This is a preprint draft. The published article can be found at: https://doi.org/10.1061/(ASCE)EI.2643-9115.0000065

Please cite this paper as:

Naser M.Z. (2022). "A Faculty's Perspective on Infusing Artificial Intelligence into Civil Engineering Education". *ASCE Journal of Civil Engineering Education*. https://doi.org/10.1061/(ASCE)EI.2643-9115.0000065.

A Faculty's Perspective on Infusing Artificial Intelligence into Civil Engineering Education

M.Z. Naser, PhD, PE
School of Civil and Environmental Engineering & Earth Sciences, Clemson University, Clemson, SC 29634, USA
AI Research Institute for Science and Engineering (AIRISE), Clemson University, Clemson, SC 29634, USA
E-mail: mznaser@clemson.edu, Website: www.mznaser.com

Introduction

The past few years have witnessed the rise of an era that establishes Artificial Intelligence (AI) as a new frontier within the civil engineering domain. A closer look into tremors arising from our academia and industry infer a general interest in AI; however, this interest is faced with a series of serious questions: Is academia or the civil engineering industry interested in graduates and engineers fluent with AI? If so, then when can we start to adopt AI *formally*? And, how can we infuse AI into existing dense curricula? While this forum paper does not claim to have all the complete answers to these questions, I hope that this forum paper sheds some light on the above, as seen from the lens of a junior faculty member at an R1 university in the USA. Perhaps some of the outlined experiences, proposed solutions, and thoughts accumulated while developing an AI-based course for civil engineers can come in handy for those who can relate to the theme of this work.

A good start to this forum paper is to define AI. On a fundamental level, AI is a *technology that enables machines to execute tasks commonly undertaken by humans*. In this technology, machines are programmed to examine data streams to 1) discover new information and/or 2) perform routine operations. From a civil engineering perspective, AI can enable civil engineers to uncover new knowledge hidden in our systems (i.e., in the form of new theories, or finding patterns that may help establish hypotheses, etc.) and/or perform computationally-structured or heuristic processes (e.g., design beams, identify commuter patterns, etc.). A key point to remember is that while civil engineers often develop automated spreadsheets, such spreadsheets are built to follow existing codal provisions or established/prior engineering judgment. On the other hand, automation via AI is not bound by the availability of existing codal procedures. Instead, AI mostly follows a data-driven holistic perspective to realize automation of routine operations. In some instances, AI can be augmented with causal features to identify cause-effect to recognize new knowledge within civil engineering problems.

Building on the works of Dunn and Carbo (1981), Felder and Silverman (1988), and Harevy et al. (2010), engineers are more likely to be *active learners* who are experimentalists in nature and thus value cause-and-effect demonstrations. As such, our domain of civil engineering contains libraries of systematically established methods of rational nature. Such methods were meticulously developed to favor methodical consistency. For example, designing structural elements, water pipeline systems, or transportation networks are exercises that require knowledge of how to apply first principles utilizing mathematical formulations of agreed-upon procedures adopted in civil engineering codes and manuals of practice.

Such a procedure entails a set of formulae or the use of neatly tabulated charts to realize a proper design/plan. If the selected design satisfies a pre-defined set of performance metrics, then the procedure ends successfully, and this particular design moves into the next stage of implementation; if not, a new iteration is undertaken to refine the initial design. The above procedure is regularly taught as part of undergraduate and graduate civil engineering courses in universities worldwide. Our students carry this knowledge with them and get to apply it in real scenarios during their tenures.

Naturally, adopting first principles implies the need for transparent methods that: 1) describe the logic that governs a phenomenon, 2) are preferably compact and easy to use, and 3) can be verified via laboratory testing (Cox et al. 2011; Sacks and Barak 2010; Shaeiwitz 1996). For example, Eq. 1 is a formula that ties a steel beam's moment capacity (M, or simply *resistance*) to *bending actions*. This formula is primarily governed by the geometric features of such a beam (specifically, the plastic section modulus, Z), together with the yield strength (f_y) of the grade of the structural steel used to fabricate the same beam:

$$M = Z \times f_y \quad (1)$$

Having such a formula goes a long way as it articulates the relationship between the aforenoted parameters and states the *causality* of an increase in either Z and/or f_y is also expected to increase the cross-sectional capacity (or *resistance*). In addition, such a formula allows a student/engineer to "see" the main parameters governing the sectional capacity of a steel beam (i.e., *resistance* equals the multiplication of plastic section modulus, Z, and the yield strength, f_y). A student/engineer can look at Eq. 1 and understands that the relationship between the right-hand side of this equation is 1) functional, 2) in multiplication format, and 3) an increase in one parameter (or, both) will lead to an increase in the resistance.

