Received: 14 April 2018 | Accepted: 16 April 2018
DOI: 10.1002/cae.21980

SPECIAL ISSUE ARTICLE

WILEY

Modeling and simulation practices in engineering education

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Funding information
U.S. National Science Foundation, Division of Engineering Education and Centers, Grant number: 1449238

Abstract

Much can be learned from the vast work on the use of computer simulations for inquiry learning for the integration of modeling and simulation practices in engineering education. This special issue presents six manuscripts that take steps toward evidence-based teaching and learning practices. These six studies present learning designs that align learning objectives, with evidence of the learning, and pedagogy. Here we highlight the main contributions from each paper individually, but also themes identified across all of them. These themes include (a) approaches for modeling-and-simulation-centric course design; (b) teaching practices and pedagogies for modeling and simulation implementation; and (c) evidence of learning with and about modeling and simulation practices. We conclude our introduction by highlighting desirable characteristics of studies that report on the effectiveness of modeling and simulation in engineering education, and with that we provide some recommendations for improving the scholarship of teaching and learning in this field.

KEYWORDS
graduate, K-12, modeling, post-graduate, simulation

1 | INTRODUCTION

Engineering workplaces are more frequently using modeling and simulation practices providing professionals with the ability to effectively complement experimental and theoretical approaches to discovery and innovation processes (e.g., Ref. [37,38,46]). As a result, engineering education policymakers and practitioners, among other stakeholders, have called for the need of educational researchers and educators to consider ways of engaging students in the practices of professional science and engineering through modeling and simulation [40,28]. For instance, agencies such as ASEE [2], ABET [1], and the Washington Accord [19], among others, have recognized the importance of these skills and have recommended their incorporation into the undergraduate engineering curriculum. To successfully integrate modeling and simulation practices into the undergraduate engineering education, a crucial step is to identify effective pedagogies, learning strategies, learning environments, and assessment tools in acquiring these practices successfully.

In educational settings, modeling practices have been introduced into the science curriculum since the early years, one of the most recent modeling types being computational modeling. Basically, computer models have been used in three different ways. First, for students to learn the art of modeling per se. In this case students learn a specific modeling language but also principles of modeling that are often referred to as what is called systems thinking [4]. For example, agent-based modeling (e.g., Ref. [23,44,51]) has found its way into pre-college and college classrooms allowing learners to infer cause and effect relationships of systems as a whole. This use of modeling comes closest to the use of models in the professional world in which case modeling is used to explore outcomes of experiments and innovations (e.g., Ref. [9,43]). Second, modeling is introduced into classrooms with the main goal being for students to acquire knowledge on the subject they are modeling [54]. In this case, students learn about topics in domains such as physics chemistry etc. For example, in Mulder et al. [34] students learned about the principles of the glucose-insulin regulatory system. Third, and the most frequent way of using computer models in education, is the case in which students learn about a domain by interaction with readymade models (online labs or simulations) [11]. By providing the model with values of input variables and observing resulting values of output variables, students are prompted to think about the underlying mechanisms in the model that cause these effects. By doing so, it is also assumed that students learn inquiry skills, both in mastering an overarching strategy in the form of an inquiry cycle [39], but also in getting skillful in the more detailed inquiry processes such as setting up hypotheses or designing experiments [10].

The use of computer simulations in K-12 for promoting science education is not new. Specifically, computer simulations have been widely used for teaching science and experimentation knowledge and skills in the elementary and secondary years. In more recent years, modeling and simulation have just started to be integrated in the context of engineering education. This, in part has been driven by the integration of engineering thinking and computational thinking as part of the math and science K-12 curriculum [49]; for instance, by the integration of agent-based simulation tools [44], computational tools [54], educational CAD tools [52], or robotics applications [16]. Similarly, there has been more emphasis on the importance of "systems thinking" and as part of that engaging students to use simulations understand how complex systems work [13].

The integration of modeling and simulation practices in higher engineering education in most cases has been coupled with the use of expert practitioners tools [26]. Many of these tools are domain-specific and require learners to first develop a level of technological proficiency before engaging in meaningful learning [21]. Furthermore, modeling practices have been primarily introduced in post-graduate education, particularly those as pertaining to the creation of computer models to reproduce phenomena or systems of interest using domain specific software, or scientific computing [29]. For instance, a study conducted with expert learners (i.e., PhD students and researchers) identified the central role of the use of computational models for conducting device design in helping experts mediate among mental representations and different external representations [3].

