University of Arkansas. While this course is received very well by the students and has led to fruitful presentations and publications, it has a low enrollment volume from undergraduate students due to its relatively high programming requirements. A more sophisticated strategy is required to equip mechanical engineering students with data science skills without disturbing the existing curriculum. Inspired by the success of computer-aided design education at the University of Arkansas and the Data Science InFusion into Undergraduate STEM Education (DIFUSE) program at Dartmouth College, we have developed course-specific machine learning modules to be integrated into mechanical engineering core courses rather than dedicated data science courses. This effort includes a nonparametric regression module for Computer Methods in Mechanical Engineering, a generative design module for Computer-Aided Design, and a genetic algorithms module for Thermal Systems Analysis and Design, among others. Through this practice, students will practice programming and machine learning skills every semester from their sophomore year and will be ready for the project-based technical elective machine learning course.

Introduction

Data science has made a significant impact on engineering research in recent years, owing to its capability of processing large volumes of data and extracting valuable physical insights. Various machine learning tools have been widely used to investigate fluid mechanics [1], [2], materials design [3]–[5], convection [6], conduction [7], and two-phase heat transfer [8], dendrite growth in electrochemical systems [9], parameter estimation of unmanned aerial vehicles [10], among others. Many data science courses have been offered on various online platforms, including Coursera, Udemy, edX, YouTube, etc. For example, the data science courses by Andrew Ng, a computer science and machine learning pioneer, and videos by Steve Brunton, a mechanical engineering professor and mathematician, offer both engineers and the general public a convenient way to pick up machine learning skills.

In higher education, to accommodate the ever-increasing needs for engineers with machine learning skills, data science courses have been developed and offered by many college programs, e.g., computer science, applied mathematics, and dedicated data science programs. Recently, more machine learning courses have been developed by engineering departments, with a specific target of fusing machine learning concepts and skills into solving engineering problems. Kiefer discussed the benefits of introducing machine learning in the early stage of engineering education [11]. Muqri et al. discussed machine learning education using Python, Octave, and MATLAB [12]. Zhang reported a one-credit-hour machine learning course taught using Excel [13]. Chalacheva reported on the development of an introductory course on artificial intelligence and machine learning in biomedical engineering [14]. The authors have developed a technical elective course *Machine Learning for Mechanical Engineers* and offered it to both undergraduate and graduate students twice, in Fall 2021 and Fall 2022 [15]. This course has led to promising achievements: i) Based on students' feedback, most of them believe that they have learned the skills they expected before enrolling in the class; ii) This course has helped many students identify the value of machine learning in various research areas through course projects and has led to fruitful presentations and publications [16]–[19].

Nevertheless, this course has shown several critical drawbacks and limitations: i) The undergraduate enrollment in this course is very low. Some undergraduate students withdraw from the course after the first few weeks due to the high programming requirements and difficult concepts of data science algorithms. For example, in Fall 2021, 10 undergraduate students enrolled in this course in the beginning but 3 of them ended up dropping the course. ii) The quality of the course projects of undergraduate students is much lower than that of graduate students in general. Based on students' feedback, this is mostly because a) the undergraduate students have limited research experience and b) some of the undergraduate students need to spend lots of time and effort getting familiar with programming. What's worse, the situation isn't getting better in Fall 2022 compared to Fall 2021 despite the efforts being made to design simpler projects for the undergraduate class and provide pseudo codes to the class. A more sophisticated strategy is required to equip mechanical engineering students with data science skills without disturbing the existing curriculum.

Inspired by the success of computer-aided design education at the University of Arkansas and the Data Science InFusion into Undergraduate STEM Education (DIFUSE) program at Dartmouth College, we have developed course-specific machine learning modules to be integrated into mechanical engineering core courses on computer methods, heat transfer, machine element design, and thermal system analysis and design, among others. These modules will be implemented as extra-credit assignments or optional project topics in the beginning and be used to replace some of the existing assignments in these courses based on the feedback from students and instructors. Through this practice, students will practice programming and machine learning skills every semester from their sophomore year and will be ready for the project-based technical elective machine learning course. The course modules are developed for basic mechanical engineering topics and can be adapted to the mechanical engineering program at many different universities.

