EDUCATING DESIGNERS FOR GENERATIVE ENGINEERING (EDGE)

"Generative design is a departure from the way that we have traditionally done design. But these technologies are not a threat, they are more like superpowers." — Jeff Kowalski, Senior Vice President, Autodesk Inc.

RATIONALE

Engineering design is commonly viewed as a complex process in which designers systematically generate, evaluate, and realize concepts for devices, systems, or processes whose forms and functions meet specified criteria while satisfying certain constraints. As the number of design problems to solve in the real world is infinite, it is important to teach students a set of fundamental principles for tackling various problems that they may encounter in the workplace. Underlying these universal principles is design thinking, a central topic in engineering research and education that has been studied extensively (e.g., Brown & Wyatt, 2010; Buchanan, 1992; Carroll et al., 2010; Dinar et al., 2015; Dorst, 2011; Dym et al., 2005; Johansson-Sköldberg, Woodilla, & Çetinkaya, 2013; Micheli et al., 2018; Razzouk & Shute, 2012; Stewart, 2011). The definition of design thinking may vary from discipline to discipline to some extent. According to Dym et al. (2005), design thinking in the context of engineering education refers primarily to the ability to iterate through the divergent-convergent questioning loop to make design decisions while thinking about systems and working in a team, which can be practically acquired through project-based learning.

The research on design thinking aims to understand how expert designers think in order to develop new methods and tools for supporting their work more effectively (Dinar et al., 2015), with an education goal to establish good models of design thinking for students to follow. But design thinking is a moving target that advances with engineering technology. The ongoing evolution of design methods and tools that change how people perceive and conceive design concepts mandates the update of design thinking to catch up with the innovation trends. The past three decades have witnessed the wide adoption and deep fusion of computer-aided design (CAD), computer-aided manufacturing (CAM), and computer-aided engineering (CAE) tools that have changed the way engineers create and test their designs. With the crucial roles that computers play in engineering, the rapid growth of computational power that is available to engineers, and the surging ocean of data that makes hardware and software smarter by the day, we have arrived at the dawn of a new industrial revolution propelled by the engine of artificial intelligence (AI). Generative design, an unprecedented development in engineering design driven by AI, represents one of the foremost human-technology frontiers that promises to revolutionize engineering and reshape the world (Lant, 2017).

Generative design is a transformative genre of design technology inspired by biological evolution. Once the design criteria and constraints of a product are specified, a generative design software program starts an evolutionary computation process that efficiently explores the entire parameter space supported by the software to find optimal solutions. During the iterative search for feasible solutions, the software automatically constructs a vast number of forms at each step, tests their functions using numerical simulations, evaluates their quality based on the given criteria and constraints, and then selects those that are closer to the goal for the next step. By repeating these computational routines many times, a variety of designs that meet the goal eventually *emerge*. Engineers then review these outputs, often with the aid of interactive visual analytics for intuitive appraisal and comparison across the board (Kastel, 2018), and choose one or more designs for prototyping. As leading companies such as Autodesk and PTC launched generative design software (Keane, 2018; PTC, 2018) and industries embraced the technologies (Heaven, 2018; Mraz, 2018), the year 2018 has heralded a new era of engineering. This paradigm shift in design methods entails a fundamental change of mindset for design thinking that must be addressed in the engineering education of future workforce. By preparing students for this shift, this project will contribute to the core research on the Future of Work at the Human-Technology Frontier, one of NSF's 10 Big Ideas, from the field of engineering.

INTELLECTUAL MERIT

Box 1: The Need for New Roles and Talent

"Reimagining a business process involves more than the implementation of AI technology; it also requires a significant commitment to developing employees with what we call 'fusion skills'—those that enable them to work effectively at the human-machine interface." — H. James Wilson & Paul R. Daugherty, in *Collaborative Intelligence: Humans and AI Are Joining Forces*, Harvard Business Review, July-August, 2018

As disruptive technologies, generative design software can take over a considerable part of design space exploration that is currently undertaken by engineers and typically regarded as a creative process. This does not necessarily mean that AI would or should replace engineers, but it does have practical implications for engineering education and workforce development (Box 1). There is no doubt that generative design will be widely adopted across industries as it can greatly help companies accelerate innovation, reduce cost, and stay competitive. The fascinating prospect of using generative design to redesign everything man-made compels us to wonder about what the world would look like decades from now and what new opportunities would be on the horizon. As the demand for engineers who can comfortably master AI to engineer the future is expected to rise, it is imperative that educational institutions take action now to teach students essential skills that empower them to flourish at this exciting human-technology frontier.

Changes in Design Thinking and Learning

Questions abound about how design thinking should evolve to reflect the radical shift from traditional design to generative design. Some profound changes will be inevitable. For instance, a hallmark of design expertise is the knowledge of precedents, which represents an understanding of the design space accumulated through experience and serves as a starting point of the quest for new designs (Boling & Gray, 2018). Now that generative design software can start from scratch to produce many sound designs even beyond human imagination, the role of designers changes from creator to curator. The existing repository of design precedents stored in the designers' memory, as well as their case-based reasoning ability to draw ideas from the repository, may no longer be needed in the creation of new designs.[1] In fact, generative design may even be preferred as it is not subject to typical fixation problems of humans that allow their prior experiences and biases to blind them to new possibilities (Crilly, 2015; Crilly & Cardoso, 2017; Jansson & Smith, 1991; Linsey et al., 2010; Nguyen & Zeng, 2017). So what should we teach students then?

To shed light on this burning question, it is helpful to compare a generative designer to a product manager who supervises a team of assistants to accomplish a development goal. A product manager translates the goal into different tasks and assigns them to different assistants, the assistants carry out the tasks and report back to the manager, and the manager reviews the results comprehensively and decides the next step. The manager operates at a higher level and the assistants operate at a lower level. Their jobs require distinctive but overlapping skill sets. The manager is generally expected to understand the overall goal and the nature of each task, know the strengths and weaknesses of each assistant, and be able to evaluate the performance of the whole team on an ongoing basis so as to adjust the strategies and priorities as needed. The job of a generative designer is not unlike that of a product manager depicted above—except that the assistants are AI entities instead of human beings. This metaphor elucidates the increasingly important concept of human-

[1] In a campaign that drew extensive public attention, DeepMind's AlphaGo Zero has demonstrated the feasibility of creating AI, *tabula rasa*, that achieved superhuman performance in the game of Go (Silver et al., 2017). The fact that AlphaGo Zero developed this extraordinary ability itself without learning from any human data, guidance, or domain knowledge beyond the game rules means that the total experience accumulated by human players through thousands of years has now been rendered completely obsolete when it comes to the question of how to make software that wins a Go game. Although most design problems in the real world are far more complicated than the game of Go and the validity of the evaluation of a design solution is subject to the accuracy of numerical simulations based on approximations (Wilkinson, 2015; Wilkinson & Hanna, 2014), it is still possible that generative design will have impacts of similar significance on engineering as the technologies mature. No wonder many practitioners view generative design as one of the most important breakthroughs in engineering in the past two decades (e.g., Krish, 2018; Reese, 2018).

AI partnership, or *collaborative intelligence* as Harvard Business Review calls it (Wilson & Daugherty, 2018), that requires the teaching of "fusion skills" based on combining the complementary strengths of humans and AI to achieve a greater technical capability. Given this industry trend in AI applications, how should we reform design thinking and design education so that students would have the appropriate mindset for viewing generative design software as their meaningful partners, rather than just some passive tools?

Computational Thinking in Engineering Design

As sophisticated technologies, generative design involves a plethora of new knowledge and skills that may seem overwhelming to novices at first glance, but many of them can be boiled down to computational thinking (Wing, 2006; Wing & Stanzione, 2016), a relatively new set of problem-solving principles (Box 2) popularized by computer scientists in recent years. As the dependency on computation has reached a high level[2] in generative design, computational thinking becomes an essential competency of a generative designer. It represents a new mode of thinking that allows engineers to develop a sense about what AI can and cannot do, know how to decompose a real-world problem into steps tractable by AI, and learn how to interact with AI to get the job done in a brand-new way. Because of this strategical importance of computation in future design work, it would be appropriate to even view computational thinking as a new engineering habit of mind, along with other engineering habits of mind such as systems thinking (e.g., Lucas, Hanson, & Claxton, 2014), that students must develop.

Box 2: Computational Thinking

The International Society for Technology in Education and the Computer Science Teachers Association have collaborated with leaders from higher education, industry, and K–12 education to develop an operational definition of computational thinking (2011) that specifies the following skills:

- Formulating problems in a way that enables us to use a computer and other tools to help solve them.
- Logically organizing and analyzing data.
- Representing data through abstractions such as models and simulations.
- Automating solutions through algorithmic thinking (a series of ordered steps).
- Identifying, analyzing, and implementing possible solutions with the goal of achieving the most efficient and effective combination of steps and resources.
- Generalizing and transferring this problem solving process to a wide variety of problems.