On the other hand, studies that have investigated the integration of modeling and simulation practices in undergraduate engineering education have reported the learning benefits of *using simulations* for conceptual learning (i.e., Ref. [6,7,15,25,47]). However, when students engage in the process of creating models, studies present inconclusive or limited results. For instance, studies conducted to evaluate undergraduate students' learning and perceptions of modeling and simulation practices for characterizing structure, simulating processes, and predicting materials' response suggest that exposing students to *building computational tools* not only promoted students' acquisition of foundational computing concepts and procedures, but also their application to the solution of well-structured engineering problems [31,32]. Other qualitative studies [27], however, have identified major obstacles students encountered when using computational modeling and simulation as part of their learning experiences. One obstacle, for example, relates to student ability to conduct mappings between the physical model, the mathematical model, and the computational model. The other relates to further instructional support (scaffolds) to be able to map different representations [30].

Regardless of when modeling and simulation practices have been introduced into science and engineering curricula, it is evident that there are different, but related processes of modeling and simulation. Also what it is clear is that different processes of modeling and simulation serve different cognitive functions as well as the integration of different science and engineering methods [24]. For instance, practices are characterized by processes involving model building and testing, which help individuals channel observations, drive resulting interpretations, and make sense of the world [17]. Model building and testing also support the creation and optimization of systems, materials, products, or processes [14,33]. Central to modeling are also the use of computer tools that facilitate sense making and optimization procedures by affording simulation practices [30,42]. Computer simulations can represent and predict a system's behavior via a reductive computational representation (e.g., Ref. [20,56]).

Research at the pre-college, college, and post-graduate levels overall have concluded that students who learn by modeling or from simulations must be supported in their modeling or inquiry processes. For example, Mulder et al. [34–36], investigated the effects of providing students with model progression facilities, heuristic worked examples, and partially worked out models) to facility the modeling and learning process. The main lessons for learning with simulations is that students need to be guided, a specific way of doing this is by providing them with scaffolds that support the inquiry processes [36,55]. A second example involving worked examples in the context of computational modeling was proposed by Vieira et al. [48]. Vieira et al. used in-code comments as a strategy for self-explanation of worked examples to engage students in a meaning-making strategy of self-exploration of the given solution. Additional practices promoted by this scaffolded approach were: (1) to connect individual lines of code to a disciplinary problem; (2) to identify effective algorithm design strategies; (3) to get familiar with the MATLAB syntax; and (4) to practice their commenting skills [48].

Much can be learned from the vast work on the use of computer simulations for inquiry learning for the integration of modeling and simulation practices in engineering education. This special issue presents six manuscripts that take steps toward evidence-based teaching and learning practices. These six studies present learning designs that align learning objectives, with evidence of the learning, and pedagogy. The following sections highlight the main contributions from each paper individually, but also themes identified across all of them. These themes include (a) approaches for modeling-and-simulation-centric course design; (b) teaching practices and pedagogies for modeling and simulation implementation; and (c) evidence of learning with and about modeling and simulation practices. We conclude our introduction by highlighting desirable characteristics of studies that report on the effectiveness of modeling and simulation in engineering education, and with that we provide some recommendations for improving the scholarship of teaching and learning in this field.

2 | MODELING-AND-SIMULATION-CENTRIC COURSE DESIGN

Rampazzo and Beghi [41] present a curricular approach for continuing education in modeling and simulation practices of Heating, Ventilation, and Air Conditioning (HVAC) systems. The approach involved a partnership between industry and academia. While the university partners were in charge of developing content and the learning materials of the course based on industry needs, the industry partners provided access to the equipment and case studies, among other resources. The course content progressed by first introducing fundamentals of HVAC systems, and then transitioned to the application of those concepts for the analysis of case studies and examples where students applied modeling, simulation, and control practices. In the process, students learned how to use a variety of software tools. This partnership approach was beneficial during the course creation because the learning experiences were based on examples that were inspired by current problems in the industrial sector. The first implementation of the course was conducted with 10 students and it was on-site. The last implementation of the course consisted of weekly 4-hr sessions delivered using active learning approaches including questions, debates, classroom exercises, and discussions. More importantly, computer simulations and modeling sessions were also performed during the weekly sessions. Such exercises consisted of having learners analyze properties of phenomena and design a variety of systems. The course was evaluated by identifying students' performance in the course in terms of knowledge, skills, and general competences, and also via a survey to identify learners' perceptions of the course. Overall, it was identified that students were able to successfully demonstrate the knowledge, skills, and competences required in the course and most of the participants were either satisfied or very satisfied with the course.