Foundations of the Current Approach

i) Computer-aided design (CAD) in the Bachelor of Science in Mechanical Engineering (BSME) program at the University of Arkansas. Based on our experience of working with our undergraduate students and feedback from industrial employers, UA students have solid CAD skills. During advising sessions, many students (from GPA 2.6 to 3.9) also confirmed that they were very confident with their CAD skills and found CAD among the most important skills during their internships. This strength relates to the CAD involvement in every semester's course since the initial introduction. As shown in **Fig. 1**, CAD is initially offered to undergraduate students in the 3rd semester (labeled in yellow circle). Starting from the 4th semester, many courses will have homework assignments or projects that require CAD, including courses involving CAD for manufacturing such as Introduction to Machine Analysis, Mechanics of Fluids, Machine Element Design, Lab III, Capstone Project II (labeled in blue circles), and computer-aided engineering (CAE) courses such as Vibrations, Lab II, and Capstone Project I (labeled in yellow circles). These courses will make the students keep practicing their CAD skills and eventually become proficient in CAD. On the contrary, after general-purpose programming is first introduced in the 4th semester using MATLAB (Computer Methods in Mechanical Engineering, labeled in red circle), it won't be needed by most subsequent courses. It is not required until students enroll in technical electives that require such skills. As a result, many Mechanical Engineering (MEEG) undergraduate students cannot write programming codes efficiently. This comparison makes it clear that if we want students to become proficient in certain skills, such skills need to be repeatedly required in MEEG courses. As such, developing and incorporating data science course modules into MEEG core courses can be a more effective way of infusing data science into the MEEG curriculum than offering standalone machine learning courses.

ii) DIFUSE Faculty Workshop by Dartmouth College. This workshop is supported by an NSF project titled "Infusing Data Science into Undergraduate STEM Education (NSF grant No. 1917002). We participated in the DIFUSE Faculty Workshop and are currently collaborating with the DALI lab at Dartmouth College to develop a data science module for Thermodynamics. DIFUSE invites faculty from different STEM disciplines to work with them to develop data science course modules, including psychology, statistics, geography, engineering, etc. So far, many data science course modules have been developed to teach data science in introductory STEM courses and posted online (https://www.difuse.dartmouth.edu/modules). Nonetheless, these course modules are spread too thin across different disciplines. While the DIFUSE program has demonstrated the need for data science in many STEM fields, it won't lead to the in-depth integration of data science into any specific program. The ongoing collaboration with the DALI lab is focused on the development of an interactive web tool to make abstract thermodynamic concepts more tangible and will have a strong synergy with the course modules discussed in the present paper.

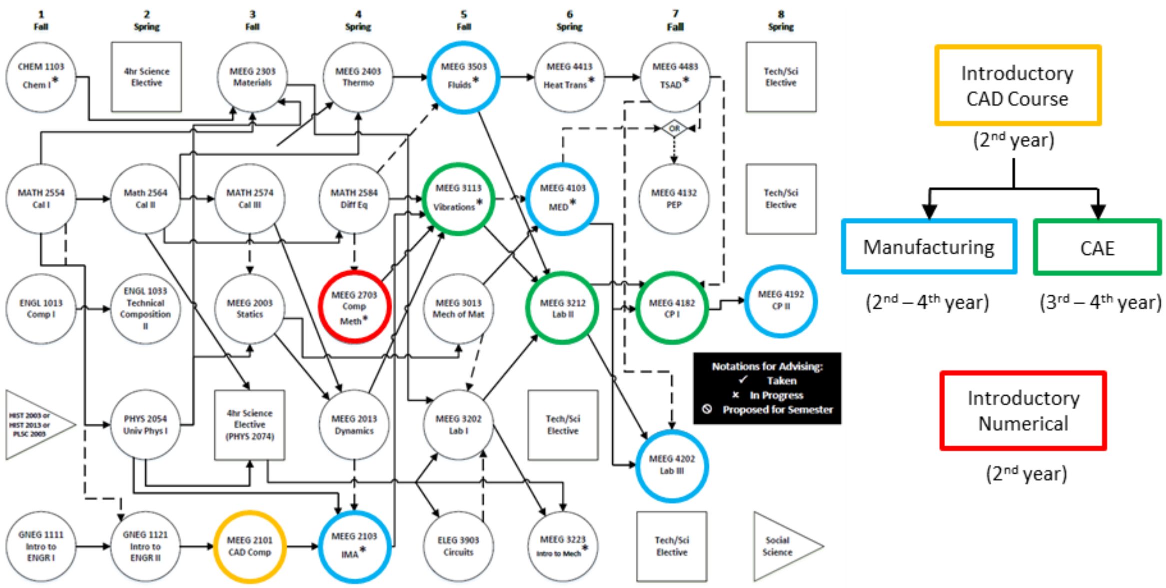

Fig. 1 Computer-aided design education in the Mechanical Engineering Program at the University of Arkansas. The flow chart is adapted from MEEG website .

Insights from Technical Elective Machine Learning Course

The *Machine Learning for Mechanical Engineers* course has yielded helpful insights into the development of data science modules, particularly related to barriers due to programming languages and the effectiveness of using machine learning skills in projects. **Fig. 2** summarizes the enrollment statistics of the machine learning course during the past two years. While this course is offered as a combined section technical elective to both undergraduate and graduate students, graduate students with some research experience dominate the enrollment. Enrolled undergraduate students only have research experiences or ongoing research projects, e.g., Honors thesis, Honors College Research Grant project, undergraduate research project, etc. While this course was initially developed for mechanical engineers, the machine learning skills and concepts covered can also be useful for other departments. As such, we have students from industrial engineering, biological and agricultural engineering, and electrical engineering enrolled in this course.