Simply put, bigger steel beams have larger resistance than smaller beams (when the beams are made from the same steel grade), and so on. In a way, Eq. 1 offers a *visual* representation and confirmation that displays *logical synergy* between the governing parameters and a sense of *trust* between faculty and students, and by extension between engineers and codal provisions. It is equally important to note that Eq. 1 can be easily verified against physical tests (further strengthening the aforementioned visualization and trust notions).

Similarly, one can also extend the above thought to more complex phenomena (say, the progressive collapse of a burning high-rise building, or the development of new construction materials with self-healing properties, or planning mass evacuation due to natural disasters). Unfortunately, at the time of this write-up, we do not have explicit nor elegant formulae to describe the aforenoted phenomena.

On a more positive note, one can explore a variety of parameters that govern the collapse susceptibility of a structure to fire by means of advanced models (i.e., finite element (FE) simulation since testing could be infeasible) (Ryu et al. 2021). Similarly, and while we do not have easy-to-use formulae to discover new construction materials, we can still leverage material simulations to arrive at material derivatives with unique properties. Likewise, we can also build agent-based models to simulate mass evacuations given various disasters scenarios to arrive at proper evacuation routes. In a way, numerical models have the capability to extend commonly adopted mathematical formulae to complex phenomena and to visually present answers to such phenomena – thereby implicitly retaining our dear first principles and the notion of transparent methods.

By now, the reader might have realized that the above discussion emphasizes two big ideas of our educational philosophy, which can be summed by: 1) *adherence to first principles*, 2) and *favoritism of transparent methods* to visualize solutions (i.e., cause and effect, etc.). The following sections show that these two big ideas are elemental to developing an AI-themed civil engineering course.

The Era of AI

Artificial intelligence (AI), and by extension its subfields, machine learning (ML) and deep learning (DL), encompasses a realm of possibilities that enables machines to perform tasks of various degrees of complexities (Russell and Norvig 2010). As such, embracing AI-based methods allows us to improve engineers' quality of work and open the door for innovative solutions that were not possible before (Tao et al. 2018).

While advancements in AI are rapidly rising, the civil engineering domain approaches such advances with hesitation and at a slow pace. This inertia is as natural as it is understandable since, logistically speaking, it is hard to change the essence of a major domain overnight – let alone within a few years. Historically speaking, innovation trends can be represented via the *S-curve* developed by Foster (1987) – see Fig. 1. This figure shows the relational stagnation and technical limits of traditional methods (dashed *S-curve*) and the *innovation*, *growth*, and *maturity* levels of new technologies (solid *S-curve*). Foster (1987) infers that it is only when modern technologies provide attractive and affordable solutions to ongoing challenges faced by their traditional counterparts that they become widely accepted and adopted. At this moment in time, AI methods are transitioning from the *innovation* phase to the *growth* phase (but remain below the level of conventional methods).

Noting the rise of AI and the steady interest reported via monitoring publication trends in this domain (see Fig. 2), one can infer that AI is expected to find a permanent residence within a typical engineering curriculum soon. Future years are anticipated to further expedite the growth of AI methods and hence the merit of planting the seeds for a foundation for AI education in engineering from now. In fact, there already exists some initiatives that integrate various forms of AI in civil engineering practices by leading firms (Hearns 2019; Hiriyur 2020; Keck and Wood 2021), as well as leading civil engineering societies (ASCE 2020; Naser and Mueller 2021).