Note that this definition has significant overlaps with design thinking, laying a foundation for a possible integration at both conceptual and practical levels.

To justify this pivotal role, we are obliged to operationalize computational thinking in design. Take problem formulation, solution automation, and data representation from the list in Box 2 for example. In generative design, problems are formulated through parameterization that decomposes a complex design problem into a set of independent variables that AI manipulates; solutions are automated through algorithms that control the workflow of AI for finding values of the parameters that meet the goal; and data are represented by models and simulations that allow for analysis of the outputs of AI. Following the metaphor of product manager, computational thinking permits a generative designer to manage a team of AI assistants using design algorithms as protocols for task communication and data analytics as tools for performance evaluation. In a way, computational thinking underpins a "meta-design" ability of a designer to *design the process of design*. The computational skillset associated with this meta-design ability is critically important in generative design. For instance, higher proficiency at designing the algorithms that drive a generative design process will result in higher efficiency in computation and higher throughputs in generation, allowing designers to find more solutions in less time and at lower cost. In practice, generative design can be supported by visual block programming, which provides students a graphical user interface for learning and applying computational thinking in generative design without requiring them to write code or scripts.

[2] To evaluate the degree to which a solution meets scientific criteria and constraints, generative design often employs numerical analysis based on scientific simulation methods such as finite difference methods and finite element methods. These methods can be computationally expensive even for a single analysis. The computational cost skyrockets as we now need to analyze numerous solutions generated at each step and for many steps. Therefore, proprietary generative design software often rely on cloud computing to expedite the computation and increase the throughput.

Project Goals and Research Questions

In the *Educating Designers for Generative Engineering* (EDGE)[3] project, the University of Arkansas (UA), the University of Illinois at Urbana-Champaign (UIUC), Oregon State University (OSU), and Concord Consortium (CC) will collaborate to define, implement, and disseminate **generative design thinking**—a new form of design thinking enhanced by computational thinking—to facilitate the teaching and learning of generative design at undergraduate levels. Guided by the method of design-based research for educational innovations (The Design-Based Research Collective, 2003) and based on open-source CAD/CAE software, we will develop an open-source generative design educational tool, named Aladdin after the legend of a magic lamp in an Arabic folk tale[4], to support independent research in this strategically important direction. Different from its commercial counterparts, Aladdin will meet typical educational requirements and constraints (e.g., it must run speedily on limited resources in common educational settings in order to be interactive and instructive) and will be freely available to anyone (at the time of writing, despite the fact that many CAD software are now free to use in education, most generative design software are *not*). Based on Aladdin, we will develop a set of project-based learning modules in architectural and energy engineering appropriate to introductory levels, licensed under Creative Commons, to facilitate the implementation and dissemination of generative design thinking. These modules will serve as the testbeds for research on the effectiveness of our technologies and pedagogies on teaching generative design and building a human-AI partnership. Research questions (RQ) from three perspectives will drive the EDGE project:

RQ1. **Theoretical perspective**: What are the essential elements of generative design thinking that students must acquire in order to work effectively at the human-technology frontier in engineering?

RQ2. **Practical perspective**: To what extent and in what ways can the project products support the learning of generative design as indicated by students' gains in generative design thinking?

RQ3. **Affective perspective**: To what extent and in what ways can AI affect the professional formation of engineers as indicated by the changes of students' interest and self-efficacy in engineering?

Throughout the project, we expect that more than 1,000 students at 13 institutions around the country will participate in this study. In addition to the three leading universities UA, UIUC, and OSU, the project will also include Fitchburg State University, Florida International University, Great Bay Community College, Harding University, Manchester Community College, Massbay Community College, Pennsylvania State University, University of Arkansas-Fort Smith, University of Arkansas at Pine Bluff, and University of California Irvine. A criterion of success for this project is that students from these diverse institutions, including three community colleges, a historically black college, a liberal arts university, and eight public universities, learn generative design skills through the project materials and demonstrate an ability to solve design problems with generative thinking as a result.

Work Plans

The goals of the EDGE project will be accomplished through the following plans:

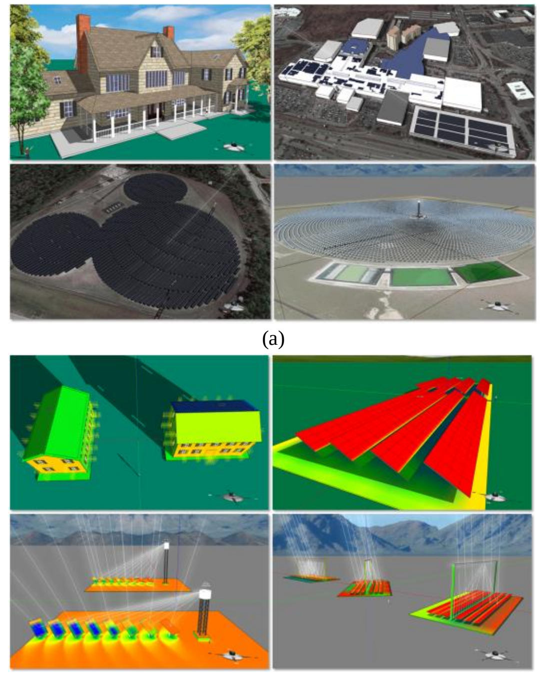
- **Define generative design thinking**. This definition will assimilate computational thinking to augment and reshape design thinking, setting up thereby 1) a theoretical foundation for the research, 2) the learning goals for students, and 3) the development goals of the project. From a pragmatic view, generative

[3] To some degree, the acronym EDGE appropriately captures the essence of this project. According to Brown and Wyatt (2010), edges in design thinking represent "the places where 'extreme' people live differently, think differently, and consume differently." Generative design may be considered as a powerful method that helps designers who do not have direct experiences with those extreme conditions to push the envelope and explore the edges.

[4] Aladdin is a tale in *One Thousand and One Nights* that features a magic lamp capable of generating whatever its owner wants. Thanks to AI, generative design has somewhat realized the dream of magic lamps for designers—they only need to specify what they want and the generative design software would bring their wishes to life. This great inspiration is the reason why we chose to name the proposed educational software after the famous folk tale.

design thinking can be defined as a transformation of design thinking proposed by Dym et al. (2005) along its four original dimensions: divergent-convergent questioning, systems thinking, decision making, and teamwork. Although the proposed theoretical study and empirical research will be based on specific tools and topics in this project, we will strive to ensure an operational definition broadly applicable to other design contexts. More explanations are provided in the "Theoretical Foundation" section.

- **Develop the open-source Aladdin software**. With the goal to support the learning and teaching of generative design, we will create Aladdin based on open-source CAD/CAE software (Figure 1) that we have developed for engineering design research and education (Xie et al., 2018). The purpose is not to reinvent the wheel but to focus on supporting students to learn basic concepts of generative design and researchers to find ways to improve this new human-AI partnership. Given that some sacrifice of accuracy in exchange for speed is generally acceptable in educational applications in which qualitative results suffice, CAE simulations in Aladdin will be accelerated using approximate methods (Wilkinson & Hanna, 2014). More details are available in the "Research and Development" section.
- **Develop curriculum modules**. Powered by Aladdin, these modules will be based on project-based learning, a common pedagogy for teaching design (Dym, Little, & Orwin, 2013). The design tasks in these modules will be generally scaffolded using the Function-Structure-Behavior (FSB) Framework developed by Advisory Board member Gero (Gero, 1990; Gero & Kannengiesser, 2004), with modifications reflecting the changes due to the use of generative technologies (for instance, the synthesis step of the FSB framework for generating structures is performed by AI in generative design). To engage students, we will adopt authentic engineering projects that can be realistically solved using generative design. We will favor cases in which generative design may result in interesting or surprising solutions as such cases can be particularly inspirational. The outlines of these modules are available in the "Research and Development" section.
- **Conduct educational research**. We will carry out three rounds of pilot tests of project technologies and materials at UA, UIUC, and OSU in the first phase of the project. In the second phase, we will collaborate with the ten other participating colleges and universities to scale up the research. To plan for the implementations at these institutions, we will provide free work-



(a)

(b)

Figure 1. Energy3D is an integrated CAD/CAE program that we have developed for engineering education in the areas of architectural engineering and renewable energy engineering. (a) The CAD part of Energy3D allows users to design a variety of systems. This set of image shows a house, a shopping center, a photovoltaic solar farm, and a concentrated solar power plant designed or modeled using Energy3D. (b) Similar to concurrent computational fluid dynamics that couples design and analysis intimately (Design News, 2010), the CAE part of Energy3D allows users to analyze a solution at any time of the design process so that users can be immediately informed by the result to help them make the next decision. This set of image shows the energy analyses of buildings, solar panel arrays, heliostat arrays, and linear Fresnel reflector arrays, as well as the visualizations of the results in the scenes. In each of these images, we deliberately juxtapose a couple of design solutions that differ only in one parameter (i.e., the orientation of a building, the inter-row spacing of solar panel arrays, the height of a solar power tower, and the alignment of the linear Fresnel reflector arrays). This kind of comparative analysis, known as tournament selection, is a basic operation in generative design that mimics natural selection: the solutions with better performance will "survive" and the rest will "perish." In essence, generative design is an automatic process for computers to "learn" what works and what doesn't work through iterative comparison and selection steps.

shops and webinars to participating instructors to familiarize them with the overall goals, project products, research instruments, and data protocols. Together with these stakeholders, we will explore the strategies and methods for integrating the instructional modules and embedding the educational research into their introductory engineering or CAD courses.