	Undergraduate	Graduate
Fall 2021	28%	72%
Fall 2022	33%	66%

	MEEG	Non-MEEG
Fall 2021	96%	4%
Fall 2022	83%	17%

Fig. 2 Student enrollment statistics of the Machine Learning for Mechanical Engineers course in Fall 2021 and Fall 2022.

Fig. 3 summarizes the statistics of students' responses to survey questions related to their familiarity with general programming in Python and MATLAB before the *Machine Learning for Mechanical Engineers* course was offered. A total of 53 undergraduate students at the senior level and 18 graduate students in the MEEG Department at the University of Arkansas participated in the surveys. The survey results reveal that the majority of the graduate students are familiar with MATLAB and most undergraduate students have some experience with MATLAB. This can be mainly owed to two factors: i) MATLAB has been used by many students for research; and ii) a core MEEG core at the sophomore level, MEEG 2703 Computer Methods in Mechanical Engineering teaches MATLAB. While most undergraduate students are unfamiliar with Python, there is a major split between not familiar at all and very familiar among graduate students. Some of the graduate students working on coding and numerical simulations may have been using Python extensively, while others may not be motivated to learn a new programming language when they're already proficient in MATLAB. Based on these observations, the *Machine Learning for Mechanical Engineers* course was offered in both MATLAB and Python. The class assignments were designed to be solvable using both machine learning packages of MATLAB and Python.

During the course, it was observed that some students tended to use the programming language that they were already familiar with, while MATLAB users decided to learn Python as an additional programming language. After the course was concluded each semester, a post-course survey was performed to understand students' difficulties with programming languages. **Fig. 4** summarizes the statistics of students' responses to the necessity of requiring a MATLAB or Python programming course as a prerequisite of the machine learning course. The results reveal that most students got challenges related to programming, and Python users encountered more serious problems. These observations suggest that programming languages have led to a major challenge for students to learn and practice machine learning skills. An earlier integration of machine learning into the engineering curriculum, e.g., when students first learn to write computer codes, may be helpful.

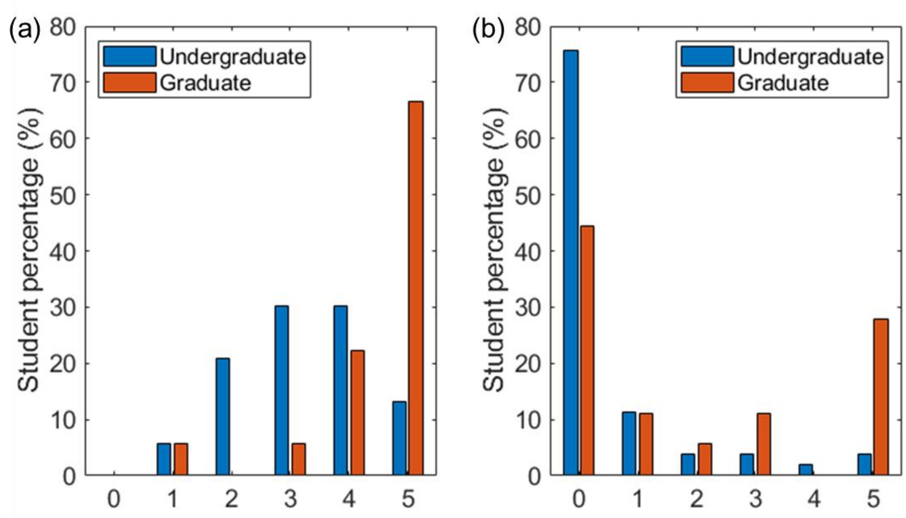

Fig. 3 Student response to post-course surveys on familiarity with programming using (a) MATLAB and (b) Python. The scale from 0 – 5 represents not familiar at all to very familiar.

