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Learning and teaching engineering design through modeling and simulation on a CAD platform

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Abstract

This paper provides a theoretical perspective of how modeling and simulation on a CAD platform can be used to teach science concepts and inform design decisions. The paper discusses the educational implications of three recent advancements in CAD technologies: system integration, machine learning, and computational design. The challenges to design energy-efficient buildings that harness solar energy are used as the engineering examples to illustrate the learning and teaching opportunities created by the modeling, simulation, and data mining capabilities of the Energy3D software, which is a CAD tool developed from scratch along the directions of the three advancements to support engineering research and education. Preliminary results from students in a physics classroom and an online course shed light on the effects of these features on guiding student to design cost-effective rooftop solar power systems for their own home buildings.

KEYWORDS
artificial intelligence, computer-aided design, data mining, engineering design, science education

1 | INTRODUCTION

In workplaces, engineering design is supported by contemporary CAD[1] tools capable of *virtual prototyping*—a full-cycle process to explore the structure, function, and cost of a complete product on the computer using modeling and simulation techniques before it is actually built [22,46]. In classrooms, such software tools allow students to take on a design task without regard to the expense, hazard, and scale of the challenge. Whether it is a test that takes too long to run, a process that happens too fast to follow, a structure that no classroom can fit, or a field that no naked eye can see, students can always design a computer model to simulate, explore, and imagine how it may work in the real world. Modeling and simulation can thereby push the envelope of engineering education to cover much broader fields and engage many more students, especially for underserved communities that are not privileged to have access to expensive hardware in advanced engineering laboratories. CAD tools that are equipped with such modeling and simulation capabilities provide viable platforms for teaching and learning engineering design, because a significant part of design thinking is abstract and generic, can be learned through designing computer models that work in cyberspace, and is transferable to real-world situations.

Some researchers [7], however, cautioned that using CAD tools in engineering practices and education could result in negative side effects, such as circumscribed thinking, premature fixation, and bounded ideation [47], which undermine design creativity and erode existing culture. To put the issues in a

[1]To simplify the terminology in this paper, CAD includes analysis that is sometimes also known as computer-aided engineering (CAE). In fact, we adopt a much more inclusive view of CAD to encompass conceptual design, geometric modeling, solid modeling, numerical simulation, visualization, automation, documentation, and communication, in addition to just technical drawing on the computer that many people still equate CAD to.

perspective, these downsides probably exist in any type of tools—computer-based or not—to various extents, as all tools inevitably have their own strengths and weaknesses. As a matter of fact, the development history of CAD tools can be viewed as a progress of breaking through their own limitations and engendering new possibilities that could not have been achieved before. To do justice to the innovative community of CAD developers and researchers at large, we believe it is time to revisit these issues and investigate how powerful modeling and simulation capabilities of modern CAD tools can address previously identified weaknesses.

The goal of this paper is to provide a review of this topic based on our work in the field of secondary engineering education where the target learners, the application environments, and the expected outcomes differ significantly from those in collegiate and professional settings. We will discuss the opportunities and challenges brought by state-of-the-art CAD software to secondary engineering education, which is growing more important than ever as engineering education has been officially incorporated into the Next Generation Science Standards (NGSS) for K-12 schools in the United States [37,40] and considered by many as a viable pathway to integrated STEM education [39]. We begin with elucidating the learning and teaching opportunities enabled by the modeling and simulation capabilities in cutting-edge CAD software in the following section.

2 | THE EDUCATIONAL POTENTIAL OF CAD SOFTWARE

The view that CAD is "great for execution, not for learning" [7] might be true for the kind of CAD tools that were developed primarily for creating 2D/3D computer drawings for manufacturing or construction. That view, however, largely overlooks three advancements of CAD technologies:

1) System integration that facilitates formative feedback: Based on fundamental principles in science, the modeling and simulation capabilities seamlessly integrated within CAD tools [61,67] can be used to analyze the function of a structure being designed and evaluate the quality of a design choice within *a single piece of software*. This differs dramatically from the conventional workflow through complicated tool chaining of solid modeling tools, pre-processors, solvers, and post-processors that requires users to master quite a variety of tools for performing different tasks or tackling different problems in order to design a virtual prototype successfully. Although the needs for many tools and even collaborators with different specialties can be addressed in the workplace using sophisticated methodologies such as 4D CAD that incorporate time or schedule-related information into a design process [25], it is hardly possible to orchestrate such complex operations in schools. In education, cumbersome tool switching ought to be eliminated—whenever and wherever possible and appropriate—to simplify the design process, reduce cognitive load [21], and shorten the time for getting formative feedback about a design idea. Being able to get rapid feedback about an idea enables students to learn about the meaning of a design parameter and its connections to others quickly by making frequent inquiries about it within the software. The accelerated feedback loop can spur iterative cycles at all levels of engineering design, which are fundamental to design ideation, exploration, and optimization. We have reported strong classroom evidence [8] that this kind of integrated design environment can narrow the so-called "design-science gap" [2,60], empowering students to learn science through design and, in turn, apply science to design.
2) Machine learning that generates designer information: For engineering education research, a major advantage of moving a design project to a CAD platform is that fine-grained process data (e.g., actions and artifacts), can be logged continuously and sorted automatically behind the scenes while students are trying to solve design challenges [65]. This data mining technique can be used to monitor, characterize, or predict an individual student's behavior and performance [51,62,64] and even collaborative behavior in a team [50]. The mined results can then be used to compile adaptive feedback to students, create infographic dashboards for teachers, or develop intelligent agents to assist design. The development of this kind of intelligence for a piece of CAD software to "get to know the user" is not only increasingly feasible, but also increasingly necessary if the software is to become future-proof. It is clear that deep machine learning from big data are largely responsible for many exciting recent advancements in science and technology and has continued to draw extensive research interest [19]. *Science* ran a special issue on artificial intelligence (AI) in July 2015 [56] and, only 2 years later, the magazine found itself in the position of having to catch up with another special issue [3]. For the engineering discipline, CAD tools represent a possible means to gather user data of comparable magnitudes for developing AI of similar significance. In an earlier paper [64], we have explained why the process data logged by CAD software possess all the 4V characteristic features—*volume*, *velocity*, *variety*, and *veracity*—of big data as defined by IBM [24].
3) Computational design that mitigates design fixation: In trying to solve a new problem, people tend to resort to their existing knowledge and experiences. While prior knowledge and experiences are important to learning according to theories such as constructivism [43] and knowledge integration [31], they could also blind designers to new possibilities, a phenomenon known as design fixation [11,12,26,32,41]. In the context of engineering education, design fixation can be caused by the perception or preconception of design subjects,

the examples given to illustrate design principles, and students' own previous designs [68]. As it may adversely affect engineering learning to a similar degree as "cookbook labs" underrepresent science learning, design fixation may pose a central challenge to engineering education (though it has not been thoroughly evaluated among young learners in secondary schools). Emerging computational design capabilities of innovative CAD tools based on algorithmic generation and parametric modeling can suggest design permutations and variations interactively and evolutionarily [6,16,28,34,54], equivalent to teaming students up with *virtual teammates* capable of helping them explore new territories in the solution space.