- **Collect and analyze student data**. In partnership with the participating institutions, we will gather formative and summative data using instruments such as demographic surveys, questionnaires, self-efficacy measures, design reports, screencast videos, software logs, classroom observations, and participant interviews. One of Aladdin's features for supporting educational research will be its capability of "stealth assessment" (Shute & Ventura, 2013; Shute et al., 2016), a non-intrusive measure of student learning based on logging their interactions with the software behind the scenes. This capacity will provide fine-grained process data for tracking student actions in generative design. The "Research and Development" section provides more details about data collection and analysis.
- **Disseminate the products**. The products of this project, including an operational definition of generative design thinking, the Aladdin software, and the instructional modules, will be disseminated to the community of K-16 engineering educators through UA's online education division, partner websites, conference presentations, and journal publications. Details are provided in the "Dissemination" section.
- **Collaborate with the Advisory Board to evaluate and advance the project.** This project will be overseen by an Advisory Board consisting of five leading experts in engineering, education, and computer science. Details are available in the "Project Evaluation" section.

The approximate **timeline** of this four-year design-based research project is as follows: In Year 1 (1/1/2020-12/31/2020), we will develop an operational definition of generative design thinking and the minimum viable versions of the Aladdin software, curriculum modules, and research instruments; in Year 2 (1/1/2021-12/31/2021), we will pilot-test the software, modules, and instruments with students at UA, UIUC, and OSU for three rounds and improve all the tools and materials based on the results of each round; in Year 3 (1/1/2022-12/31/2022), we will hold our first participant workshop and scale up our field tests to all the partnering institutions while continuing to analyze student data and improve project products; in Year 4 (1/1/2023-12/31/2023), we will focus on presenting results, publishing papers, and disseminating products while continuing with another round of revisions, implementations, and data collection.

TEAM AND EXPERTISE

Our multidisciplinary leadership team consists of 1) **Dr. Zhenghui Sha**, a design researcher at UA whose expertise is design theories and methods with a focus on decision-making in complex systems engineering, 2) **Dr. Darya L. Zabelina**, a psychology researcher at UA whose study focuses on understanding creativity and imagination as well as the influence of technology on them, 3) **Dr. Molly Goldstein**, an engineering researcher at UIUC who specializes in design education, 4) **Dr. Onan Demirel** is a design researcher at OSU who develops design theories and methods to explore the interdependencies and coevolution of human elements in engineering systems, and 5) **Dr. Charles Xie**, a computational and learning scientist at CC who has developed open-source CAD/CAE software based on computational fluid dynamics (Xie, 2012) and building energy simulation (Xie et al., 2018). In addition, faculty members from ten other institutions, listed in Table 2, will join the team as consultants, bringing their expertise in engineering education on board to help review and implement the underlying technologies, instructional materials, and research plans around generative design thinking. The project will be overseen by an Advisory Board consisting of **Dan Banach** (technical manager at Autodesk), **Dr. Yan Fu** (technical leader at Ford Motor), **Dr. John Gero** (design researcher at the University of North Carolina at Charlotte), **Dr. Jeffrey Grossman** (scientist and educator at Massachusetts Institute of Technology), and **Rachel Switzky** (director of UIUC's Siebel Center for Design). Combined, the extended team has experience in engineering design, engineering education, computer science, software development, curriculum development, and educational research. We are uniquely qualified and well prepared to develop the envisioned innovations and conduct the proposed research.

THEORETICAL FOUNDATION

The effectiveness of design methods depends on the type of design medium. Before generative design, pencil-and-paper sketching, computer-based drawing, and parametric design[5] are the main medium tools. In this proposal, design using these tools is categorized as traditional design, as opposed to generative design. A simple way to distinguish them is that designers operate predominantly in the parameter space in traditional design and predominantly in the objective space in generative design (the relationship between the two spaces is illustrated in Figure 2). More specifically, the theoretical foundation of this proposal builds on the categorized differences between traditional and generative design practices summarized in Table 1.

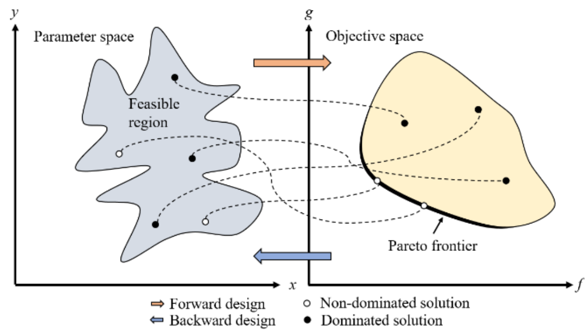


Figure 2. Generative design transforms the designer workspace from the parameter space to the objective space. This simplified illustration uses two parameters and two objectives as an example. It does not mean that the parameter and objective spaces have to be 2D or must have the same dimensionality.

Table 1: Some practical differences between traditional and generative design from different aspects.

Aspects	Traditional Design	Generative Design
Starting point	Initial geometry (possibly the result of some conceptual design) is required to begin iterative revision and optimization.	Initial geometry is not required—all the intermediate and final forms are automatically generated from scratch (*tabula rasa*).
Design concurrency	Functions and manufacturability of a CAD model are analyzed separately, often by different teams later. The results may lead to modifications of the CAD model.	Functions and manufacturability are considered from the beginning and coded as inputs into the generative design software. Generated CAD models function as expected and are manufacturable.
Design direction	**Forward design** from the parameter space to the objective space: Designers start with their best guesses for the values of the parameters extrapolated from their prior experience and then check whether the chosen values indeed meet the objectives.	**Backward design** from the objective space to the parameter space: Designers start with setting up the objectives for generative design software based on the specified criteria and constraints and then use the software to find the values of the parameters that meet the objectives.
Solution search	Designers tweak all the parameters of a CAD model manually and use intuition to guide the search for favorable designs. The results are often expected (i.e., designers somewhat foresee them).	Generative design software automatically tweaks all the parameters, evaluates the change of performance after each adjustment, and uses evolutionary algorithms to search for favorable designs. Some results may be unexpected.

[5] In this proposal, we draw a distinction among **generative design**, **parametric design**, and **topology optimization**. The three technologies have significant similarities that can sometimes lead to confusions. Parametric design is a method in which a design solution is traditionally created by manipulating design parameters and their relationships manually (e.g., using a slider to tune a parameter and create a new structure). In other words, parametric design, as characterized by Oxman and Gu (2015) for example, normally does not use AI to automatically search for solutions. Generative design, on the other hand, uses AI to create many solutions for designers to pick and choose. As it often involves a lot of options, generative design is sometimes referred to as "optioneering" (e.g., Gerber et al., 2012; Holzer & Downing, 2010). It is typically viewed as a new computational design method based on parametric design (many parametric design software have now provided scripting functionality, one way or another, for designers to realize generative design and other design automations, though). Another related method, topology optimization, is also considered as a subset of generative design (Reese, 2018). Generally speaking, topology optimization is a computational technique for optimizing an existing design developed through traditional methods, rather than a technique for exploring the entire design space from scratch. In practice, topology optimization is often used in lightweighting—material removal from a baseline design without compromising its intended functions.

Decision making	A **sequential decision-making** process: Designers obtain the final design that meets all criteria and constraints by revising a single-state CAD model iteratively.	A **parallel decision-making** process: Designers explore and compare many alternatives produced by generative design software in parallel and then choose the final solution from them.
Idea abundancy	Designers create a few design alternatives that represent a limited number of ideas for balancing multiple objectives, often based on research and brainstorming results.	Generative design software creates a large number of design alternatives along the Pareto frontier in the objective space that represent many different ideas for trade-offs among multiple objectives.
Teamwork	A team of engineers with different expertise (e.g., CAD/CAM/CAE specialists) collaborates from ideation to finalization through ongoing brainstorming and iterative improvements.	A team of engineers collaborates with AI and among themselves. Teamwork builds on an understanding of what AI can do to enhance human creativity and productivity and what humans should do to leverage AI and overcome its limitations.