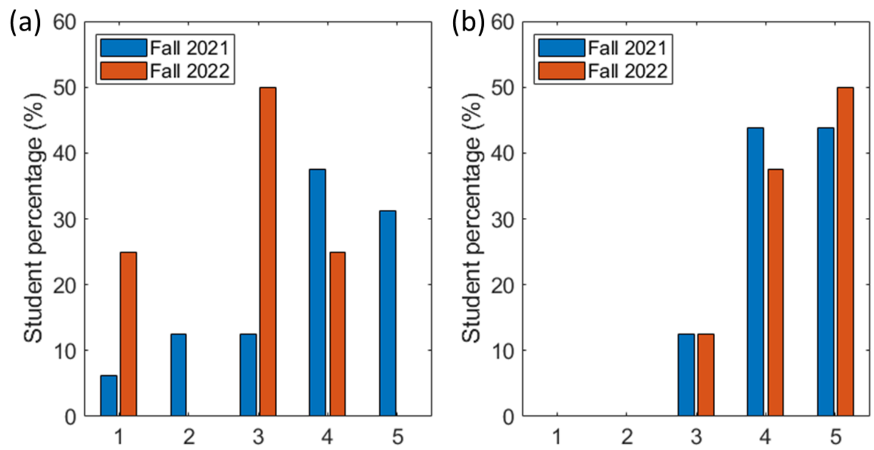

Fig. 4 Student response to post-course surveys on adding (a) MATLAB and (b) Python programming courses as a prerequisite for this course from the Fall 2021 class and Fall 2022 class. The scale of 1, 2, 3, 4, and 5 represents "strongly disagree," "disagree," "neutral," "agree," and "strongly agree," respectively.

The post-course surveys also include questions about students' assessment of their level of understanding of machine learning skills after taking this class. As shown in **Fig. 5**, most students are confident that they have a good knowledge of the machine learning skills covered in this class (**Fig. 5a**) and believe that practice through homework assignments is critical to their understanding (**Fig. 5b**). Most students evaluate their familiarity with supercomputing to be mediocre, which is a required component for graduate students and optional for undergraduate students in this course. It might be wise to remove supercomputing from the current course so that students can focus on learning and practicing machine learning.

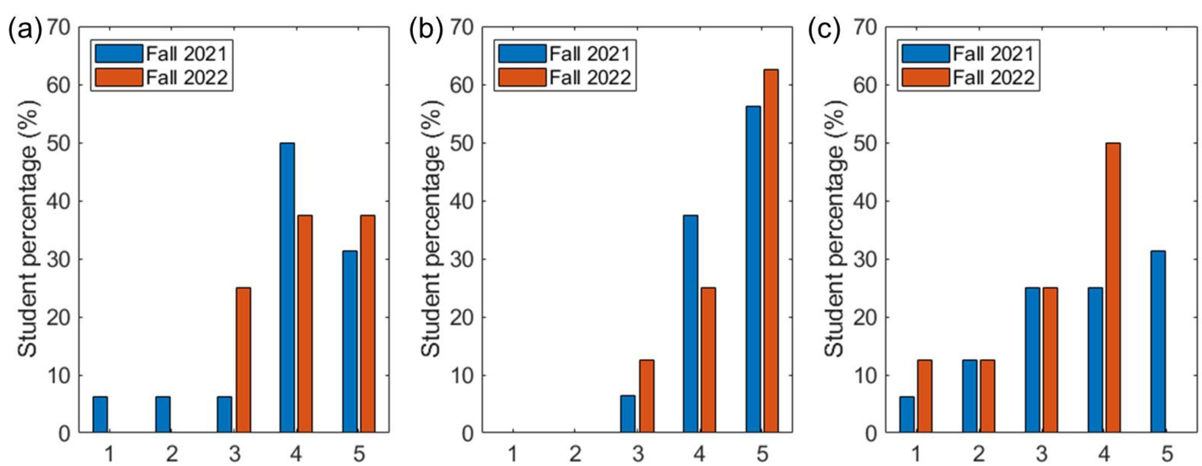

Fig. 5 Student response to post-course surveys from the Fall 2021 class and Fall 2022 class. The scale of 1, 2, 3, 4, and 5 represents "strongly disagree," "disagree," "neutral," "agree," and "strongly agree," respectively. The questions are (a) I have learned how to use the machine learning tools covered in the lecture and homework assignments (PCA, CNN, RNN, MLP, etc. and feel comfortable using them as numerical tools when dealing with big data in my future career or study. (b) Practice through homework assignments is critical to my understanding of

the machine learning tools covered in the lecture. (c) I am comfortable with using supercomputing clusters if they are made available to me in my future job and study.

Course Module Development Plan

Based on the inspiration from CAD education at the University of Arkansas and the DIFUSE program at Dartmouth College, we will develop data science course modules that can be incorporated into existing MEEG core courses. Students will learn and practice a bit of data science in each course and gradually become familiar and comfortable with solving engineering problems using data science algorithms (**Fig. 6**). This paper will discuss three data science modules that will be integrated into existing MEEG core courses, including i) nonparametric regression for MEEG 2703 Computer Methods in Mechanical Engineering, ii) generative designs for MEEG 4103. Machine Element Design and iii) genetic algorithms for MEEG 4483 Thermal Systems Analysis and Design. The developed modules will include source codes with embedded tutorials and instructions using MATLAB live script and Jupyter Notebook (for the Python version). The modules will introduce built-in MATLAB commands/examples and available Python packages for machine learning and deep learning to reduce the challenges in coding. The developed course modules will be made available to the public using open-source repositories on GitHub and File Exchange.