These three aspects, which can all be considered as the results of applying modeling and simulation to engineering design to some degree, have the potential to transform CAD software from pure engineering tools into powerful learning environments that promise to boost engineering education at the secondary level, as further explained in the next section.

3 | CHALLENGES IN SECONDARY ENGINEERING EDUCATION

Unlike college students and professional engineers, young students in middle and high schools have yet to develop abstract mental models and design thinking skills that empower them to imagine and reason about engineering systems that they are challenged to design. They frequently need instructional support like formative feedback to help them forge their mental models and shape their design intuition. These essential elements for engineering education are often insufficiently provided in real classrooms as they require tremendous efforts from teachers for individual students. When students are challenged to solve complex open-ended design problems with a large solution space, the workloads for teachers would escalate to such a high level that it is infeasible for teachers to guide each and every student through the entire design process. In many complicated situations, even though teachers are available to provide instruction, accurate assessment of students' subtle design decisions and proper recommendations for their next steps can only be achieved through systematic analyses of their work that may be too time-consuming to be practical. On the other hand, it is important to also note that engineering design is essentially an inventive process and should be taught as such [14]—any reduction of engineering design to step-by-step "follow-me design" is a violation of the core principle of engineering. Although creativity is a fundamental element of engineering, a recent literature review reveals that very little is known about how to teach for creativity [49]. In cases when unleashing student creativity is an expected outcome, teachers must find ways to stimulate students' imagination, break their fixation, spur their exploration, and even manage their emotions [53]. However, studies found that, while many teachers value the concept of creativity, there exists a discrepancy between their claims of valuing creativity and the realities of their classrooms [9]. A poor understanding of creativity, the lack of authentic engineering design experiences among teachers, the scarcity of tools that support student to explore freely, and the curricular restrictions imposed by the high-stakes testing environment can all contribute to the difficulties in creativity education.

These challenging areas of engineering learning and teaching are exactly where modern CAD software can demonstrate their extraordinary value as educational tools. Modeling and simulation in CAD software can be used to generate formative feedback to students based on computationally analyzing their work in real time, removing a large part of the burden of formative assessment on teachers. Feedback can be delivered through rich, manipulable visualizations and graphs that convey important information in a vivid and efficient way. Computational generation of novel solutions using exploratory tools like parametric or generative design provides teachers a promising technology to stimulate students in ideation and lead them to think outside the box. In the following sections, we describe two categories of applications of modeling and simulation in our Energy3D software based on the system integration and machine learning aspects described in the previous section (educational applications of computational design are currently under development in Energy3D and will be presented in the future). As a brief introduction, Energy3D is a CAD tool that aims to support anyone to learn to design renewable energy and energy efficiency solutions in the real world (http://energy3d.concord.org). It is powered by fast building energy and solar energy simulation kernels that have an overall accuracy within ±5–15% of sensor data, operational data, or benchmark data. The building simulation part has been independently validated using the Building Energy Simulation Test (BESTEST) standardized by the U.S. Department of Energy and the International Energy Agency for evaluating various simulation tools [17]. Recently, the software was used by engineering researchers to design cost-effective renewable energy systems to power mobile hospitals in war-torn countries such as Libya [23]. Despite its power rivaling that of professional CAD software, it has been proven to be friendly to students—thousands of middle school students in Indiana have used it to design sustainable neighborhoods [18].

4 | INFORMING DESIGN WITH SCIENTIFIC SIMULATION

In this paper, we use building energy simulations [5,10] in Energy3D as examples to explain how they can support science learning and inform engineering design. Two important features make Energy3D an appropriate tool for learning and teaching design. The first one is its intuitive interface for 3D modeling (e.g., building-block-based construction of 3D structures like Minecraft and handy copy/paste support for objects in 3D space) and its graphical representations of simulation results (e.g., interactive visualizations of data such as surface heat maps). Without the extensive support of data visualizations in Energy3D, modeling and simulation would have been a data nightmare that overwhelms students with an ocean of numeric outputs or a black box that yields only final results without details under the hood for connecting the dots, as is in many professional building energy simulation packages. The second one is its predictive power that provides quantitative results to help students make design decisions. While it is important for students to acquire conceptual understanding before they can steer their designs in the right direction, conceptual understanding alone may not suffice to make specific decisions that are quantitative by nature. Put it simply, engineering design is not just about "how it works" (qualitative conceptual understanding), but "how much it should be" (quantitative decision making). Without the accurate results predicted by simulation-based analyses in CAD software, students would not be able to evaluate their design choices and arrive at optimal solutions.

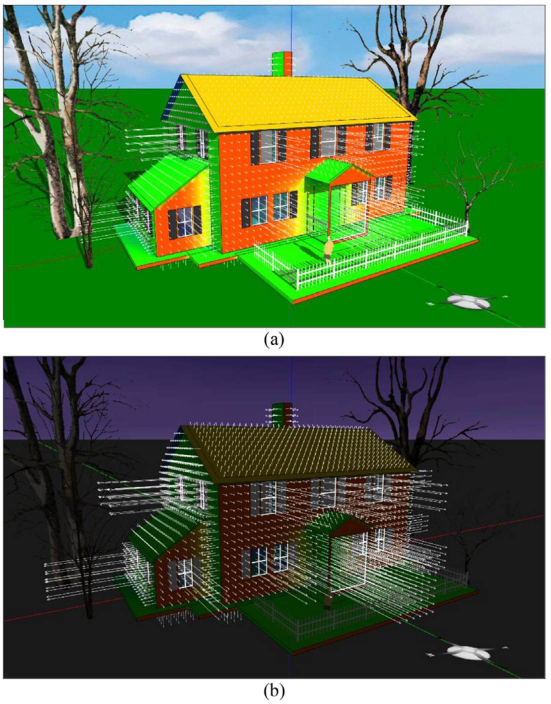


FIGURE 1 Modeling and simulation in a CAD environment can provide salient, dynamic visualization of science concepts and engineering principles that can inform engineering design at each step. (a) A visualization of heat fluxes across the building envelope of a house in Massachusetts at noon on January 1st shows the heat losses at different parts of the house (e.g., more heat escapes from the windows than from the walls or roofs); (b) The visualization shows that more heat is lost at midnight than at noon as indicated by longer heat flux vectors on the building envelope

4.1 | Visualizing science in design

Many science concepts and engineering principles are related to invisible properties or processes of the subjects. For instance, the heat transfer across a building envelope is unseen but important to the design of a zero-energy building that, on an annual basis, consumes no more energy than the amount of renewable energy it generates on the site [33]. Building energy simulations with Energy3D can create visual representations of heat transfer on top of the building being designed. For example, the amounts of heat transferred through different parts of a house at any given time can be calculated by such a simulation and represented by arrays of heat flux vectors with different lengths. Such a vectorial representation immediately suggests that more energy is lost through the windows than the roofs and walls in the winter (Figure 1a). Varying the time of the day causes the heat flux vectors to change their lengths, indicating that more energy is lost at night than during the day (Figure 1b). Interactive visualizations like these allow students to see the qualitative effect of the governing scientific law, which is Fourier's Law of Heat Conduction in this case, *on their own designs*.