The practical differences described in the table above can be used as a starting point to formulate an operational definition of generative design thinking. As a necessary side note, we distinguish generative design thinking from earlier work on including a computational dimension in design thinking. Researchers (e.g., Oxman, 2017b) and practitioners (e.g., Bhooshan, 2017) of parametric design, mostly from the field of architectural design, have been working on building a general theory of *parametric design thinking* for guiding the learning and practice of parametric design.[6] As parametric design is a subset of generative design, parametric design thinking may be viewed as part of generative design thinking.

Box 3: Pareto Frontier as Human-AI Boundary

Most design problems in the real world have multiple objectives. A multi-objective AI engine will output a set of solutions along the Pareto frontier, where it is impossible to improve the performance of a solution on one objective without compromising the performance on another. From the perspective of human-AI collaboration, the Pareto frontier is where AI reaches its limit. Beyond this point, human judgement is needed to decide on the final solution from the Pareto set in order to complete the design process. If designers find no suitable solution in the current Pareto set, they will have to revisit the objectives or adjust the constraints and then use AI to regenerate a new set. Hence, the iterative divergent-convergent thinking loop applies also to the objective space and thus generative design as well.

To make a connection to other foundational work, generative design thinking can be considered as a generalization of design thinking proposed by Dym et al. (2005), as mentioned earlier. In their view, design thinking drives continuous transformations from the concept domain to the knowledge domain through the divergent-convergent questioning loop. Despite the universality of this statement, traditional and generative design differ significantly in the operation of the iterative divergent-convergent loop (Figure 3). The iteration in traditional design is primarily based on changing the parameters (which are inputs to CAD models), whereas the iteration in generative design is primarily based on changing the objectives (which are inputs to AI engines). As explained in Box 3, this difference is largely due to the division of design tasks between human and AI in generative design. For readers who may be wondering why design objectives can be altered, note that, while some objectives may be fixed upon the client's request, many others are often adjustable and negotiable due to the uncertainties in real-world engineering. Sometimes it is also mathematically infeasible for AI to find a solution that satisfies all the objectives in the way they are prescribed. Under such a circumstance, designers must revise the objectives and try again. Thus, the divergent-convergent loop still runs in generative design: Divergent thinking leads designers to explore solutions with different, even extreme, objectives (e.g., various budget levels or performance expectations) and convergent

[6] According to Oxman (2017b), earlier studies of parametric design thinking have focused primarily on the intersection of three research areas: parametric design models and tools, cognitive models of design knowledge, and process models of design. Key concepts in parametric design thinking include (Oxman, 2017a), for example, 1) parametric schema, which represents a mathematical model for generating shapes, 2) associative relations, which define the interaction rules among the parameters of a design model for re-editing purposes, and 3) algorithmic thinking, which drives the coding of a set of rules to execute certain computational procedures that generate the desirable structures.

thinking guides them to find the best solution for the client's situation. In relation to systems thinking, generative design places more explicit emphasis on the functional level. In addition to thinking about the relationships among the parameters of a system, generative designers must break down an expected function of the system into a set of executable objectives for AI to find the optimal values of the parameters that form a system solution. For selecting the final solution that fits the bill from a myriad of options, designers often rely on visual analytics to perform complex multi-criteria decision analysis (e.g., Kastel, 2018; Woodbury et al., 2017; Zaman, Stuerzlinger, & Neugebauer, 2017). This data-intensive decision-making and trade-off process requires students to learn and apply computational thinking skills related to data analysis and graphic representations. Compared with traditional design, these data analytics skills are more important in generative design as designers must now sift through many alternatives and make many decisions before settling down to the final solution. The EDGE project will enact these new ways of thinking in design education through the following research and development plans.

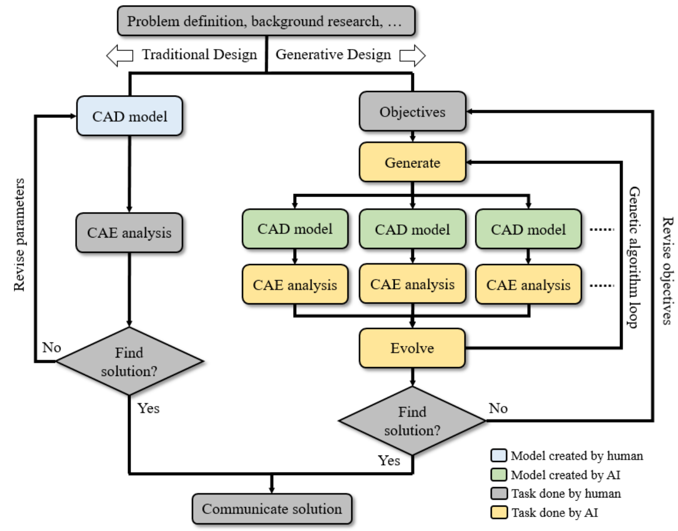


Figure 3. This diagram shows a comparison between typical processes of traditional and generative design. In both processes, designers still must start with the same initial steps, such as defining the problem, conducting the background research, and specifying the criteria and constraints, and end with the same final steps, such as communicating the final solution with justifications for the design decisions. The main differences are in the iterative steps from the initial solution to the final solution, which often constitute the bulk of design. A traditional designer typically makes decision on a single solution, revises the related parameters, and evaluates the changes from version to version. This single-state model (Terry & Mynatt, 2002) requires the design to be in one, and only one, state at any particular time, thereby imposing a sequential progression that is at odds with the "wicked" nature of design (Buchanan, 1992). By contrast, generative design represents a new way to step through the iterative process. A generative designer sets the inputs to AI that define the objectives, use AI to generate a matrix of outputs, and then scour the outputs for best solutions. After exploring the outputs, the designer can refine the objectives and generate a new batch of solutions for comparison. This parallel, multi-state model represents a better way to think about design where there may be multiple competing solutions to a problem waiting to be discovered.

RESEARCH AND DEVELOPMENT

The research and development of this project will follow the "cycle of innovation" envisioned by NSF through design-based research (The Design-Based Research Collective, 2003). On the one hand, we will develop the Aladdin software and curriculum modules to support research on generative design thinking. On the other hand, our research findings will spur the improvement of the software and modules that aim at promoting generative design thinking.

Software Development

The proposed Aladdin software will provide a research and education platform at the intersection between AI and design. We will build its AI engines based on evolutionary computation methods such as multi-objective genetic algorithms (Deb, 2001; Deb et al., 2002) for designing with multiple criteria and constraints. As the field of AI is advancing at a rapid speed, we will also explore new algorithms as the project unfolds and adopt new ones as appropriate to enhance Aladdin's intelligence and versatility.

Generative design software rests on CAD/CAE software. If the AI engines are the "brain" of generative design software, CAD/CAE software are the "body" that provides the basic capabilities of form and function modeling. As mentioned earlier, Aladdin will use Energy3D (Figure 1) as the CAD/CAE foundation.

To support the learning and practice of generative design, Aladdin will add three new subsystems: 1) **Visual programming**: a block-based programming environment (Figure 4) similar to the Grasshopper plugin for the Rhinoceros CAD software that allows students to specify the parameters and objectives as the inputs to the AI engines and connect different software modules to control the generative design process, 2) **Process visualization**: a dynamic dashboard with real-time animations that allow students to monitor the progress of generative design and "see AI at work," much like the "white-box testing" that reveals inner workings of algorithms for software debugging and performance tuning, and 3) **Visual analytics**: an interactive graphic environment that provides analytic tools for students to "mine" the final solutions from a large number of AI outputs. Embodying the core ideas of generative design in visual and interactive forms, these subsystems will create an intuitive learning environment that even non-programmers can explore without being impeded by the lack of coding experience. In such a way, a significant part of generative design becomes visual programming in which students configure and connect graphic building blocks to manage complex workflow. To support the research on student learning in this interactive environment, Aladdin will log all the student interactions with it in the background, producing a stream of structured fine-grained data that allows the entire interaction process to be reconstructed for in-depth analysis. This "high-fidelity" behavior data may shed light on students' thinking processes. To the best of our knowledge, this research capability is not available in any other generative design software and will be a unique contribution of the EDGE project to this emerging field of study.