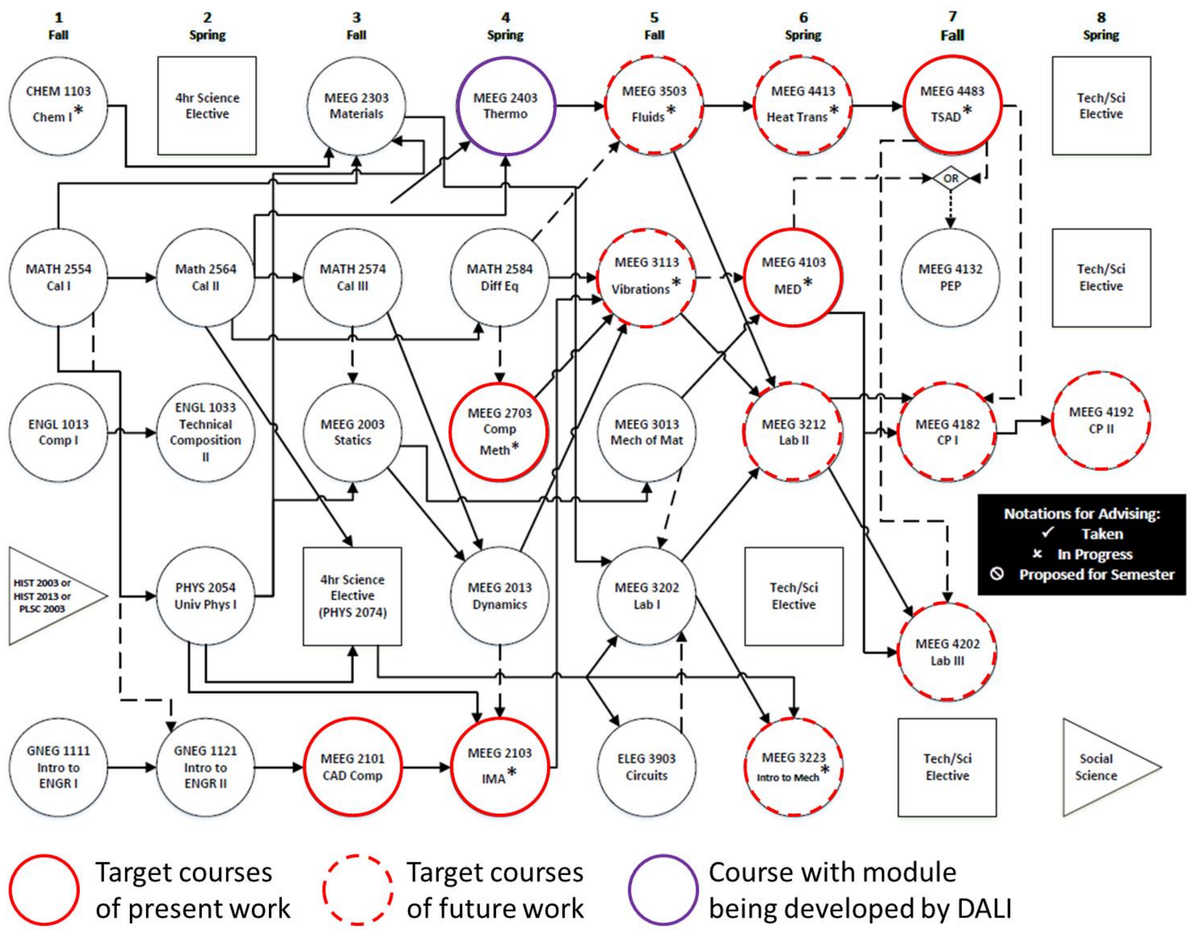

Fig. 6 Plan for data science course module development and infusion into the BSME curriculum at the University of Arkansas.

Module 1: Nonparametric Regression for Computer Methods

Regression is a statistical approach that has been extensively used in engineering research projects. Current engineering education has mainly focused on linear regression or other parametric models that assume specific functional forms for the relationship between the dependent and independent variables. Nevertheless, nonparametric models that allow for higher flexibility and generalizability of the relationships are more robust for handling complex and nonlinear relationships against outliers. This module will be implemented as an assignment in the Computer Methods course to compare multiplayer perceptron (MLP) neural networks and Gaussian processes regression (GPR) for regression analysis of acoustic-thermal signals [20], [21]. **Fig. 7** shows a representative example of comparing MLP and GPR for heat flux predictions using acoustic signals during pool boiling. Regression of acoustic signals is very challenging due to the stochasticity of the noises and high-frequency features of the signals. Both models are trained on the spectral data of the acoustic signals and the corresponding heat fluxes. Multilayer perceptron (MLP) is a type of neural network that is composed of multiple layers of interconnected neurons. The MLP model used in **Fig. 7a** includes 5 hidden layers with Rectified Linear Unit (ReLU) activation function. MLP is a parametric model since the functional forms are pre-set. GPR is a Bayesian-based non-parametric regression method, which defines a probability distribution over possible functions describing the data. The main advantage of GPR is that it allows for estimating uncertainties of predictions, making it a powerful tool for regression analysis of noisy data or data with experimental uncertainties. As shown in **Fig. 7**, GPR performs much better than MLP for acoustic-based heat flux predictions, owing to its advantage in handling data with large fluctuations and uncertainties.