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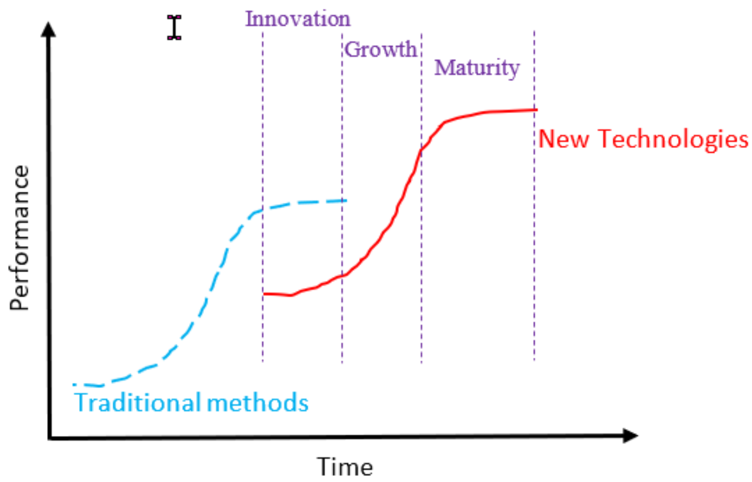


Fig. 1 Illustration of Foster's *S-curve*

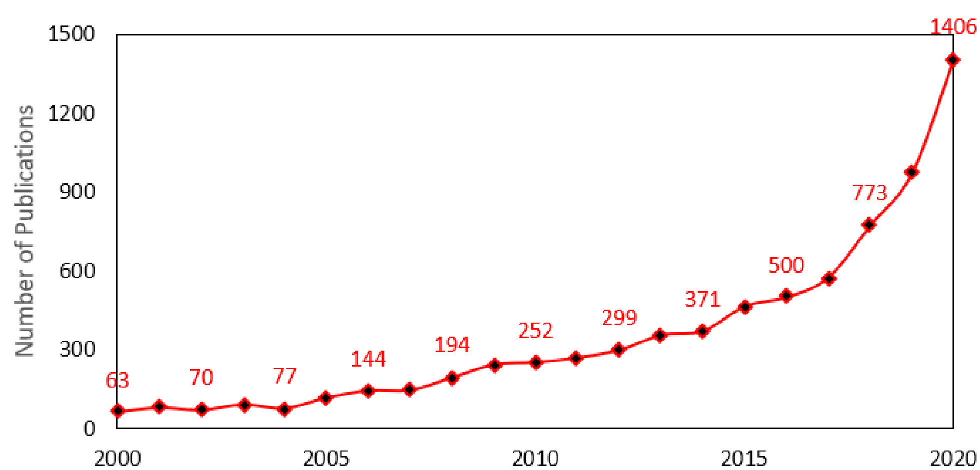
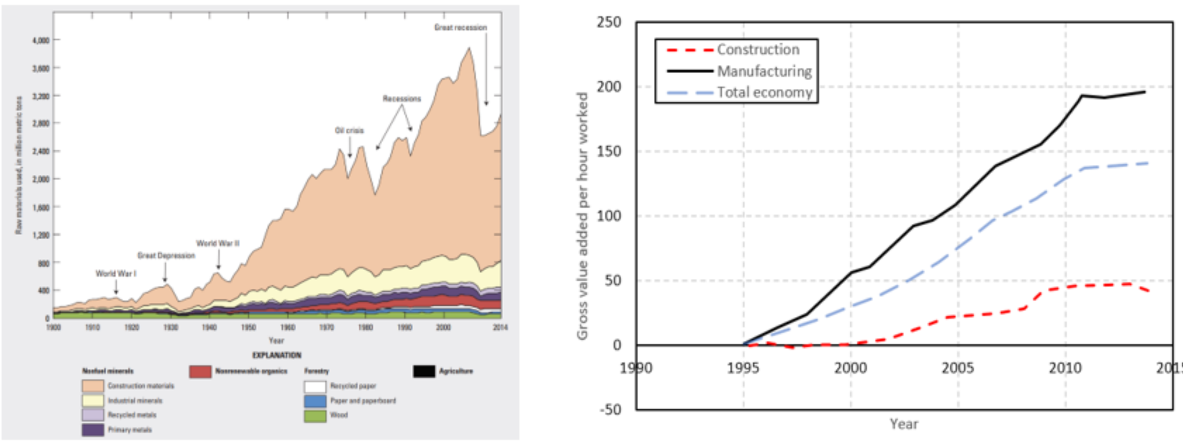