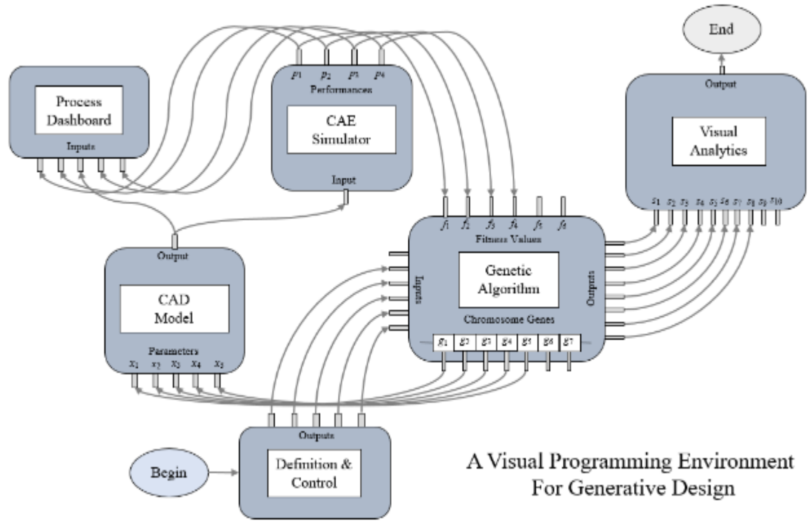
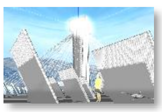


Figure 4. The Aladdin software will feature a visual programming environment that supports generative design. Software modules such as CAD, CAE, dashboards, AI engines, and analytics will be represented graphically in this environment as blocks that encapsulate their major functionalities. Programming the generative design process is simplified mainly as configuring and connecting the inputs and outputs of these modules to manage the data flow, allowing students to learn and apply computational thinking in a visual and intuitive way (without having to write computer code or scripts).

Curriculum Development

The goal of the curriculum development in this project is to create instructional modules that support project-based learning of generative design and facilitate the corresponding educational research. As generative design is so new, there is little information about what has been tried in the classroom. Due to the lack of this information, we will draw examples from the literature about what have been done by professional designers. For instance, generative methods have been used by researchers to design building envelopes of energy-efficient or zero-energy buildings (e.g., Berquist et al., 2017; Caldas, 2008; Caldas & Norford, 2002; Kastel, 2018; Touloupaki & Theodosiou, 2017; Yang et al., 2017; Yu et al., 2015) and eco-friendly urban communities (e.g., Rakha & Reinhart, 2012; Walmsley & Villaggi, 2019). We will also leverage the expertise within our team in the field of generative solar power design. For example, Advisory Board member Grossman's research group at MIT has used a genetic algorithm to invent "three-dimensional photovoltaics" (Myers, Bernardi, & Grossman, 2010); Co-PI Xie has been working on generative design of concentrated solar power that consists of a tall tower surrounded by thousands of heliostats (Xie, 2018). With some engineering simplification and educational enhancement, these proven examples can be transformed into student projects in our instructional modules. Table 2 lists these possible design projects.

Table 2: Three types of sample projects for generative design that Aladdin will support.

Subject	Projects	Design Parameters and Objectives
Architectural Engineering 	Design a zero-energy building that consumes no more energy than it generates on-site over the course of a year.	The energy efficiency of a building is affected by its envelope. The design parameters of a building envelope include, but are not limited to, the architecture (shape), the orientation of the building, the window-to-wall ratio on each side, the solar heat gain coefficient of each window, the colors of the walls and roofs, the renewable energy sources such as rooftop or ground-mounted solar panels and geothermal heat pumps, the energy storage such as batteries, and the material properties of each building component such as the heat capacity, thermal conductivity, and light absorptivity. The objectives for performance assessment are typically energy consumption for maintaining thermal comfort, living area or volume for occupants, and construction cost.
Solar Engineering 	Design a photovoltaic or concentrated solar power plant that achieves high productivity and cost effectiveness.	The electricity output of a solar power plant is affected by the layout of the photovoltaic panels or reflection mirrors. The design parameters of a photovoltaic solar farm include, but are not limited to, the size and shape of the field, the tilt angle of solar panels, the azimuthal angle, the distance between rows, the type of tracker, and the properties of solar panels such as the solar cell efficiency and its operating temperature. The design parameters of a concentrated solar power tower include, but are not limited to, the aperture of the heliostats, the reflectance of the mirrors, and the height of the tower. In both types of solar power plants, the objectives are energy outputs, land-use efficiency, and construction cost.
Urban Design & Planning 	Design an urban area that is functional, convenient, attractive, and sustainable.	The livability of an urban area is affected by the availability, density, and layout of residential buildings, official buildings, green spaces, stores, transportation, microgrids, and other facilities. The design parameters include sizes, properties, costs, and revenues of these facilities. The objectives consist of carry capacity, walkability, massing, solar access, and other indicators that can be computationally evaluated.

All the screenshots in this table were taken from Energy3D, the CAD/CAE software that Aladdin will be based on.

As many students may not have adequate experience and concrete understanding of traditional design, we will implement a **comparative approach** in these instructional modules, which first challenges students to solve a design problem using the traditional method and then using the generative method (this is possible with Aladdin because it will be able to fall back to a conventional CAD/CAE tool by simply disconnecting its CAD/CAE parts from the AI engines). This successive strategy will create opportunities for students to compare traditional and generative methods in the same design context with the same design tool and for researchers to compare student learning of traditional and generative design.

Research Goals and Participants

The research of the EDGE project will answer three questions, copied as follows: **RQ1**: What are the essential elements of generative design thinking that students must acquire in order to work effectively at the human-technology frontier in engineering? **RQ2**: To what extent and in what ways can the project products support the learning of generative design as indicated by students' gains in generative design thinking? **RQ3**: To what extent and in what ways can AI affect the professional formation of engineers as indicated by the changes of students' interest and self-efficacy in engineering? RQ1 seeks to substantiate generative design thinking, with the goal to provide educators an operational, versatile, measurable, and yet simple conceptual framework that can be used to define the learning goals and assessment rubrics for students. RQ2 seeks to validate the effectiveness of the technologies and materials developed in this project on fostering the learning of generative design, with the goal to provide educators a package of solutions that can be readily used to reproduce positive learning outcomes in diverse settings. RQ3 seeks to understand the impacts of AI on the development of future engineering workforce, with the goal to identify new mechanisms for engaging and empowering students with the emerging human-AI partnership that will become common in the workplace. In a sense, RQ1 and RQ2 complement each other from theoretical and practical perspectives and can therefore be studied in a concerted way. For instance, to determine whether we should make a point about generative design thinking, we should in principle be able to map it to a learning outcome observable through an instrument that addresses RQ2.

Over the course of the project, we estimate that more than 1,000 students from the three leading universities and ten satellite colleges and universities around the country (Table 3) will participate in this study. To enable close collaboration among these institutions and create a community of researchers and educators who spearhead the research and education of generative design, we will also allocate funding to support the participating faculty members at these institutions to join the project as consultants to review the instructional materials, facilitate the research activities, and even co-author research papers.

Table 3: Ten other colleges and universities will join the project (see their letters in the Supplementary Documents).

Institution	State	Instructor
Fitchburg State University	MA	Sanjay Kaul
Florida International University	FL	Monique Ross
Great Bay Community College	NH	Peter Dow
Harding University	AR	James Huff
Manchester Community College	NH	Dan Larochelle
Massbay Community College	MA	Shamsi Moussavi
Pennsylvania State University	PA	Catherine Berdanier
University of Arkansas-Fort Smith	AR	Ron Darbeau
University of Arkansas at Pine Bluff (historically black college)	AR	Mansour Mortazavi
University of California Irvine	CA	Natascha Buswell

Data Sources and Analysis

We will employ three different types of instruments to investigate RQ1/RQ2 comprehensively. First, we will develop and use **questionnaires** based on multiple-choice and constructed-response questions to measure students' ability to think generatively and computationally *after* they have used the project materials. The questionnaires will include, but will not be limited to, items that probe into students' ability to describe the differences between generative and traditional design, decide on the roles of humans and AI in a design project, and formulate the steps for solving a design problem using the generative approach and computational thinking. As generative design is so new, we can assume that most students have not been exposed to it before and there is thus no need to administer a pre-measure to establish a baseline. Simple descriptive statistics can therefore be applied to analyze the data collected from these questionnaires. Considering the fact that generative design thinking is based on traditional design thinking and computational thinking, the development of these assessment items will follow the design principles used in existing work on assessing design thinking (e.g., Crismond & Adams, 2012; Purzer et al., 2015) and computational thinking (e.g., Brennan & Resnick, 2012; Grover, Bienkowski, & Snow, 2015), such as Evidence-Centered Design (Mislevy & Haertel, 2006). Second, we will use students' **design reports**, which are required in our instructional modules for students to complete a design project, as another type of data source. Design reports are an important part of learning in which students reflect on their own experiences. As students document their design rationales and processes, their reports can be highly indicative of the degree of learning. To quantify the learning outcomes from these reports, we will develop coding rubrics for scoring generative design thinking. To ensure inter-rater reliability, multiple researchers of our team will grade the reports using the same rubrics. Any discrepancy in ratings will be resolved among the researchers before the scores are finalized for the next level of aggregation and analysis. Third, we will use **stealth assessment** (Shute et al., 2016) based on Aladdin's ability to capture design behavior from fine-grained process data logged behind the scenes. This technique will stem from PI Sha (Panchal, Sha, & Kannan, 2017; Rahman et al., 2018; Sha, Kannan, & Panchal, 2015) and Co-PI Xie's research (Xie, 2015; Xie et al., 2014a; Xie et al., 2014b) on characterizing design thinking using behavior data logged by CAD software. Different from the previous research that collected and analyzed only the CAD actions, this project will also include students' actions within the visual programming environment of Aladdin. As prior research has shown that data analytics can be used to understand and gauge students' learning of computational thinking based on their "digital footprints" or "clickstreams" in visual programming environments (e.g., AmoFilvà et al., 2019; Berland et al., 2013; Blikstein et al., 2014; Grover & Korhonen, 2017), we expect this data-driven approach can be used to assess generative design thinking as well. For instance, we can analyze students' decision-making process and divergent-convergent thinking process with the logged data about how students connect the visual blocks to set up the data flow. One simple way to visualize design processes is to project the parameters and objectives from students' intermediate design artifacts onto the corresponding spaces as scatter plots, radar charts, or parallel coordinates. This part of analysis will also draw from the expertise of Co-PIs Goldstein and Zabelina on assessing divergent-convergent thinking and trade-off conceptions (Goldstein, Adams, & Purzer, 2018; Zabelina & Ganis, 2018).