At the post-graduate level (MSc and PhD levels), Chasiotis and Karnavas [8], followed a detailed and systematic approach for embedding knowledge of principles of brushless direct current (BLDC) motor design and performance analysis on a computational tool. Because of the complexity of the learning domain, the development of this tool represents a scaffolding approach that can make complex topics and procedures more accessible to learners. This design approach exemplifies the practices of modeling and simulation where authors started by identifying specifications, created the computational tool, and concluded with a validation and verification process. In addition, Chasiotis and Karnavas [8], also present a preliminary analysis in a classroom setting where 36 graduate students engaged in a process of designing a BLDC motor throughout the duration of the course. As part of the learning process students were engaged in multiple practices including specification of models, mapping model specification with corresponding analytical equations, analysis of the model using finite element methods, simulation of model's behavior, visualization of results, interpretation, and validation of the results by comparing to theoretical models, among other practices. Data from the course indicates that overall student performance was satisfactory with only one student failing the class. Similarly, according to students' perceptions of the course as evidence from a survey collected at the end of the course, students demonstrated positive perceptions on the influence of the tool on their knowledge on BLCD machines fundamentals.

At the undergraduate level, Dickerson and Clark [12], also followed a classroom-based simulation-centric approach throughout the duration of an entire course. The course was about microelectronic circuits where students transitioned from analyzing electrical circuits containing simple linear elements, to analyzing circuits containing complex, nonlinear components. Students were also engaged in electronic design of systems where they assess how low-level device parameters had an impact on the overall system. The main computational tool used throughout the semester was the Simulation Program with Integrated Circuit Emphasis (SPICE). The effectiveness of the course was thoroughly evaluated by identifying (a) the impact of the approach as compared to previous offerings of the course that used a traditional lecture-based approach coupled with simulation-based homework assignments, and (b) students' perceptions of the teaching approach on their learning. When students were compared in terms of performance using the final exam as well as based on essay questions, it was determined that there was a statistically significant improvement on the students' performance on the simulation-centric approach. The difference was of 10 points on the total exam score of 100 points, and a three point difference in the essay-question on the total score of 20 points. The effect sizes for both were determined to be large. In addition, student responses to interviews and surveys determined that the approach was helpful and positive, and students were able to identify specific benefits such as their ability to visualize results, test the results of hand calculations, and applying hands-on learning, among others.

Also at the undergraduate level, but in the area of specialization of neuromorphic engineering applications, Korkmaz et al. [22], presented a simulation-centric 3-week training course. The course integrates advanced topics in the areas of biophysical neuron models, oscillator models, and neural networks as forms of Central Pattern Generator (CPG) models, combining them with hardware structures to create robotics applications. Software tools included MATLAB and its sub-tool SIMULINK to aid model-based design processes, which provided automatic code generation, testing, and verification of embedded systems capabilities. Forty-nine students in their last term of their engineering education enrolled in this course. Students were exposed to theoretical concepts delivered in a lecture format coupled with practical modeling and simulation applications. The training course was evaluated in terms of student learning of the modeling, simulation and implementation stages of the CPGs through a midterm exam, and students' perceptions of the educational approach via a survey. Results of the evaluation indicate that overall students improved their knowledge of the subject domain and acquired an ability to use modeling and simulation skills for designing, analyzing, and realizing engineering applications. The perceptions of the learning experience were also overall positive.