Fig. 2 Publications noting AI methods in structural engineering (2000-2020) [arrived at by searching "artificial intelligence" and "structural engineering" using the Dimensions scholarly database (Dimensions 2021)]

In lieu of the more theoretical illustration shown in Figs. 1 and 2, Fig. 3 shows the tonnage of used construction materials between 1900-2014 as compiled by the U.S. Department of the Interior (Matos 2017). As one can see, our industry rises above all in terms of consumption. Yet, it plummets when compared in terms of labor productivity, as evident against the manufacturing sector or overall economy (McKinsey 2021). The above implies that we have a very active domain that also happens to have poor productivity. One path to improving our productivity is to embrace means that allow us to better our productivity. Such a mean can be attained by embracing AI to automate routine tasks, thereby increasing our productivity and allowing us to focus on other fronts with high demand for work-hours.



(a) Tonnage used (from (Matos 2017)) (b) Labor productivity (McKinsey & Company) (McKinsey 2021)

Fig. 3 Further insights into the performance of the construction industry

A Faculty's Role in Shaping Civil Engineering Education

It is my perspective that faculty members can help shape the trajectory of their students. Traditionally, this can be attained by offering suitable courses that nicely mesh with students' needs, industry standards, as well as curriculum and accreditation requirements.

A fundamental question then arises, what are the learning objectives for a civil engineering course on AI? While a thorough answer to this question may require a series of society-wide discussions to arrive at an accepted norm for common ground, I believe that the objectives of such a course can be grouped under three components; 1) introduce the principles of AI and contrast these principles to that of the traditional methods often adopted in our domain (scientific method, statistical and empirical analysis), 2) present case studies that highlight the potential of AI and pinpoint the high merit space of where AI can be most impactful to civil engineers, and 3) provide a platform of our students to practice, collaborate, develop and create AI solutions for our problems.

We also need to appreciate that, and just like other methods of investigation, AI may not apply to all of our problems. Thus, for the most part, I do not suppose that the majority of our engineers are expected to become AI programmers – just like the fact that many are not experts of finite element (FE) modeling. I do, however, believe that the majority of our engineers are expected to be familiar with AI as well as applying AI – in parallel to their familiarity with setting up experiments, statistical methods, and FE modeling. Building on the rise of big and small data research, and success stories of AI implementation in parallel engineering fields that often grow in line with civil engineering (i.e., mechanical and aerospace engineering, etc.), it is my belief that an introductory and dedicated course on AI for senior undergraduates/early graduate students will come in handy for future generations of civil engineers.

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From a practical perspective, adding a new and permanent course or a series of advanced/specialized courses to an already dense engineering curriculum can be challenging. However, if such a course is to be an elective course, then it would ease the burden on students and curriculum committees. In all cases, one must be cognizant of the fact that using AI methods is *likely* to require students, and faculty, to learn *some degree* of coding or computer programming. Since coding is not a commonly offered course in a civil engineering curriculum, then difficulties might arise in the nature of a proposed elective course on AI. Given the limited duration of a typical course (~ 16 weeks), it could be demanding to develop a complete course that covers both the technical aspects of AI and the application side of this technology.

While the above focuses on *teaching AI by programming*, new initiatives now provide *coding-free* AI platforms with friendly interfaces that allow users to simply *apply* AI without the need to hassle with programming (i.e., *Scikit*, *R* software). Such initiatives are driven by the desire to *teach AI by application* as a means for inclusive learning. In such initiatives, a user can use a platform to apply AI to its full potential without coding as the graphical interface provides such a user with visual options to operate and manipulate data and algorithms. Such an interface can be thought of as a finite element (FE) package where the user does not code a FE model or solve associated matrices but instead builds a FE model via a graphical interface. The aforenoted initiatives bring new opportunities to widen the inclusive application of AI and possibly smoothen the integration of AI into our curriculum. However, learning how to navigate an AI software without an emphasis on AI's principles may not be an optimal teaching practice. Hence, the following solutions and ideas can be of merit.