As the main target of RQ3, self-efficacy represents students' beliefs about their capabilities of performing the tasks necessary to achieve a desired outcome. A legitimate concern with AI is that, if students achieve the design goal with help from AI, would their self-efficacy in engineering increase as a result of the accomplishment or decrease as a result of feeling replaced by AI? To understand these issues, we will mainly rely on multifaceted pre/post-measures for self-efficacy in engineering based on synthesizing earlier work (e.g., Carberry, Lee, & Ohland, 2010; Hutchison et al., 2006; Marra et al., 2009). As a reference, our measures will probe students' self-efficacy in traditional design as well. We plan to also examine the dependence of students' self-efficacy in generative design on their computational thinking skills gleaned from the results of our questionnaires for RQ2. We hypothesize that students' self-efficacy gains in generative design are proportional to their ability to understand how AI works to generate novel designs computationally. To analyze these self-efficacy changes, we will use repeated measures ANOVA and ANCOVA.

Across the board, we will gather demographic information as confounding variables for our analyses to reflect the diversity of participants. In addition, we will administer classroom observations to capture usability issues of the Aladdin software, student engagement with the software and the design projects, and instructional needs reflected in student-teacher and student-student interactions that are not covered by the instructional modules. At the end of each implementation, we will select a few students/teachers for interview. The purpose of these interviews is to 1) reconstruct learning and teaching processes through participants' retrospective self-reporting, 2) reveal participants' subjective experiences of learning or teaching with the software and materials, and 3) validate the findings from other research instruments.

BROADER IMPACTS

Generative design represents a groundbreaking application of AI in engineering that promises to transcend human limitations, augment their creativity, and accelerate product development. As the vast majority of colleges and universities teach CAD skills or offers CAD certificate programs, there exists a tremendous need to upgrade those courses or programs and ready students with generative design skills for future work. Because of this strategic importance, the outcomes of this project will likely influence stakeholders in the fields of engineering education, workforce development, design research, and artificial intelligence. The proposed generative design thinking will be infused into undergraduate engineering courses through free online materials to foster adoption of computational thinking in design and ignite changes of design thinking on a large scale. The open-source Aladdin software will provide students and teachers in underserved communities a free alternative to commercial software.

DISSEMINATION

As an intellectual output of the EDGE project, generative design thinking will be disseminated mainly through publications and presentations. Overall, the project was conceptualized with transferability and propagation in mind. We have formed a collaborative with four leading institutions and ten satellite institutions to ensure the outcomes of the project will not be limited to only a handful of classrooms. The project will develop the open-source Aladdin software and the free instructional modules that any other institution outside this project can adopt to reproduce the outcomes. In addition, we plan to also collaborate with the Global Campus, UA's distance education branch, to experiment with online dissemination by converting our instructional modules into their online short courses that can be bundled with certificate programs. We expect these short courses to attract many distance learners interested in innovative technologies.

PROJECT SUSTAINABILITY

Generative design is an ongoing development that will drive engineering in the decades to come. As such, we are optimistic about the future of this research direction. The sustainability of the EDGE project is ensured by the development of the Aladdin software, which will continue to serve the community of engineering research and education after the expiration of NSF funding. We will also work with the Advisory Board and other collaborators to actively explore various means to sustain the results of this project. For instance, the success of research on generative design thinking in this project may qualify us to develop profitable training materials for commercial software such as Autodesk's Fusion 360.

PROJECT EVALUATION

This project will rely on the expertise of the Advisory Board to evaluate its performance. Each year, the members will attend an on-site meeting with project staff from the four partnering institutions and also work with staff remotely throughout the year on formative evaluation and feedback. Each member is expected to spend up to four days per year on these efforts. The evaluation will focus on six questions: 1) To what extent has the project accomplished the research and development goals?; 2) To what extent has the project found evidence of improved student learning of generative design?; 3) To what extent has the project found evidence of increased student interest in engineering?; 4) How effectively does the project support instructors?; 5) How is the scientific integrity and technical quality of the technologies and materials?; and 6) How has the project created broader impacts? At the beginning of the project, the board will work with project staff to develop a benchmarked set of project performance indicators based on these questions and a data protocol that specifies what data should be collected and how (e.g., number of presentations and publications by project staff). Arranged into a rubric, the performance indicators will provide clear criteria for project success (summative evaluation) and benchmarks used throughout the four project years to show how the project qualitatively and quantitatively improves its performance (formative evaluation). As the majority of the evaluation data will be a subset of the research data, project staff will prepare and analyze these data for the board to review based on the performance benchmark and the data protocol. The board and staff will discuss and resolve any issue in data interpretation and analysis methods. Based on the analysis results, the board will compile an annual evaluation report, to be included in the project's annual report submitted to NSF. The report will also include recommendations for improvements.

RESULTS FROM PRIOR NSF SUPPORT

The EDGE project is based on the following prior work: **1) A Fine-Grained Data-Driven Approach to Studying Sequential Decision-Making in Engineering Systems Design** (CMMI-1842588, $225,000, 2018–2020, PIs: Sha & Xie). **Summary of results:** This project has developed experimental protocols and case studies for fine-grained data-driven research on sequential decision-making in design. **Intellectual merits**: Process mining provides a high-resolution lens for probing into design thinking, enabling researchers to identify patterns and strategies not evident through other means of observation. **Broader impacts**: This approach can lead to valuable insights impactful on design education and practice. **Publications**: One conference paper and two conference posters. **2) Large-Scale Research on Engineering Design Based on Big Learner Data Logged by a CAD Tool** (DUE-1348530, $999,921, 2014-2018, PIs: Xie & Nourian). **Summary of results**: This project developed the Visual Process Analytics for mining large-scale datasets of design processes collected through CAD software. **Intellectual merit**: This project studied the interplay between science learning and engineering design using a data-intensive approach. **Broader impacts**: Data mining is emerging as a promising method for assessing student learning. This project contributed to this frontier from the perspective of engineering education. **Publications**: Seven journal papers and eight conference papers. **3) SmartCAD: Guiding Engineering Design with Science Simulations** (DRL-1503196, $2,192,610, 2015-2019, PIs: Xie & Nourian). **Summary of results**: This project expanded Energy3D's capacities in the direction of science simulation and adaptive feedback. **Intellectual merit**: This project develops CAD software that can generate formative feedback to guide students based on computationally analyzing their work in real time. **Broader impacts**: This project demonstrates that modern CAD tools can support engineering education at a level and scale comparable to the role of modeling and simulation in science education. **Publications**: Three journal papers and three conference papers.

PERSONNEL AND ROLES

Senior Staff

Dr. Zhenghui Sha, Assistant Professor of Mechanical Engineering, will serve as the PI. He holds a Ph.D. in mechanical engineering from Purdue University. He will lead the overall project research and development. **Dr. Darya L. Zabelina**, Assistant Professor of Psychology at UA, will serve as a Co-PI. She holds a Ph.D. in cognitive neuroscience from Northwestern University. She will lead the educational research on the learning and teaching of generative design from cognitive and affective perspectives. **Dr. Molly Goldstein**, Senior Lecturer and Director of the Product Design Lab at UIUC, will serve as a Co-PI. She holds a Ph.D. in engineering education from Purdue University. She will lead the theoretical and empirical studies on generative design thinking. **Dr. Onan Demirel**, Assistant Professor of Mechanical Engineering at OSU, will serve as a Co-PI. He holds a Ph.D. in industrial engineering from Purdue University. He will lead the research on the human-AI partnership. **Dr. Charles Xie**, a senior scientist at CC, will serve as a Co-PI. He has 20 years of experience in STEM innovations. He has created a series of scientific and engineering simulation tools used by over a million people and authored 35 peer-reviewed journal papers. He is the winner of the 2016 U.S. Department of Energy's JUMP Smartphone Innovation Challenge and the recipient of a 2011 SPORE Prize from *Science*. He will lead the software and curriculum development.