4.2 | Connecting multiple concepts

Multiphysics simulation is an important capability of modern CAD software [44] as it allows users to study complex real-world problems in which multiple types of physics mechanisms jointly drive the processes (which is, as a matter of fact, the way Mother Nature works). To this end, Energy3D couples computational engines of solar radiation and heat transfer to simulate building energy consumption and generation. Such a capability provides students with opportunities and contexts to learn the connections among concepts across different domains of science. Understanding the interplay among multiple concepts and thinking about systems design are often critical to engineering projects, especially when the concepts represent different directions of design prioritization that must be compromised to attain an optimal solution. For instance, a cool roof (Figure 2a) can save energy in the summer by reflecting more sunlight off and absorbing less heat than a standard roof [58], but the exact saving depends also on the insulation level of the roof. The more the roof is insulated, the less its exterior color matters, giving the designer more flexibility to choose any color or material for the roof. Understanding this relationship requires students to connect the physics of light absorption at the exterior surface of the roof and the physics of heat transfer between the inside and

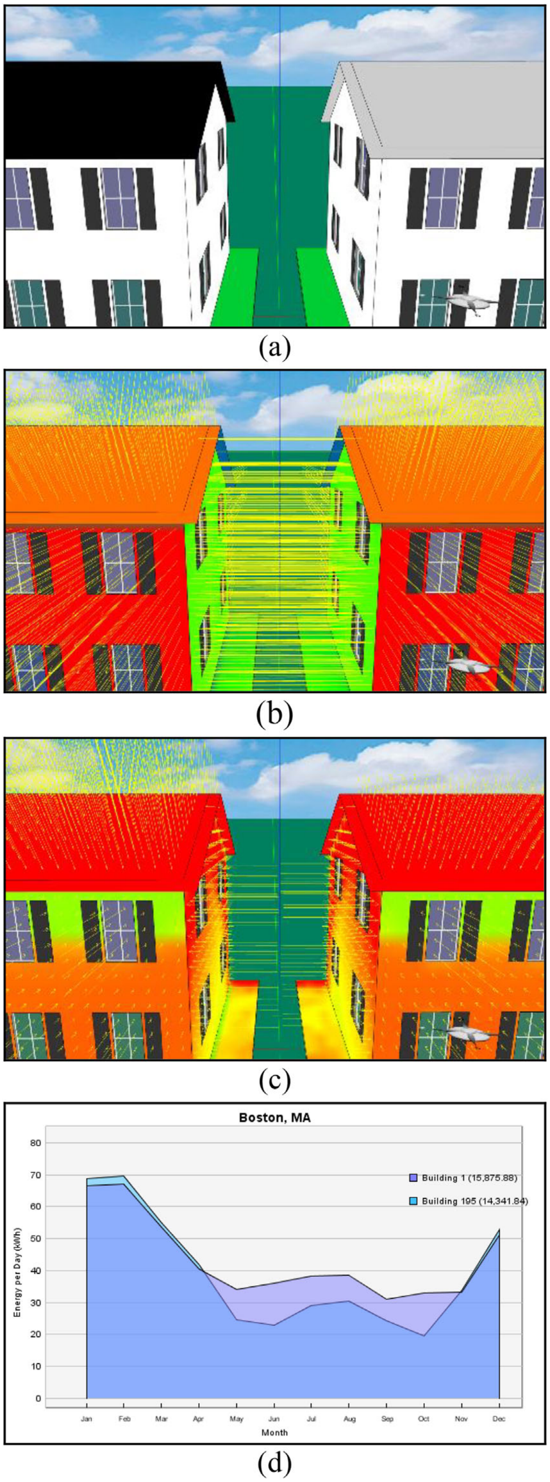


FIGURE 2 (a) Comparative simulations of a dark- and light-colored roof connect the concepts of solar radiation and heat transfer through multiphysics modeling. (b) The solar radiation color map and heat flux vector field show the solar heating and heat transfer of the roof on January 1st in Massachusetts; (c) The same for July 1st; (d) A comparison of the monthly energy usage curves of the two houses indicates that the one with the dark roof uses a bit less energy in the winter but significantly more in the summer

outside of the house through the cross-section of the roof. In Energy3D, the former is represented by the solar radiation color map on a surface and the latter by the heat flux vectors superimposed on the surface (Figures 2b and 2c). The net effect of solar radiation and heat transfer on the annual energy consumption of a house can be represented by an area chart that shows the monthly usages (Figure 2d). The visualization of heat flux vectors may also remedy a possible misconception that solar radiation warms up the house through the roof in the winter. In fact, in a cold climate, the sun may never give energy directly to the house through the roof. The reason that a dark-colored roof may reduce the heating cost in the winter is because the solar heating raises the temperature of the exterior surface, lowers the temperature difference across the cross-section of the roof, and thereby reduces the heat loss through it. Students can observe this effect by comparing the lengths of the heat flux vectors on the southern part of the roof that faces the sun and the northern part that does not face the sun as much (not shown in the images in Figure 2) or the lengths of the heat flux vectors on the dark-colored roof and those on the light-colored one (shown in Figure 2b).

4.3 | Driving design decisions

Trade-off and optimization among design variables that sometimes have conflicting effects on the system performance are central tasks in engineering design. For example, although a house in a cold climate tends to lose more thermal energy through its windows in the winter, it is also heated by the solar energy that shines through them during a sunny day. The latter is important in the design of passive solar buildings [29] that can dramatically save energy for heating and cooling [20]. Exactly what the optimal dimension of a custom-sized window should be or how many fixed-size windows should be used depends on the balance between the energy loss through heat transfer and the energy gain through solar radiation. The thermal loss and radiative gain through a window are controlled by the U-value (the inverse of the R-value) and the solar heat gain coefficient (SHGC) of the window, respectively. To complicate the matter even further, the balance is also largely affected by the location of the house, the seasonal differences of the environmental factors (e.g., the air temperature and the sun path), and the orientation of the windows (e.g., south-facing or west-facing). As such, designing a zero-energy house in southern Maine is very different from designing a zero-energy house in central Florida—the former is in Climate Zone 6 (cold climate) and the latter is in Climate Zone 2 (hot climate) according to the International Energy Conservation Code [42]. Based on the typical meteorological year (TMY) weather data [36] of nearly 700 regions worldwide, Energy3D can accurately calculate heating and cooling energy usage of buildings at different locations around the world. With this capability, Energy3D simulations empower students all over the world to explore sustainable building design in their own areas, as illustrated by the examples for Portland, ME and Orlando, FL in Figure 3. Although one can argue that common sense can also be used to reason about the examples, only quantitative results predicted by numerical simulations can help students make a precise decision about exactly how large the window area should be in an optimal design of fenestration under a specific circumstance.