These four studies present instances in which modeling and simulation tools and practices were implemented throughout the duration of an entire course and were placed at the center of the teaching approach. These four studies also present differences particularly as related to the target audience and the context of delivery. While in the case of Rampazzo and Beghi [41], the focus was on practitioners from a research and development area in a company, Chasiotis and Karnavas [8] focus was on master and doctoral students. Dickerson and Clark [12], presented an approach with undergraduate students from an introductory course in a traditional classroom setting, and Korkmaz et al. [12], presented a case of a training course for advanced undergraduate students. The design of each course first took into consideration specific learning outcomes instructors wanted to accomplish. Interestingly, in all cases the learning outcomes included the understanding of fundamental concepts, modeling, and simulation skills applied to analysis or design activities, and the use of computational software. Specific assessment methods were also proposed for each of the objectives identified. This alignment between learning outcomes and evidence of the learning is critical first step for the design of learning environments [50]. Once this alignment is achieved the next step focuses on identifying the pedagogy and delivery method. To this end, the integration of in-class modeling and simulation coupled with short lectures, and active learning approaches culminating with a design project seemed to be an effective approach to not only help students develop deeper foundational knowledge and insights, but also to promote analytical and design skills, and the use of practitioners tools. More work is needed with larger class-sizes to identify under what conditions this modeling and simulation centric approach can be scalable.

3 | TEACHING PRACTICES AND PEDAGOGIES FOR MODELING AND SIMULATION IMPLEMENTATION

Igual et al. [18] performed a systematic literature review to identify how modeling and simulation practices have been introduced for teaching power harmonics. In this literature review 19 papers were analyzed in detail to characterize the learning outcomes being taught with modeling and simulation in the domain of power harmonics; assessment methods of learning outcomes and course evaluation methods, instructors' perceptions of their integration of these practices into their teaching as well as pedagogical methods they used, and other usability and adoption considerations such as development platforms and software availability. Considering teaching methods specifically, it was identified that modeling and simulation practices are introduced mainly first following a traditional instructor-centered teaching approach such as lectures, followed by a student-centered approaches such as project and problem based learning.

Dickerson and Clark's [12] study presented specific teaching strategies that were identified as effective approaches for integrating modeling and simulation practices. Such pedagogies included self-directed learning coupled with group-based laboratories. The teaching approach primarily followed a challenge-based approach in which students were first introduced to a practical problem before being introduced to the theory. Student support was promoted via pair-simulation, adapted from pair-programming approaches. A second approach to support student learning was the think-pair-share strategy where students first worked a problem individually, then in groups to compare and improve their answers and then via a whole class discussion to build consensus. The use of active learning methods was evaluated via classroom observations using the Classroom Observation

Protocol for Undergraduate STEM (COPUS) [45] from two class sessions. Based on the results of the analysis it was determined that indeed the class sessions were active and interactive with a significant amount of discussion time between students and the instructor.

Indeed the integration of modeling and simulation practices can promote student-centered approaches to teaching in more active-learning environments. Modeling and simulation practices are also ideal candidates to engage learners in project-based learning, challenge-based learning, and inquiry-based learning. These active learning approaches can provide instructors with specific guidance on how to implement pedagogies that can result in meaningful learning while at the same time promote teamwork and communication skills. The previous section reported studies that demonstrated how modeling and simulation practices were integrated at the macro-level focused on semester-long courses. Studies at the micro-level demonstrating how modeling and simulation practices can be guided through research-based instructional strategies are also needed (see Ref. [5]). For instance, with two groups of high school learners, Xie et al. [53], provide the description of two different implementations. One implementation was in a 2-week in-class unit and a second implementation took place in a 4-week online summer course. Specifically, Xie et al. [53] implemented a challenge-based learning unit where students engaged in a design project. Guidance was provided through a design report that prompted students to present a summary of the evaluation of each of their designs including the results of their analysis of specific criteria. Embedded scaffolding consisted of prompts that guided students through their analysis process along with a trade-off matrix that elicited students to compare and contrast the advantages and disadvantages of each of their designs. Results that compared learning gains between pretest and posttest assessments revealed a significant increase on student science learning and engineering design knowledge.