Advisory Board

Dan Banach is a technical manager of the North America Manufacturing Education Program at Autodesk. His work focuses on the training of Fusion 360, which supports generative design. He has authored 24 books on Autodesk software. **Dr. Yan Fu** is a technical leader in product development and strategy analytics at Ford Motor. She has conducted research in process design using a multi-objective optimization framework. **Dr. John Gero** is a Professor of Computer Science at the University of North Carolina at Charlotte. He is an internationally recognized expert in the fields of design theory, computer-aided design, artificial intelligence in design, and technology policy. **Dr. Jeffrey Grossman** is the Morton and Claire Goulder and Family Professor in Environmental Systems and a professor in the Department of Materials Science and Engineering at Massachusetts Institute of Technology. He has been named a MacVicar Fellow of MIT for his contributions to engineering education. **Rachel Switzky** is the Director of UIUC's Siebel Center for Design. A designer with strong operational skills in working with Fortune 100 companies over the past 20 years, she is currently leading efforts to infuse design thinking across undergraduate education at UIUC.

Collaboration Plan

Research and development will be modularized and allocated to each team member for their leaderships based on their expertise as discussed above. The team will meet weekly through videoconference, in addition to regular project coordination. We will also work with the consultants at ten other institutions to carry out scale-up research. Each year, we will gather together to meet with the Advisory Board in person to report project progress, facilitate project evaluation, and plan for future work.

REFERENCES

AmoFilvà, D., AlierForment, M., JoséGarcía-Peñalvo, F., FonsecaEscudero, D., & JoséCasañ, M. (2019). Clickstream for learning analytics to assess students' behavior with Scratch. *Future Generation Computer Systems, 93*(4), 673-686.

Berland, M., Martin, T., Benton, T., Petrick Smith, C., & Davis, D. (2013). Using Learning Analytics to Understand the Learning Pathways of Novice Programmers. *Journal of the Learning Sciences, 22*(4), 564-599. doi:10.1080/10508406.2013.836655

Berquist, J., Tessier, A., O 'brien, W., Attar, R., & Khan, A. (2017). *An Investigation of Generative Design for Heating, Ventilation, and Air-Conditioning*.

Bhooshan, S. (2017). Parametric design thinking: A case-study of practice-embedded architectural research. *Design Studies, 52*, 115-143.

Blikstein, P., Worsley, M., Piech, C., Sahami, M., Cooper, S., & Koller, D. (2014). Programming Pluralism: Using Learning Analytics to Detect Patterns in the Learning of Computer Programming. *Journal of the Learning Sciences, 23*(4), 561-599. doi:10.1080/10508406.2014.954750

Boling, E., & Gray, C. M. (2018). Use of Precedent as a Narrative Practice in Design Learning. In B. Hokanson, G. Clinton, & K. Kaminski (Eds.), *Educational Technology and Narrative: Story and Instructional Design* (pp. 259-270). Cham: Springer International Publishing.

Brennan, K., & Resnick, M. (2012). *New frameworks for studying and assessing the development of computational thinking*. Paper presented at the Annual American Educational Research Association Meeting.

Brown, T., & Wyatt, J. (2010). Design Thinking for Social Innovation. *Development Outreach, 12*(1), 29-43. doi:10.1596/1020-797x_12_1_29

Buchanan, R. (1992). Wicked Problems in Design Thinking. *Design Issues, 8*(2), 5-21. doi:10.2307/1511637

Caldas, L. (2008). Generation of energy-efficient architecture solutions applying GENE_ARCH: An evolution-based generative design system. *Advanced Engineering Informatics, 22*(1), 59-70.

Caldas, L., & Norford, L. K. (2002). A design optimization tool based on a genetic algorithm. *Automation in Construction, 11*(2), 173-184.

Carberry, A. R., Lee, H.-S., & Ohland, M. W. (2010). Measuring Engineering Design Self-Efficacy. *Journal of Engineering Education, 99*(1), 71-79.

Carroll, M., Goldman, S., Britos, L., Koh, J., Royalty, A., & Hornstein, M. (2010). Destination, Imagination, and the Fires Within: Design Thinking in a Middle School Classroom. *International Journal of Art & Design Education, 29*(1), 37-53.

Computer Science Teachers Association. (2011). Operational Definition of Computational Thinking for K–12 Education. Retrieved from http://www.iste.org/docs/ct-documents/computational-thinking-operational-definition-flyer.pdf?sfvrsn=2

Crilly, N. (2015). Fixation and creativity in concept development: The attitudes and practices of expert designers. *Design Studies, 38*(3), 54-91.

Crilly, N., & Cardoso, C. (2017). Where next for research on fixation, inspiration and creativity in design? *Design Studies, 50*(3), 1-38.

Crismond, D. P., & Adams, R. S. (2012). The Informed Design Teaching and Learning Matrix. *Journal of Engineering Education, 101*(4), 738-797.

Deb, K. (2001). *Multi-objective optimization using evolutionary algorithms*: Wiley.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation, 6*(2), 182-197. doi:10.1109/4235.996017

Design News. (2010). Mentor Graphics' FloEFD Ushers in Concurrent CFD. Retrieved from https://www.designnews.com/content/mentor-graphics-floefd-ushers-concurrent-cfd/150276210543087

Dinar, M., Shah, J. J., Cagan, J., Leifer, L., Linsey, J., Smith, S. M., & Hernandez, N. V. (2015). Empirical Studies of Designer Thinking: Past, Present, and Future. *Journal of Mechanical Design, 137*(2), 021101-021101-021113. doi:10.1115/1.4029025

Dorst, K. (2011). The core of 'design thinking' and its application. *Design Studies, 32*(6), 521-532.

Dym, C. L., Agogino, A., Eris, O., Frey, D., & Leifer, L. (2005). Engineering design thinking, teaching, and learning. *Journal of Engineering Education, 94*(1), 103-120.

Dym, C. L., Little, P., & Orwin, E. (2013). *Engineering Design: A Project-Based Introduction* (Fourth ed.): Wiley.

Gerber, D., Lin, E., Bai, P. P., & Solmaz, S. A. (2012). *Design optioneering: Multi-disciplinary design optimization through parameterization, domain integration and automation of a genetic algorithm*. Paper presented at the SimAUD.

Gero, J. S. (1990). Design prototypes: a knowledge representation schema for design. *AI Magazine, 11*(4), 26-36.

Gero, J. S., & Kannengiesser, U. (2004). The situated function–behaviour–structure framework. *Design Studies, 25*(4), 373-391.

Goldstein, M., Adams, R. S., & Purzer, Ş. (2018). Investigating middle-school students' conceptions of trade-off conceptions in design. *International Journal of Engineering Education, 34*(2B), 609-618.

Grover, S., Bienkowski, M., & Snow, E. (2015). *Assessments for Computational Thinking in K-12*. Paper presented at the The 46th ACM Technical Symposium on Computer Science Education, Kansas City, Missouri.

Grover, S., & Korhonen, A. (2017). Unlocking the Potential of Learning Analytics in Computing Education. *ACM Transactions on Computing Education, 17*(3), 1-4. doi:10.1145/3122773

Heaven, D. (2018). The designer changing the way aircraft are built. Retrieved from http://www.bbc.com/future/story/20181129-the-ai-transforming-the-way-aircraft-are-built

Holzer, D., & Downing, S. (2010). Optioneering: A New Basis for Engagement Between Architects and Their Collaborators. *Architectural Design, 80*(4), 60-63. doi:doi:10.1002/ad.1107

Hutchison, M. A., Follman, D. K., Sumpter, M., & Bodner, G. M. (2006). Factors Influencing the Self-Efficacy Beliefs of First-Year Engineering Students. *Journal of Engineering Education, 95*(1), 39-47. doi:doi:10.1002/j.2168-9830.2006.tb00876.x

Jansson, D. G., & Smith, S. M. (1991). Design fixation. *Design Studies, 12*(1), 3-11.

Johansson-Sköldberg, U., Woodilla, J., & Çetinkaya, M. (2013). Design Thinking: Past, Present and Possible Futures. *Creativity and Innovation Management, 22*(2), 121-146. doi:doi:10.1111/caim.12023

Kastel, J. v. (2018). *Visual Analytics for Generative Design Exploration.* (MsC Building Technology), Delft University of Technology.