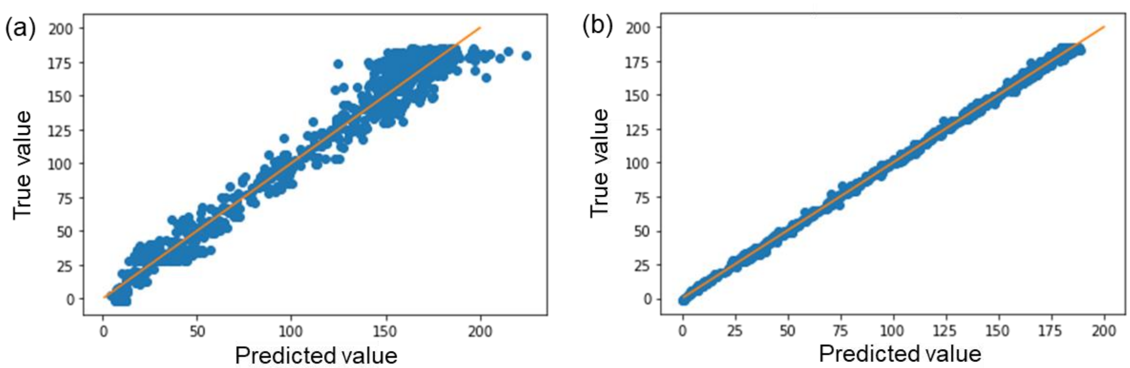

Fig. 7 Representative comparison between parametric and nonparametric regression showing model-predicted value versus true values using (a) MLP and (b) GPR for acoustic-based heat flux predictions.

Module 2: Generative Designs for Machine Element Design

This module presents an assignment for students to use generative designs to optimize the topologies of target devices and characterize their performance. The workflow is described below. First, students will need to create CAD drawings using software such as SolidWorks. They will then import these drawings to generative design and modeling software, e.g., nTopology, to generate multiple topologies that promise improved performance. In this step, students will explore different options for generating new designs and optimizing topologies.

Fig. 8 shows a case study for generative designs of air-cooled heat sinks using nTopology [19]. Next, the design files from nTopology will be exported to numerical simulation packages, e.g., COMSOL or ANSYS, to perform numerical simulations of the generated designs and identify the optimal design. Limited by course hours, this module will only require generative designs and numerical characterization. Interested students can further explore this direction under the supervision of faculty by manufacturing the identified optimal designs in the machine shop or 3D printer lab, and performing experimental characterization of the manufactured devices. This module will have a strong synergy with the existing MEEG courses such as MEEG 2101 Computer-aided Design, MEEG 4103 Machine Element Design, and MEEG 5263 Introduction to Micro Electro Mechanical Systems which teaches COMSOL simulations. This module will also benefit from our work on promoting undergraduate education in CAM and CNC machining [22].

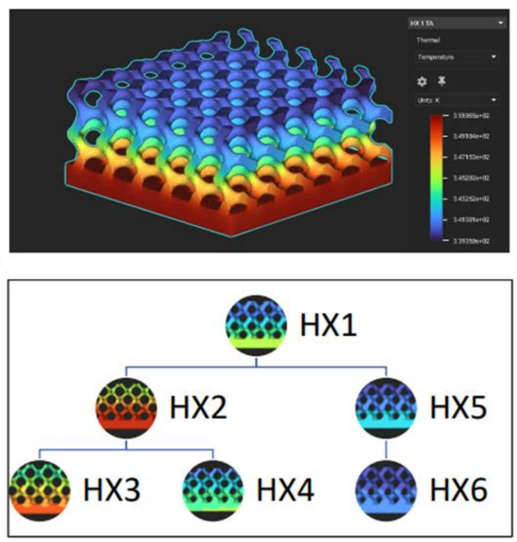

Fig. 8 Generative designs of compact lightweight air-cooled heat sinks using nTopology [13].