5 | INFORMING DESIGN WITH DATA MINING

In the previous section, we have shown how results from modeling and simulation in a CAD tool can be visually presented to students to inform their design decisions. The information is often provided to students based on evaluating the current states of their designs without concern for their past states. But if an experienced instructor were available to help, he or she might also review a student's past actions to get some ideas about how the student arrived at the current solution. This information can be useful in making sense of the student's current work and deciding the appropriate instructional strategy for his/her next step. It is, therefore, valuable for an intelligent CAD system to also simulate, to some extent, this kind of human capability. This research area is known as *user modeling* in the context of human-computer interaction [15] and *learner modeling* in the context of intelligent tutoring systems [55]. In a CAD system, we can more explicitly call it *designer modeling*. Generally speaking, designer modeling draws upon one or more learning or design theories, targets a set of learning or design goals, and uses the designer's process data as input. In the current version of Energy3D, process data primarily include actions, artifacts, simulation results, and educational assessments. These data encompass rich information that may shed light on the quality of learning processes and the evidence of learning outcomes. In a sense, the data may reflect students' design thinking and decision making processes, which are not only assisted by the CAD tool but also regulated by interventions outside it such as brainstorming and mentoring. This instructional sensitivity of the CAD logs, confirmed in a June 2013 field test involving 70 high school students [65], is a proof that the type of process data logged in a piece of CAD software like Energy3D is capable of capturing the effects of outside-the-software interventions and can be used to characterize temporal patterns in students' responses to interventions. In this section, we will discuss the collection and visualization of process data, introduce the concept of intelligent agents for generating adaptive feedback, and present our work in using the regular expression technique to mine patterns in event sequences.

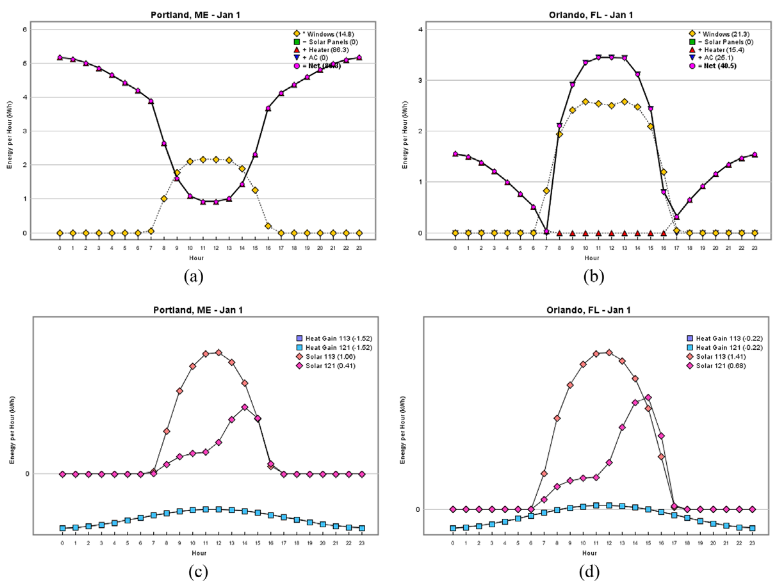


FIGURE 3 Results of building energy simulations in Energy3D are displayed as graphs. Upper images: The hourly heat usage of a house vs. the hourly solar heat gain through its windows on January 1st in Portland, ME (a) and Orlando, FL (b), respectively, revealing that solar heating decreases the energy use of the house in Portland (which needs heating during the day to maintain the indoor temperature at 20 °C) but increases the energy use of the house in Orlando (which needs air conditioning during the day to maintain the indoor temperature at 20 °C). Lower images: The hourly energy loss and gain through a south-facing window and a west-facing window of the same size on January 1st in Portland, ME (c), and Orlando, FL (d), respectively, revealing that the solar heat gain from the west-facing window peaks in the afternoon and is much less than that from the south-facing window at both locations

5.1 | Seeing design processes

Unlike many other CAD tools, Energy3D was created with a vision to support machine learning from fine-grained process data and eventually develop an intelligent system for guiding engineering design learning and practice [63]. We have incorporated data mining features in the software architecture throughout the development process. For example, upon receiving an undoable action such as adding a solar panel, the Undo Manager of Energy3D will signal its Process Logger to record all of the information related to it, such as the position of the solar panel, the type of the solar panel, and the timestamp of the action. Non-undoable actions are also handled by the Process Logger in a similar way. As a result, Energy3D is capable of capturing all student work unobtrusively in the background for "stealth assessment" [52]. For readers who are curious about how the data look like, Figure 4 shows three graphical representations of the logged action data—histogram, scatter plot, and cumulative graph—that somewhat resemble Atman, Deibel, and Borgford-Parnell's three visual representations for engineering design [4] but with flexible controls of process granularity from individual user interface actions to categorized domain level tasks. A critical benefit of collecting this kind of fine-grained process data are that they can be used to reconstruct the entire design and learning process with all the important details restored for analysis. This analysis technique, which we call "design replay," has been used by researchers to investigate students' design behaviors entangled with their self-reflection processes related to the application of science concepts [45]. It may also be worthwhile to explore in the future whether the design replay can be used by teachers as a monitoring tool to observe students' learning processes and by students as a metacognitive tool to review their own design processes.

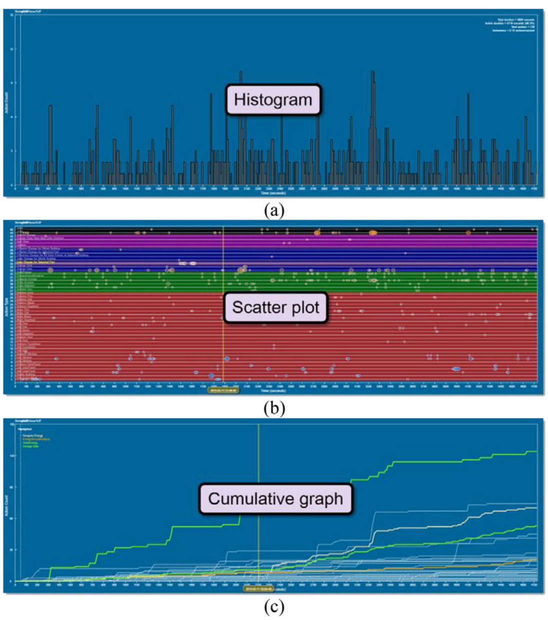


FIGURE 4 Three graphic representations of actions logged in about 80 min. (a) Histogram shows the total number of actions within each time bin. (b) Scatter plot shows the number of actions of different types within each time bin. (c) Cumulative graph shows the growth of the total number of actions of different types. Each representation reveals a different view of the data or a different aspect of the process

5.2 | Creating adaptive feedback

The ultimate reason for collecting the process data during design is to provide just-in-time feedback to students based on analyzing these data in real time. The general framework of intelligent agents [48] best explains how such formative feedback can be realized in Energy3D (Figure 5). An intelligent agent consists of "sensors" and "actuators" connected to an environment in which it operates (in our case this is a CAD environment). Sensors are used to monitor design events and collect design artifacts from students and actuators to invoke feedback to them. A pedagogical model can be implemented by using an event-condition-action rule engine that regulates the designer's behavior based on mining the sensor data and responding accordingly using a decision tree model. For instance, similar to conformance checking in business process mining [59], such a pedagogical model can be used to check the conformance of students' design procedures to certain expectations. In education, conformance checking may constitute a large part of teachers' day-to-day work. In engineering design, for example, there are circumstances under which several types of action must all happen, and even must happen in a given sequence, in order to solve a problem. For instance, if students have run simulations within the CAD software, data collection and analysis tasks