4 | LEARNING WITH AND ABOUT MODELING AND SIMULATION PRACTICES

It is evident that the integration of modeling and simulation practices into engineering education can have many advantages. Specifically, modeling and simulation tools and practices can afford engineering students and practitioners the study and design of highly interdisciplinary and complex systems such as HVAC, power harmonics, and neuromorphic engineering applications. Throughout the collection of papers in this special issue many of the educational advantages of computational modeling and simulation tools can be identified. For instance, Igual et al. [18], through their literature review identified that one of the biggest perceived advantages of integrating modeling and simulation practices in engineering education is providing students with the ability to solve real-world problems in a classroom setting. Another identified benefit was that such practices can help students develop deeper understanding of the theoretical concepts, promote creativity and motivation to learn. These perceived advantages by students or instructors are attributed primarily to the power of visualization, however, other aspects are also considered such as lower-risk and lower-cost considerations. Interestingly, Igual et al. [18] also identified that instructors found the teaching of the related topics easier when integrating modeling and simulation practices. Instructors also reported higher quality of their own teaching. In their assessment of the course Dickerson and Clark [12] reported similar perceived benefits. Among them are students' ability to (a) do hands-on learning while engaging in design experience and other real applications; (b) have access to non-visible phenomena; (c) be exposed to practitioner's tools; (d) check or verify one's work; (e) get insights into how simulation results differ from hand calculations, among others.

When the target audience is younger learners, learning supports, and feedback mechanisms become highly relevant in order for students to benefit from the experience. Xie et al. [53], took this aspect into consideration when they designed and implemented engineering challenges with an educational CAD tool called Energy 3D. Educational supports taken into consideration were the ability to provide learners with a way to visualize science concepts when engaging in design. Specifically, Energy 3D provides students with the capability to simulate multiple science concepts in multiple contexts enabling them to engage in systems thinking. This is afforded by the underlying Multiphysics computational engines that performed the calculations with the results presented as rich visualizations and graphs. A second educational support relates to providing students adaptive just-in-time feedback. This can be afforded by intelligent agents combining data mining and machine learning techniques.

5 | IMPLICATIONS FOR RESEARCH IN MODELING AND SIMULATION TEACHING AND LEARNING

This special issue also presents two exemplar studies that followed more rigorous methods to provide evidence of the learning. Specifically, Dickerson and Clark [12], applied multiple assessment methods that measured how active a teaching approach was, and the evidence of student learning by triangulating interviews with surveys and classroom assessments. Furthermore, authors also made a strong case of student learning by comparing the effectiveness of the simulation-centric approach to teaching versus a lecture-based approach to teaching. In the process, authors made a compelling case by providing not only descriptions of overall performance in both cases, but also providing statistical evidence after performing an inferential analysis and evaluating p values. Furthermore, Dickerson and Clark [12], also provided effect sizes that quantified the difference between students' performance in the two groups. Xie et al. [53], applied similar analyses and reported learning gains from pretest and posttest measures providing statistical evidence and a quantified measure of the difference. In both studies, Dickerson and Clark as well as Xie et al. supplemented their analysis with qualitative methods. Dickerson and Clark performed a thematic analysis on students' responses reporting their perceived benefits of using modeling and simulation in their course. The responses were double-coded to check for consistency. Xie et al. qualitative methods consisted of analysis of design journals and two case studies reporting the analysis of logged process data of students who completed a high-performance design and a low-performance design.

To make a compelling case for the integration of modeling and simulation practices in engineering education, we need more studies that report effective approaches for supporting the integration of this practices in a classroom setting. This need is well-aligned with what Igual et al. [18], identified in their review of the literature. They pointed out the pressing need for stronger evidence of the learning when integrating modeling and simulation practices. According to the authors only two of the 19 papers evaluated reported some comparative measures of learning. Specifically the two studies identified compared results between pretest and posttest assessments. No inferential analysis, however, was provided. That is, no evidence was provided regarding whether or not the improved performance was significant or not. Thus, there is a need for more studies that provide more rigorous measures of learning with modeling and simulation in specific, but also from the use of computer applications in engineering education in general. We therefore invite the community to go beyond measures that report on students' level of satisfaction or perceived learning, (a) to studies that clearly demonstrate direct evidence of the learning reporting on what students are capable of doing and learning as they engage with modeling and simulation practices and (b) to studies that demonstrate a clear learning advantage aimed at integrating computational tools and related practices as part of the learning process as compared to traditional approaches where modeling and simulation practices are not integrated.

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How to cite this article: Magana AJ, de Jong T. Modeling and simulation practices in engineering education. *Comput Appl Eng Educ*. 2018;26:731–738. https://doi.org/10.1002/cae.21980