Module 3: Genetic Algorithms for Thermal Systems Analysis and Design

This module implements genetic algorithms (GA) to optimize the design of heat exchangers. Compared to exhaust search and more commonly-used gradient-descent optimization, GA requires a much shorter computational time and avoids being trapped by local minima, and is thus a very promising approach for high-degree-of-freedom system design (**Fig. 9a & b**). This module will provide necessary materials and guidelines for interested instructors to incorporate the module into a heat transfer-related course in the Mechanical Engineering curriculum in place of an existing problem/project or as an extra-credit problem/project, including but not limited to Heat Transfer, Thermal System Analysis and Design, Convective Heat Transfer. **Fig. 9c** shows an example of using a GA-based search process for the design optimization of square micropillar arrays for pool boiling critical heat flux (CHF) enhancement. This optimization problem involves three design parameters, including the diameter, pitch, and spacing of the pillar arrays, and uses the coupled wicking and evaporation model for CHF calculation [23]. The education objective of this course module is to help the students: i) understand and be able to implement the GA algorithm in MATLAB or/and Python; ii) comprehend the pros and cons of physics-based and data-driven approaches for design optimization; and iii) practice programming skills from constructing the flow chart, and pseudo code, to final code development, debugging, and testing.

The learning objectives will be accomplished via the following specific tasks, including i) identifying a representative heat exchanger design problem by surveying instructors at the University of Arkansas and other institutions; ii) Survey undergraduate and graduate students at different levels on their understanding of algorithms for design optimization and heat exchanger performance; iii) Design course module content including problem statement, lecture notes, and implementation plan; iv) Develop and test source codes; v) Present course module to instructors via email and conference presentation and request feedback. This course module will be developed based on our research experience in heat exchanger design and education experience in the course module development [22], particularly, the technical elective course *Machine Learning for Mechanical Engineers* at the University of Arkansas [15], [17]–[19].

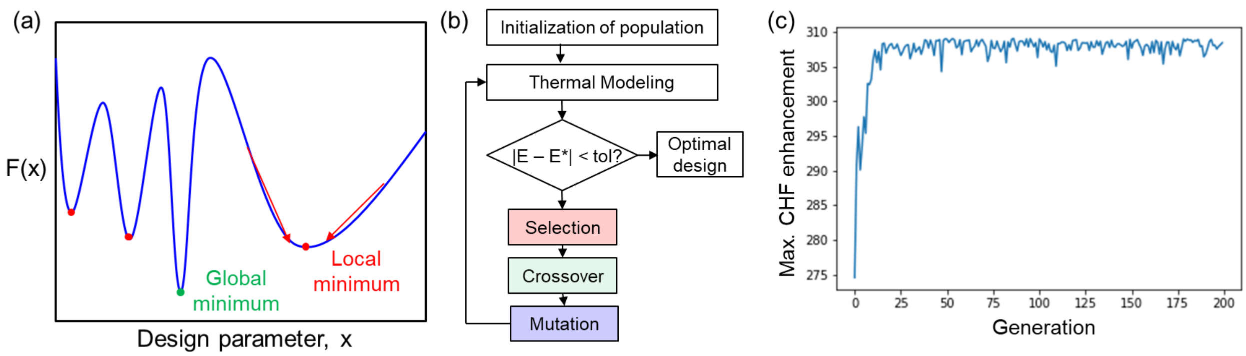

Fig. 9 (a) Local and global minima during optimization. (b) a simplified flow chart for GA. (c) Variation of the critical heat flux enhancement with each iteration of the GA-based search process for optimal micropillar array design.

Conclusions

This paper discusses the plan to develop and implement data science modules into existing core courses of the mechanical engineering program. Technical elective machine learning courses in engineering programs have been demonstrated to be very promising and effective in training students with data science skills to solve engineering problems. Nevertheless, their impact is limited by the prerequisites and close ties to research projects. The three data science modules discussed in the present paper, including global optimization, nonparametric regression, and generative designs, will be integrated as extra-credit/optional assignments to existing mechanical engineering courses. These modules will lower the technical difficulties of learning machine learning skills for undergraduate engineering students.

Acknowledgments

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References

[1] S. L. Brunton, B. R. Noack, and P. Koumoutsakos, “Machine Learning for Fluid Mechanics,” *Annu Rev Fluid Mech*, vol. 52, pp. 477–508, 2020, doi: 10.1146/annurev-fluid-010719-060214.

[2] G. Novati, H. L. de Laroussilhe, and P. Koumoutsakos, “Automating turbulence modelling by multi-agent reinforcement learning,” *Nat Mach Intell*, vol. 3, no. 1, pp. 87–96, 2021, doi: 10.1038/s42256-020-00272-0.

[3] P. Roy Chowdhury, C. Reynolds, A. Garrett, T. Feng, S. P. Adiga, and X. Ruan, “Machine learning maximized Anderson localization of phonons in aperiodic superlattices,” *Nano Energy*, vol. 69, no. October 2019, p. 104428, 2020, doi: 10.1016/j.nanoen.2019.104428.

[4] Y. Yao *et al.*, “High-entropy nanoparticles : Synthesis-structure-,” *Science (1979)*, vol. 000, no. 0000, p. 3103, 2022, doi: 10.1126/science.abn3103.