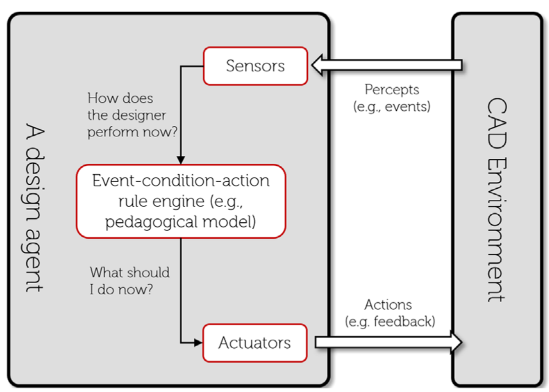


FIGURE 5 Design instruction in a CAD environment can be personalized using a simple reflex agent that observes a designer's actions through "sensors" and reacts accordingly through "actuators." An event-condition-action rule engine provides the pedagogical intelligence

are expected to follow in order to complete a meaningful loop of inquiry. Intelligent agents capable of automatically checking conformance of design behaviors may free teachers up from this laborious work and allow them to focus on high-level instruction.

5.3 | Mining event sequences

The event data stream recorded by the Process Logger of Energy3D is high-dimensional as there are a myriad of action types and each may have many attributes. As the first step to reduce the dimensionality and make the problem tractable, we can code the event sequence into a text string, with a single character representing a type of action (or multiple characters if the number of types needed to be addressed exceeds the limit of the alphabetical set), similar to the coding of the amino acid sequence of a protein in bioinformatics. For example, in the string shown in Figure 6, A stands for an event of simulation-based analysis, W for an event of changing the insulation value of a wall, P for an event of modifying a building other than W that is consequential to its energy use (e.g., changing the color of a wall, resizing a window, adding a solar panel to a roof, etc.), an asterisk for an event that is irrelevant to the current analysis, a question mark for a help-seeking event, a number sign for an event of recording data, and an underscore for a pause longer than a threshold. After translating the event sequence into a text string, we can then use a regular expression (regex)—a sequence of characters that define a search pattern—to check whether an expected condition can be found in the string (so as to inform a pedagogical agent to react accordingly). In the following paragraph, we will explain this regex technique with a concrete example.

This example is concerned with a design step that requires students to choose a proper insulation value for a wall. Assuming that students do not fully understand the relationship between the insulation value of a wall and the energy use of a building, they must first conduct a series of experiments to explore the relationship. This can be considered an inquiry process embedded to inform design and we want to make sure that students follow the principles of scientific inquiry. Bruce Alberts, former president of the National Academy of Sciences and former Editor-in-Chief of the Science Magazine, defined one of the fundamental principles of inquiry by arguing that "One of the skills we would like all students to acquire through their science education is the ability to explore the natural world effectively by changing one variable at a time, keeping everything else constant" [1]. In our case, the occurrence of both W and P between two As indicates that the student changed multiple variables at a time, rendering the results of energy simulations inappropriate for assessing the effect of the insulation value. The proposed regex technique provides a simple solution. The regex $(A([{}^\wedge P]{*}?W+?[{}^\wedge P]{*}?)(? = A)) + ?$ can be used to find whether there are alternating patterns between W and A, and whether the intermediate events include P, tolerant of any other events that do not violate the inquiry principle (such as collecting data or seeking help). A pattern that has multiple alternating W and A characters suggests a high probability of inquiry, but the existence of other types of energy-changing modification events such as P may compromise the rigor or weaken the probability and should be called out by the pedagogical agent. Regular expressions like this can thus serve as concise pattern indicators for the agent to rapidly characterize student behavior and check their performance. As regex is supported by many programming languages, our approach can be easily generalized to other software as well.

6 | FIELD TESTS

To test the affordances of leading-edge CAD software like Energy3D described in this paper, we conducted two small-scale field tests with U.S. high school students in two different settings in 2016 and 2017, respectively. Both tests used our Solarize Your Home Project based on Energy3D, which is briefly described as follows.

6.1 | The Solarize Your Home Project

The Solarize Your Home Project is an instructional module that supports students to model their own home buildings using Energy3D and design three different photovoltaic solar panel arrays to meet their families' needs for electricity. Students are encouraged to work and think like solar engineers while their parents pretend to be the "clients." As Energy3D can import Google Earth images based on addresses or geolocations, students can easily sketch up their own home buildings on top of the satellite images. Once they create 3D models of their home buildings, they add solar panels to the roofs and calculate the daily or yearly outputs using solar energy simulations in Energy3D. They can also

FIGURE 6 A text string can be used to represent a sequence of events occurred during a design process. Colors are for visual cuing. The meaning of the characters are explained in the text

use the Group Analysis tool to select a group of solar panels and compare their daily or annual yields to decide which part of the roof is more favorable for electricity generation. The main goal of a rooftop solar design challenge is to meet the annual energy usage of the home building as much as possible. Energy3D allows students to enter the actual monthly kilowatt hour (kWh) usage from their electricity bills and overlay this information on top of the simulation results so that they can compare the outputs of their designs with the goal more easily. An important constraint is that the solar power system must be under a certain budgetary limit. To address the possibility of large differences in solar potential across home buildings and provide students an opportunity to explore solar array systems with more options, students are given three budgetary levels to design for: $20,000, $40,000, and $60,000. The total project cost is determined solely by adding up the cost of solar panels that also factors in installation costs and other overhead costs. Students are given three different models of solar panels from different manufacturers to choose from, with the solar cell efficiencies ranging from 16% to 22% and higher-efficiency panels costing more than lower-efficiency ones. While designing, students fill out a design report. The report contains a summary of each of their designs and its performance against the criteria, a series of scaffolding questions to guide their analysis of each design, and a trade-off matrix where students list the advantages and disadvantages of each design in order to help them make a final recommendation to their parents.

6.2 | Research participants

The 2-week pilot test of the Solarize Your Home Project in 2016 involved 27 ninth-grade students (17 girls and 10 boys) in a physics class of an urban high school in Massachusetts of the United States. After a year of development and improvement, we tested the design project again in 2017 with 37 high school students (9–12th grade, mostly from the northeastern part of the United States) who enrolled in two sections of a 4-week online summer course administered by the Virtual High School (VHS). Among the online students, however, only 25 (15 girls and 10 boys) consented to participate in our study. This paper reports the results from the students in two field tests who gave us permission to use their data in the study.

6.3 | Data collection and analysis methods

Several types of data were collected from both the in-class and online cohorts of students, including pre/post-test of science and engineering knowledge, embedded assessments in the form of design journals, students' process data as captured in Energy3D, self-reports and CAD models of students' final designs, and an exit survey about the overall learning experience. We will discuss these types of data and the corresponding analysis methods in the following sections.