We could offer "*bits & pieces*" of AI in existing courses. For example, courses with heavy software or analytical components can prove an attractive destination for such an effort. *Statistical methods* or *Numerical methods* is a common junior/senior course that introduces students to various numerical techniques, including optimization. The integration of AI methods into numerical-based courses can be perceived as organic and complimentary. Similarly, courses of similar nature to numerical methods can be designed to contain "*bits & pieces*" in a harmonizing manner. For example, in a given department, the number of courses offered in conjunction and/or in parallel are often known beforehand. In fact, there exist pre-defined cycles of courses that apply to elective and graduate courses (i.e., course CEXXXX is offered every third semester and so on). As such, an overall plan for delivering "*bits & pieces*" about AI in such courses could be designed wherein students are introduced to AI concepts throughout their education. This plan can take into account the expertise of associated faculty members wherein faculty with strong programming backgrounds can lead the *teaching AI by programming,* and those with application backgrounds can lead the *teaching AI by application* components of a well-designed plan.

Given the above, interested students will be exposed to a more consistent knowledge of AI across multiple courses within the same semester or throughout parallel semesters. In this particular example, a series of courses at the sophomore, junior, and senior levels could include chapters/modules on basic AI programming or the application of AI platforms to solve common problems.

The following comes to mind; students enrolled in a *statics* course can be encouraged to verify hand calculations of equilibrium problems using small programming scripts (simple or pre-built algorithms). This exercise is then re-introduced at a *mechanics* course to arrive at internal stresses within a body. Then, courses on this track (say, *theory of structures* and *structural design*) can build on students' experiences to apply basic AI algorithms to help solve stability problems or optimize structural components. In those higher-level undergraduate courses, which often include a class project, students can be provided the option to develop an AI model to accompany the classical means of addressing their projects (say, to develop an AI model via an AI platform that selects the lightest and most economical standard steel section to satisfy a set of loading conditions vs. attempting to solve the same problem via the iterative and commonly used procedure often introduced to students). Finally, a cornerstone project could potentially include a structured component on AI (i.e., through basic programming or direct application) and perhaps compare a human-led design to that of an AI-leveraged design. In all cases, faculty could opt to motivate their students by awarding bonus points or honors options to encourage the use of AI.

Exercises for elective courses and those of hybrid nature (i.e., offered for senior undergraduate transitioning to graduate school and early graduate students) can be the form of case studies that parallel AI-themed educational material aimed at sparking the interest of undergraduate and/or complementing research projects/theses of graduate students. For example, a faculty member can task undergraduate students to develop an AI model to predict the sectional capacity of a beam and task graduate students to develop an advanced AI model to predict the stress/strain distribution of the same beam at failure. Results from both groups can then be compared against a laboratory test (or FE simulation) of an identical beam. An exercise of this magnitude is perhaps feasible to conduct on at each course offering, and if appropriately designed, may be able to mesh all three aspects of investigations, namely; physical testing, FE simulation, and AI modeling, to our students. The above methodology could be extended to other disciplines of civil engineering.

For graduate students, exercises that tie classical and first principles in solving a particular problem to that using AI methods can be helpful to justify the use of AI. At this level, AI can be thought of as a method to guide engineering intuition to discover new knowledge or form new hypotheses. For instance, a graduate student can develop a *physics-informed model* (e.g., an AI model that is constrained to satisfy first principles) or a *causal model* (e.g., an AI model that examines the cause-and-effect of a phenomenon occurs as opposed to trying to associate the occurrence of the phenomenon from a data-driven perspective) to solve research questions pertaining to the student's thesis/project. Some of the problems that could be of interest may include creating AI models to monitor structural cracking, the safety of workers in sites, surveying, traffic detours in the wake of an accident, etc.

In lieu of the above and capitalizing on the fact that AI does not require heavy laboratory facilities such as those often needed in civil engineering departments, but rather requires handheld computational workstations and open-source packages (i.e., *Python*, *R*) reduces the logistical and monetary resources necessary for practicing AI. As such, summer courses, extra curriculum activities, Massive Open Online Courses (MOOCs), and in-semester seminars can also be intelligently used to introduce civil engineering students to the concepts and principles of AI.