[5] C. Hu, Y. Zuo, C. Chen, S. Ping Ong, and J. Luo, “Genetic algorithm-guided deep learning of grain boundary diagrams: Addressing the challenge of five degrees of freedom,” *Materials Today*, vol. 38, no. September, pp. 49–57, 2020, doi: 10.1016/j.mattod.2020.03.004.

[6] H. Babaee, P. Perdikaris, C. Chryssostomidis, and G. E. Karniadakis, “Multi-fidelity modelling of mixed convection based on experimental correlations and numerical simulations,” *J Fluid Mech*, vol. 809, pp. 895–917, 2016, doi: 10.1017/jfm.2016.718.

[7] J. Wang and N. Zabaras, “A Bayesian inference approach to the inverse heat conduction problem,” vol. 47, pp. 3927–3941, 2004, doi: 10.1016/j.ijheatmasstransfer.2004.02.028.

[8] L. Zhou, D. Garg, Y. Qiu, S. M. Kim, I. Mudawar, and C. R. Kharangate, “Machine learning algorithms to predict flow condensation heat transfer coefficient in mini/micro-channel utilizing universal data,” *Int J Heat Mass Transf*, vol. 162, p. 120351, 2020, doi: 10.1016/j.ijheatmasstransfer.2020.120351.

[9] R. Kumar, T. Dhara, H. Hu, and M. Chakraborty, “Visualization-Based Prediction of Dendritic Copper Growth in Electrochemical Cells using Convolutional Long Short-Term Memory,” *Energy and AI*, vol. 10, p. 10023, 2022.

[10] A. E. Fernandez, F. Programs, H. Transfer, and F. Mechanics, “UAV Parameter Estimation Through Machine Learning,” in *ASEE 2021 Gulf-Southwest Annual Conference*, 2021. doi: 10.33423/jsis.v16i3.4447.

[11] S. F. Kiefer, “Machining Experience in a Freshman Mechanical Engineering Class,” *ASEE Annual Conference and Exposition, Conference Proceedings*, 2022.

[12] M. Muqri, Z. Muqri, and S. Muqri, “Leveraging the power of Python, Octave and Matlab for Machine Learning,” in *ASEE Annual Conference and Exposition, Conference Proceedings*, 2022. [Online]. Available: www.slayte.com

[13] Y. Zhang, “Teach machine learning with excel,” *ASEE Annual Conference and Exposition, Conference Proceedings*, vol. 2020-June, 2020, doi: 10.18260/1-2--35268.

[14] P. Chalacheva, “Work-in-Progress: Development of an Introductory Machine Learning Course in Biomedical Engineering,” in *ASEE Annual Conference and Exposition, Conference Proceedings*, 2022.

[15] H. Hu and C. Heo, “Integration of Data Science into Thermal-Fluids Engineering Education,” in *Proceedings of the ASME 2022 International Mechanical Engineering Congress and Exposition*, 2022, IMECE2022-88193.

[16] C. Dunlap, J. Pummill, and H. Hu, “Infusing High-Performance Computing and Machine Learning in Mechanical Engineering Education,” in *2022 ASEE Midwest Section Conference*, 2022.

[17] C. Dunlap, H. Pandey, and H. Hu, “Supervised and Unsupervised Learning Models for Detection of Critical Heat Flux during Pool Boiling,” in *Proceedings of the ASME 2022 Heat Transfer Summer Conference*, 2022, HT2022-85582.

[18] H. Pandey, W. Waldo, and H. Hu, “Non-Intrusive Cooling System Fault Detection and Diagnostics Using Acoustic Emission,” in *Proceedings of the ASME 2022 Heat Transfer Summer Conference*, 2022, HT2022-85429

[19] C. Miller, “Generative Designs of Lightweight Air-Cooled Heat Exchangers,” University of Arkansas, Honors Thesis, 2022.

[20] C. Dunlap, H. Pandey, J. Marsh, E. Weems, and H. Hu, “Remote thermal measurements with regression of acoustic emissions,” in *Proceedings of the ASME 2023 Heat Transfer Summer Conference*, 2023, pp. HT2023-106939.

[21] C. Dunlap, H. Pandey, E. Weems, and H. Hu, “Nonintrusive Heat Flux Quantification Using Acoustic Emissions During Pool Boiling,” SSRN 4313756, 2022.

[22] S. Pierson, J. Goss, and H. Hu, “Enhancing Undergraduate Mechanical Engineering Education with CAM and CNC Machining,” in *ASEE Midwest Section Conference 2022*, 2022.

[23] H. Hu, J. A. Weibel, and S. v. Garimella, “A coupled wicking and evaporation model for prediction of pool boiling critical heat flux on structured surfaces,” *Int J Heat Mass Transf*, vol. 136, pp. 373–382, 2019, doi: 10.1016/j.ijheatmasstransfer.2019.03.005.