7 | ASSESSMENT OF KNOWLEDGE GAINS USING PRE/POST-TESTS

Before starting the Solarize Your Home Project and immediately upon the completion of the project, students took a knowledge assessment with 15 questions related to the understanding of science and engineering knowledge relevant to the project. These pre/post-test assessments were administered only in the two online classes in 2017 as we had not completed the development of the assessment items back in 2016.

7.1 | Pre/post-test assessment items

The pre/post-tests consist of open-ended responses and multiple-choice questions. The assessment items include several released questions from various public sources, such as the North Carolina Earth/Environmental Science Final Exam, Earth and Space Sciences by Educational Testing Service, and Earth Science in the California Standards Test, that are applicable to this study. In addition, we also developed ad hoc items sensitive to this project following the principles of Evidence-Centered Design (ECD) for educational assessments [35] and addressing the need to measure the three-dimensional learning as required by NGSS [38] (e.g., "include multiple components that reflect the connected use of different scientific practices in the context of interconnected disciplinary ideas and crosscutting concepts"). For example, a question adopted from the California Standards Test asks students why more solar energy reaches an equatorial region than a polar region. But this question gauges only students' understanding about a particular concept in earth science. To probe students' ability to transfer and connect this science concept to engineering practice, we couple it with the following question "For homes located in Miami, Florida (latitude 25.8° N), on which of the following roofs would the same number and type of solar panels produce most electricity (assuming that the solar panels only take up a quarter of the roof space)?" The question shows images of a steeply-pitched roof, a mildly-pitched roof, and a flat (zero pitch) roof. A similar question further tests students' ability to apply their science understanding of the solar path to make an engineering decision: "The house below is located in Boston, Massachusetts (42° N, 71° W). The homeowner plans to install a solar electric system on the rooftop. Four possible locations for the solar panels are shown in the image. Explain why each location either is or is not a good place for maximizing the electricity production of the solar panels." Assessment items like these can be used to test our assertion that a CAD tool like Energy3D can help students learn knowledge much beyond learning how to use the tool per se.

7.2 | Pre/post-test results of science and engineering learning

We used a paired *t*-test to compare the means of students' answers to seven multiple-choice questions in the pre/post-test assessments in order to determine whether there was any observable change in their knowledge. After eliminating students who did not complete either the pre or posttest, there were 23 valid paired pre/post-test results (Table 1). The *t*-test reveals the two means are distinct, with a *p*-value of less than 0.00015, suggesting the intervention resulted in significant learning gains for students. To better understand the strength of students gains, we calculated the effect size of the difference through Cohen's d. The results indicated a large effect size with Cohen's d = .954, suggesting the intervention had a strong impact on students learning. While these results appear to be promising, it must be cautioned that the effect was observed with a small sample size.

8 | ANALYSES OF EXIT SURVEYS, FINAL DESIGNS, AND SELF REPORTS

We administered an anonymous exit survey with participants in both the 2016 physics class and 2017 online classes. The results from the two 2017 online classes show that, when asked whether students would recommend the Solarize Your Home Project to others, 19 out of 23 respondents indicated that they would, three indicated that they would not, and one did not respond to this specific question. Of the 19 positive responders, twelve would recommend unconditionally and the rest would recommend conditionally (usually with a condition like "this is a good class if you like engineering or science"). Partly because the test in the 2016 physics class was completed right before the summer break, we received only ten responses in our exit survey. The results show that seven out of those ten responders would recommend, two would not, and one did not respond to the question. Box 1 shows a few student quotes from both the in-class and online cohorts that can be used to cross-validate their recommendations. We conclude that students' experiences were overall positive in both settings.

Box 1. Student quotes from the Exit Survey

"I found this course to be enjoyable and educational. It was neat to be able to design a house and install solar panels on it, see how the sun travels, and what areas on a house receive the most sun in a day." (Online student)

"It is an excellent opportunity to learn about a topic that, in my opinion, there aren't very many opportunities to learn about. The class was a good mix of science and engineering, and I enjoyed learning about the processes that are required to design an efficient solar system." (Online student)

"...it helps people learn more about solar panels easier. You don't really have to google any of the answers since everything is just right there, in the program. I would also recommend this to other students because it's a fun way to learn, and it definitely interests anyone that participates in it." (In-class student)

". . .it's a refreshing project to do in an Engineering class and you can apply many concepts such as design and redesign." (In-class student)

In many engineering projects, the quality of students' design work can serve as an arguably reliable indicator for evaluating their performance and learning. Figure 7 shows a collection of eight students' final designs of residential rooftop solar energy systems from the 2017 online cohort (unfortunately, for some technical reasons, we were able to collect the final design models from only 12 students). We found that the majority of these 12 students were able to sketch up realistic 3D models of their own home buildings—some of them are fairly complex as shown in Figure 7—with the online support provided by the instructor at VHS, who did not have any previous experience in CAD software and completed a 10-hr of professional development only prior to the online course. On the one hand, this is a remarkable outcome considering the fact that the asynchronous instructional support in an online course is commonly perceived as insufficient for supporting complex authentic project-based learning. Part of this success might therefore be attributable to the feedback mechanisms in Energy3D built to help students evaluate their design choices with modeling and simulation at any time, often in the absence of an instructor's input. On the other hand, we have to caution

TABLE 1 *T*-test results of pre/post-test difference

Measure	Pretest mean (SD)	Posttest mean (SD)	*T*-score (*n*)	*p*-value
Result	3.30 (1.40)	4.48 (1.47)	4.58 (23)	<0.00015***

$^{***}p < 0.001$.