Such efforts can be further supplemented by certificates or participant awards. A point system that spans 2-3 summers might come as attractive to students, especially if the certificate can be associated with a prominent society (i.e., American Society of Civil Engineers, etc.), or a domain authority (e.g., The Computing Community Consortium), or student honor organizations (Chi Epsilon, etc.). A close working relationship between engineering departments (i.e., civil engineering and computer science) can help facilitate such certifications and plan for events that mesh and converge civil engineering and computing students via competitions. This exercise can help engage students and seekers of continued education from cross disciplines and can also be viewed as an excellent team-building workout.

Now and Tomorrow

Oftentimes, and whenever a new technology is introduced, such technology is faced with reluctance and challenges. Thus, the successful integration of AI into civil engineering education should answer the existing challenges that may hinder (i.e., Does our community see merit in AI? Does this merit warrant addition to our curriculum? Does the industry see value in civil engineers with AI expertise? Etc.), or slow its adoption (e.g., How to navigate departmental visions? How to balance faculty research interest? What can we do to smoothen accreditation requirements? Etc.). Additional challenges may include, but are not limited to, a lack of transparency in AI algorithms (i.e., the notion of blackboxes which conflicts with engineering training described earlier) and trust (as in we value and favor methods that enable engineers to understand the rationale behind AI predictions as a mean to be trustworthy and accountable).

Ongoing research efforts are trending in the right direction to answer many of the noted questions. For example, AI-based start-ups in civil engineering are rising. Such start-ups, if not founded by civil engineers, will require and will involve civil engineers graduates. In addition, a look into the academic realm showcases major research funding shifts towards creating AI solutions for civil engineering problems. This may shed some light on the future importance of AI in our domain. Similar efforts are being targeted at refining AI to make it more descriptive, transparent, and explainable, which are key components to ensure that AI meshes with our educational philosophy (Dosilovic et al. 2018; Feng et al. 2021; Naser 2021a; b; Rudin 2019; Zaker and Flint 2021).

Other challenges may also arise on other *practical* fronts. For example, faculty are tempted to follow codal provisions when preparing courses (i.e., ACI 318 is a prime source of inspiration to faculty and students interested in concrete structural design, the Highway Capacity Manual is often referred to in transportation lectures, OSHA's Construction Industry Regulations is a primary resource for construction and safety practices, etc.). Yet, we lack such a guiding document for AI. Do we teach AI as an *application* or as a *fundamental science*? How can we approach these fronts? What types of AI should be prioritized (supervised learning vs. unsupervised learning)? On the one hand, these are burning questions that may not be answered soon. Yet, we may not truly need them to be fully answered before introducing AI to our domain.

It is of utmost importance to establish guiding principles and to learn objectives and outcomes for how AI can be integrated into the civil engineering domain that fulfills accreditation requirements. While standardization may sound familiar to civil engineers given the large number of

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standardization committees involved in the development of codal provisions etc., this effort, which requires years of development, may come in handy in the years to come and once research on this front stabilizes. A more needed effort is to develop guidance documents on best practices supplemented with examples and case studies. Recent efforts are currently underway, and we hope to see them succeed in the coming years (Jarrahi 2018).

A clear line of communication should be established between academia and our industry to identify where AI is best suited for our needs. Once this line is identified, future courses/education efforts (continued education) can be tailored. Efficiency is an inherent characteristic to engineers, and perhaps it is of merit that in some scenarios, engineers need to learn how to apply AI, as opposed to developing new AI tools. While developing civil engineering-specific tools sounds intriguing, the general population of engineers may not need to be proficient in AI development, as much as in understanding the basics of AI and how AI can be deployed in their domain (Borah et al. 2019).

This forum paper invites interested individuals to showcase other solutions further and share expertise and experiences on its theme. A collective and convergent effort from various backgrounds will be appealing and can start spinning the wheel in the right direction towards integrating AI themes in civil engineering education.

Data Availability

No data, models, or code were generated or used during the study.

Acknowledgment

I would like to thank the Editors and Reviewers for their support of this work and constructive comments that enhanced the quality of this manuscript.

Conflict of Interest

The author declares no conflict of interest.

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