Keane, P. (2018). Generative Design Comes to Fusion 360. Retrieved from https://www.engineering.com/DesignSoftware/DesignSoftwareArticles/ArticleID/16862/Generative-Design-Comes-to-Fusion-360.aspx

Krish, S. (2018). Why Optimization is not Generative Design. Retrieved from https://medium.com/nyc-design/why-optimization-is-not-generative-design-bc8ac3afddef

Lant, K. (2017). Generative Design Could Radically Transform the Look of Our World. *Futurism.* Retrieved from https://futurism.com/generative-design-could-radically-transform-the-look-of-our-world/

Linsey, J. S., Tseng, I., Fu, K., Cagan, J., Wood, K. L., & Schunn, C. (2010). A Study of Design Fixation, Its Mitigation and Perception in Engineering Design Faculty. *Journal of Mechanical Design, 132*(4), 041003-041003-041012. doi:10.1115/1.4001110

Lucas, B., Hanson, J., & Claxton, G. (2014). *Thinking like an engineer: Implications for the education system*. Retrieved from https://www.raeng.org.uk/publications/reports/thinking-like-an-engineer-implications-full-report

Marra, R. M., Rodgers, K. A., Shen, D., & Bogue, B. (2009). Women Engineering Students and Self-Efficacy: A Multi-Year, Multi-Institution Study of Women Engineering Student Self-Efficacy. *Journal of Engineering Education, 98*(1), 27-38. doi:doi:10.1002/j.2168-9830.2009.tb01003.x

Micheli, P., Wilner, S. J. S., Bhatti, S. H., Mura, M., & Beverland, M. B. (2018). Doing Design Thinking: Conceptual Review, Synthesis, and Research Agenda. *Journal of Product Innovation Management, 0*(0). doi:doi:10.1111/jpim.12466

Mislevy, R. J., & Haertel, G. D. (2006). Implications of Evidence-Centered Design for Educational Testing. *Educational Measurement: Issues and Practice, 25*(4), 6-20.

Mraz, S. (2018). NASA Uses Generative Design on Next-Generation Interplanetary Lander. Retrieved from https://www.machinedesign.com/cad/nasa-uses-generative-design-next-generation-interplanetary-lander

Myers, B., Bernardi, M., & Grossman, J. C. (2010). Three-dimensional photovoltaics. *Applied Physics Letters, 96*(7), 071902. doi:10.1063/1.3308490

Nguyen, T. A., & Zeng, Y. (2017). A theoretical model of design fixation. *International Journal of Design Creativity and Innovation, 5*(3-4), 185-204. doi:10.1080/21650349.2016.1207566

Oxman, R. (2017a). Parametric design thinking. *Design Studies, 52*, 1-3.

Oxman, R. (2017b). Thinking difference: Theories and models of parametric design thinking. *Design Studies, 52*, 4-39.

Oxman, R., & Gu, N. (2015). *Theories and Models of Parametric Design Thinking*. Paper presented at the ECAAEE Vienna, Austria.

Panchal, J. H., Sha, Z., & Kannan, K. N. (2017). Understanding Design Decisions Under Competition Using Games With Information Acquisition and a Behavioral Experiment. *Journal of Mechanical Design, 139*(9), 091402-091402-091412. doi:10.1115/1.4037253

PTC. (2018). PTC Adds Artificial Intelligence and Generative Design Capabilities to Enhance and Expand its CAD Portfolio with Acquisition of Frustum [Press release]. Retrieved from https://www.ptc.com/en/news/2018/ptc-acquires-frustum

Purzer, Ş., Goldstein, M., Adams, R. S., Xie, C., & Nourian, S. (2015). An exploratory study of informed engineering design behaviors associated with scientific explanations. *International Journal of STEM Education, 2*.

Rahman, M. H., Gashler, M., Xie, C., & Sha, Z. (2018). Automatic Clustering of Sequential Design Behaviors. (51739), V01BT02A041. doi:10.1115/DETC2018-86300

Rakha, T., & Reinhart, C. F. (2012). *Generative Urban Modeling: a Design Work Flow for Walkability-optimized Cities*. Paper presented at the SimBuild.

Razzouk, R., & Shute, V. (2012). What Is Design Thinking and Why Is It Important? *Review of Educational Research, 82*(3), 330-348. doi:10.3102/0034654312457429

Reese, S. (2018). Think Generative Design Is Overhyped? These Examples Could Change Your Mind. Retrieved from https://www.autodesk.com/redshift/generative-design-examples/

Sha, Z., Kannan, K. N., & Panchal, J. H. (2015). Behavioral Experimentation and Game Theory in Engineering Systems Design. *Journal of Mechanical Design, 137*(5), 051405-051405-051410. doi:10.1115/1.4029767

Shute, V., & Ventura, M. (2013). *Stealth Assessment Measuring and Supporting Learning in Video Games*. Retrieved from Cambridge, Massachusetts: http://mitpress.mit.edu/sites/default/files/titles/free_download/9780262518819_Stealth_Assessment.pdf

Shute, V., Wang, L., Greiff, S., Zhao, W., & Moore, G. (2016). Measuring problem solving skills via stealth assessment in an engaging video game. *Computers in Human Behavior, 63*, 106-117.

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., . . . Hassabis, D. (2017). Mastering the game of Go without human knowledge. *Nature, 550*, 354. doi:10.1038/nature24270

https://www.nature.com/articles/nature24270#supplementary-information

Stewart, S. C. (2011). Interpreting Design Thinking. *Design Studies, 32*(6), 515-520.

Terry, M., & Mynatt, E. D. (2002). *Recognizing creative needs in user interface design*. Paper presented at the Proceedings of the 4th conference on Creativity & cognition, Loughborough, UK.

The Design-Based Research Collective. (2003). Design-Based Research: An Emerging Paradigm for Educational Inquiry. *Educational Researcher, 32*(1), 5-8.

Touloupaki, E., & Theodosiou, T. (2017). Energy Performance Optimization as a Generative Design Tool for Nearly Zero Energy Buildings. *Procedia Engineering, 180*(1178-1185).

Walmsley, K., & Villaggi, L. (2019). Generative Urban Design: A Collaboration Between Autodesk Research and Van Wijnen. Retrieved from https://medium.com/autodesk-university/generative-urban-design-43f4ea48039d

Wilkinson, S. (2015). *Approximating Computational Fluid Dynamics for Generative Design*. University College London, London, UK.

Wilkinson, S., & Hanna, S. (2014). Approximating Computational Fluid Dynamics for Generative Tall Building Design. *International Journal of Architectural Computing, 12*(2), 155-177. doi:10.1260/1475-472x.12.2.155

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative Intelligence: Humans and AI Are Joining Forces. *Harvard Business Review*, 114-123.

Wing, J. M. (2006). Computational Thinking. *Communications of the ACM, 49*(3), 33-35.

Wing, J. M., & Stanzione, D. (2016). Progress in Computational Thinking, and Expanding the HPC Community. *Communication of the ACM, 59*(7), 10-11.

Woodbury, R., Mohiuddin, A., Cichy, M., & Mueller, V. (2017). Interactive design galleries: A general approach to interacting with design alternatives. *Design Studies, 52*, 40-72.

Xie, C. (2012). Interactive Heat Transfer Simulations for Everyone. *The Physics Teacher, 50*(4), 237-240.

Xie, C. (2015). Visual Process Analytics. *@Concord, 19*(2), 4-6.

Xie, C. (2018). Generative Design of Concentrated Solar Power Towers. Retrieved from https://medium.com/@charlesxie/generative-design-of-concentrated-solar-power-towers-9c5f6f2304d2

Xie, C., Schimpf, C., Chao, J., Nourian, S., & Massicotte, J. (2018). Learning Engineering Design through Modeling and Simulation on a CAD Platform. *Computer Applications in Engineering Education, 26*(4), 824-840.

Xie, C., Zhang, Z., Nourian, S., Pallant, A., & Bailey, S. (2014a). On the Instructional Sensitivity of CAD Logs. *International Journal of Engineering Education, 30*(4), 760-778.

Xie, C., Zhang, Z., Nourian, S., Pallant, A., & Hazzard, E. (2014b). A Time Series Analysis Method for Assessing Engineering Design Processes Using a CAD Tool. *International Journal of Engineering Education, 30*(1), 218-230.

Yang, M.-D., Lin, M.-D., Lin, Y.-H., & Tsai, K.-T. (2017). Multiobjective optimization design of green building envelope material using a non-dominated sorting genetic algorithm. *Applied Thermal Engineering, 111*(1255-1264).

Yu, W., Li, B., Jia, H., Zhang, M., & Wang, D. (2015). Application of multi-objective genetic algorithm to optimize energy efficiency and thermal comfort in building design. *Energy and Buildings, 88*(1), 135-143.

Zabelina, D. L., & Ganis, G. (2018). Creativity and cognitive control: Behavioral and ERP evidence that divergent thinking, but not real-life creative achievement, relates to better cognitive control. *Neuropsychologia, 118*(9), 20-28.

Zaman, L., Stuerzlinger, W., & Neugebauer, C. (2017). *MACE: A New Interface for Comparing and Editing of Multiple Alternative Documents for Generative Design*. Paper presented at the Proceedings of the 2017 ACM Symposium on Document Engineering, Valletta, Malta.