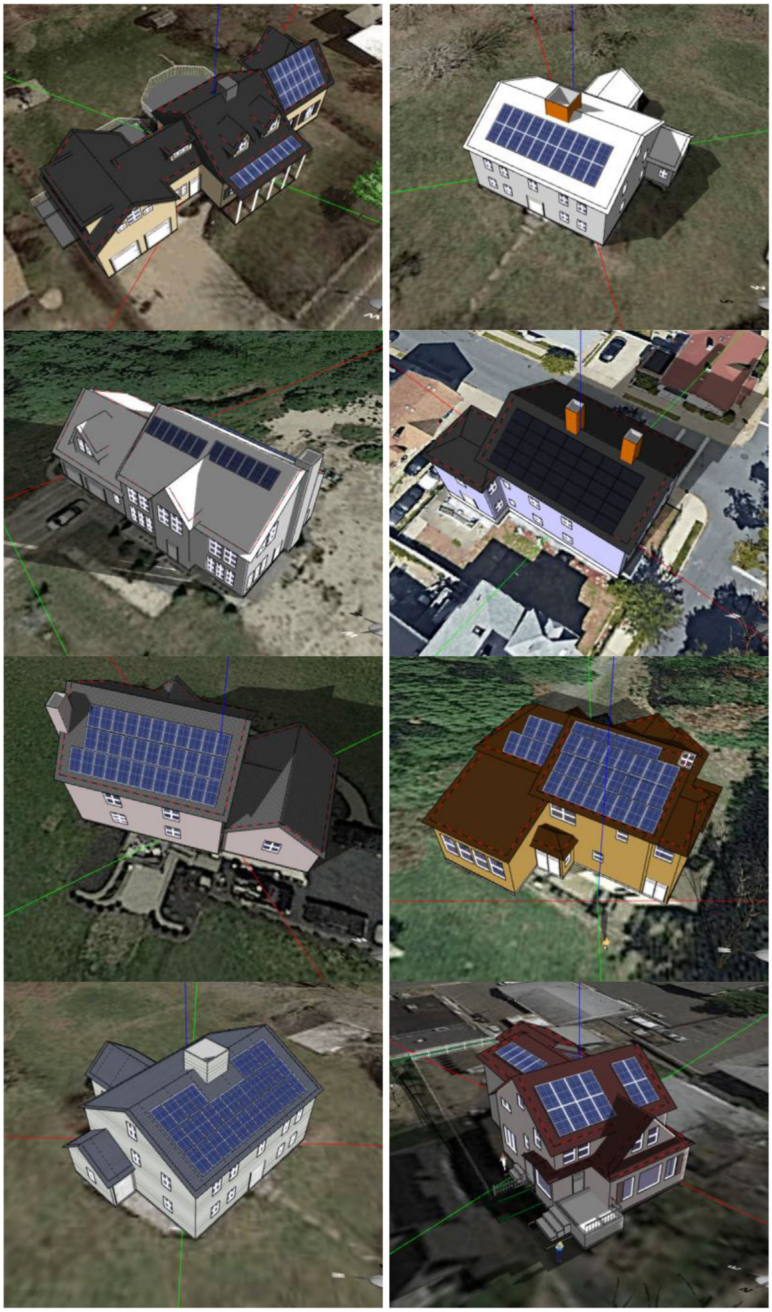


FIGURE 7 Sample designs of residential rooftop solar power systems from students who enrolled in an online summer course administered by the Virtual High School in 2017

that this outcome could also be due to the fact that these online students were motivated enough to invest their time in the project as they signed up for the summer course in the first place.

Students justified their solar system design with evidence collected from the simulations that they performed with Energy3D. While solving the design challenge, students were asked to record their iterations and what they learned from analyzing their designs using Energy3D simulations. Analyzing these design journals, which were collected through the learning management system used in the online course, we found that students reported three major types of insights from using the annual, daily, and group solar yield analysis tools in Energy3D. First, students discovered how the parameters of the solar panels negatively or positively affected the outputs. By testing out several solar panel parameters, students were able to understand what they represent and how they affect the output. For example, one student wrote "I also learned that by increasing the efficiency of a small portion of panels can greatly increase the amount of energy produced..." This insight might have helped the student choose high-efficiency solar panels for small roof space that cannot fit many solar panels. Seventeen of the 22 students in the online cohort reported their findings of this kind in their design journals. Second, students learned about the hourly outputs of solar panels over the course of a day and across different seasons of the year. For example, one student stated that "these analyses have shown me that the amount of energy produced by the panels is at its maximum in the middle of the year and minimum in the beginning and end of the year. . ." Ten students reported that examining the graphs produced by the analysis tools revealed the temporal patterns of solar radiation to them and led them to try different strategies for optimizing their solar arrays. Third, students learned about the relationship between the location of a solar panel on the roof and the orientation of the sun in the sky. One student explained that "I noticed that the incidence angle was closer to being zero when the panels were farther down on the roof. . ." Seven students reported learning about this detailed relationship. By systematically examining the performance of solar panels in different locations relative to the sun, they began to discover the importance of solar panel orientation to the electricity output.

9 | QUALITATIVE ANALYSIS OF PROCESS DATA

In this section, we present the results of qualitative case studies of two students who completed a high-performance design and a low-performance design, respectively, of a rooftop solar system for their own houses from the 2016 pilot test in the physics classroom where the process data logs were collected. Case studies take a holistic view at subjects of interest and promote incorporating all relevant data and details about said subjects or cases into the analysis [66]. Case studies allow us to capture the richness of students' action logs and also to compare students' full design processes. Additionally, data visualization was used to represent students' action logs as visualization can integrate many different types of data into "beautiful evidence" [57] (see also Figure 4).

The performance of a student design was measured primarily by the cost effectiveness, which is calculated as the total cost of the solar panel array divided by the annual electricity output of the system (i.e., the cost per kWh generated by the solar panels). A lower cost per kWh is suggestive of a better design. The two selected cases demonstrate different degrees to which students utilize the modeling and simulation capabilities of Energy3D. Additionally, the cases represent some of the variations typically observed in students' final designs. Thus, these cases can shed light on the way in which students use the CAD software to arrive at their final designs.

9.1 | Case I: A high-performance design

Figure 8a shows the recorded actions over the course of the project in the first case. Each gray band in the graph represents the class period of each day. The lower portion of the graph

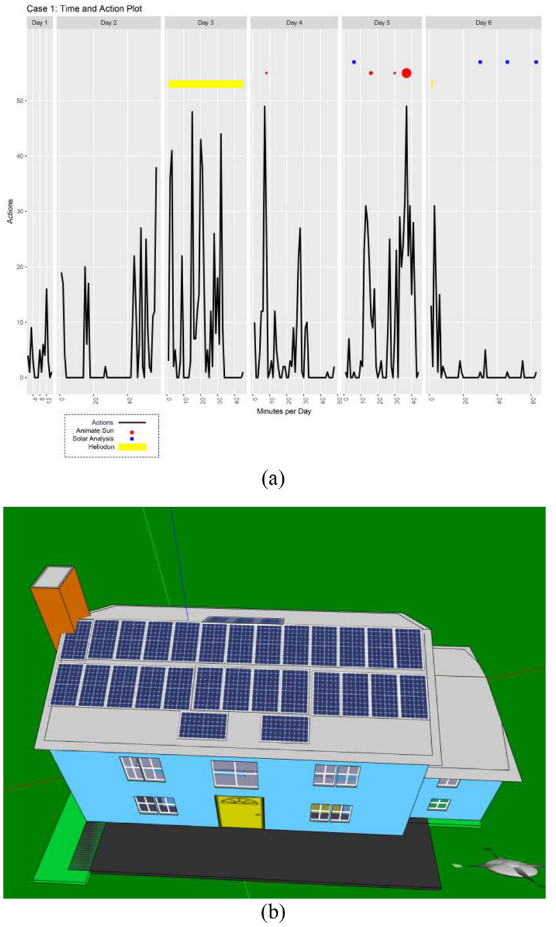
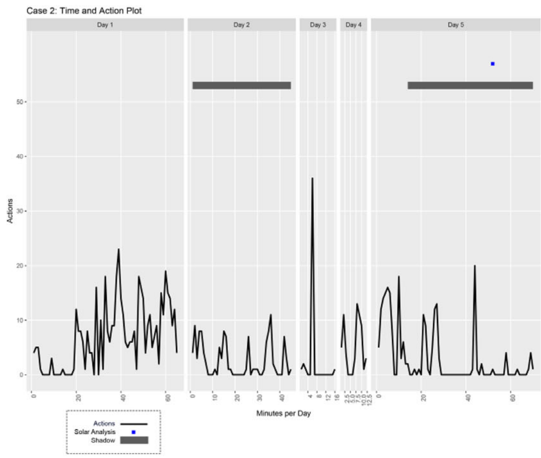


FIGURE 8 (a) A graph that shows the overall activity of the student in Case I. The analytical activity using simulations is also shown in the upper part. (b) The final design of the student

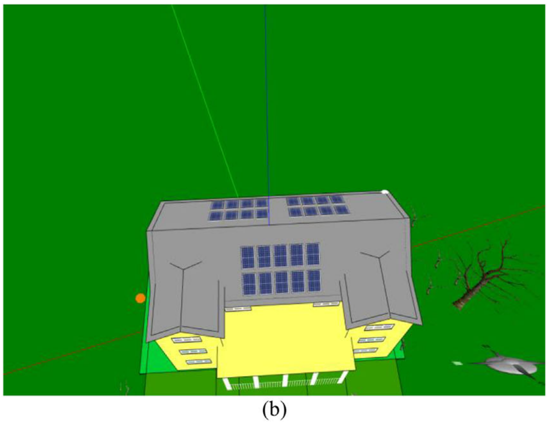
shows the student's overall level of activity. The upper portion shows his use of analytical tools. Note that the gray bands are only as wide as the total duration of time in which an action was taken and recorded by Energy3D within the class period. In other words, if a student takes no more action in the last 15 min of the class period, the log of the daily activity is shortened by 15 min.

Our analysis focuses on finding clues from the process data about how visual energy simulations in Energy3D facilitate students to develop understandings of science concepts and become informed by the conceptual understanding. Figure 8a indicates that the student was wrapping up the 3D model of his house on the third day and started the solar array design after that. The yellow bar in the upper area of the gray band for the third day represents the period in which he used the Heliodon, which is a tool in Energy3D for simulating and visualizing the path of the sun across the sky at different times of the day on different days of the year for different locations on the Earth. The Heliodon allows students to examine how much sunlight each part of a house gets at any time and make connections to the sun's position and path relative to the building under investigation. Without interacting with the Heliodon, students would most likely miss the opportunity to develop a holistic understanding of the sun path, which is fundamentally important to solar energy engineering. The red circles along the upper part of Figure 8a indicate instances when the student used the Heliodon in conjunction with an animation tool that simulates the sun's continuous movement on a given day. The larger the circle is, the more frequently the student ran the animation to observe the solar radiation on the building throughout a day. During the use of these simulation tools, the student also changed the date to explore the seasonal differences. These actions occurred from time to time during the 5th day as he moved on to the final stage of his design.

Running the simulation of the sun path is helpful in developing conceptual understanding, but students need quantitative results to inform their designs. The blue squares in Figure 8a indicate the times at which the student ran the Annual Yield Analysis tool, which predicts the yearly output of the solar array system under design. As can be seen in Figure 8a, the student started to use this simulation tool on the 5th day and continued to use the tool several times on the 6th day, when he had to compare multiple designs and evaluate their relative performances. At the culmination of the project, the student finished three different designs with the best one achieving a cost effectiveness of \$2.04/kWh.



(a)



(b)

FIGURE 9 (a) A graph that shows the overall activity of the student in Case II. The analytical activity using simulations is also shown in the upper part. (b) The final design of the student

9.2 | Case II: A low-performance design

In this case, the logged data shows that the student was highly active at the beginning (the 1st day) and toward the end of the project (the 5th day), as seen in Figure 9a. But he was somewhat inactive in the middle of the project (the 3rd and 4th days). The gray bars in the upper areas of Figure 9a indicate the student was using the Shadow Analysis tool, which visualizes the shadows casted by surrounding trees and different parts of the house on the roof, the walls, or the ground. Exploring shadows can help students identify areas of the roof where the solar panels should be installed and evaluate whether a tree should be removed to boost the outputs of the solar panels. On the 5th day, this student performed the only annual yield analysis for his design—he never ran the simulation analysis again. The lack of information from simulations was probably responsible for a much less cost-effective final design with \$3.58/kWh (high investment, low return), compared with the student in Case I.

9.3 | Comparing the two cases

At the bare minimum, the logged data reveal that the student in Case I was active a full day longer than the student in Case II. Our records of student absences show that both students attended the same number of days. It appears the student in Case II may have been disengaged in one of these days. Note that, while Case I had greater activity spikes on the action graph, some caution may be needed to interpret the results as some of the actions, such as rotating a building or viewing the scene from different angles, may not be directly consequential to the final design. Furthermore, action frequencies alone may not be a reliable gauge for measuring students' final product as students may move through the design at different speeds. However, where students' differences in action may matter is their use of modeling and simulation tools within the CAD software. The student in Case I actively used the Heliodon and animated the sun path across seasons, which may have informed him of better locations to position the solar panels. Indeed, the final design of the student (Figure 8b) shows that he placed the majority of the solar panels on the south-facing part of the roof where they receive more direct solar radiation, whereas the student in the other case placed many solar panels on the north-facing side of the roof where they receive much less direct solar radiation (Figure 9b). Furthermore, by analyzing several design alternatives, the student in Case I may have acquired a greater picture of how the solar system can be optimized to generate more electricity and increase the cost effectiveness. In contrast, although the student in Case II did use the Shadow Analysis tool, a thorough analysis of all of his actions suggests that he never changed the time and date or ran an animation. It is, therefore, reasonable to conclude that he was yet to develop a conceptual understanding of the science involved sufficiently deep to inform his design and, as a result, his design decisions were made with limited information and understanding. Through this comparative analysis, we can start to see the differences in students' interactions with the modeling and simulation tools built in Energy3D and the relationship between these differences and their design performances. It is important to note that this relationship is not limited to the Solarize Your Home Project. In a separate study with 83 ninth-grade students on the Zero-Energy Building Design Project [26], we found that students substantially improved their knowledge as a result of working with Energy3D. Their learning gains were positively associated with three types of design actions—representation, analysis, and reflection—measured by the cumulative counts of relevant actions captured by Energy3D.

10 | CONCLUSION AND DISCUSSION

This paper provides a theoretical perspective of how modeling and simulation on a CAD platform can be used to teach science concepts and inform design decisions. The paper discusses the educational implications of three recent advancements in CAD technologies: system integration, machine learning, and computational design. Energy-efficient building design challenges are used as the engineering examples to illustrate the learning and teaching opportunities created by the modeling, simulation, and data mining capabilities of the Energy3D CAD software. Scientific simulation can visualize science in action, connect multiple concepts, and drive design decisions. Data mining can be used to see design processes, mine event sequences, and create adaptive feedback. These features make Energy3D not only a tool for execution of design ideas but also a tool for learning of science concepts and engineering principles. Although we have not explicitly collected data and developed instruments to zero in how Energy3D may also support creative ideation, it is possible that the learning of science and engineering driven by the formative feedback based on modeling and simulation in Energy3D could directly or indirectly contribute to the development of idea fluency [13]. This is an interesting research question that we can address in the future.

Preliminary field test results from a physics classroom and an online course shed light on the effects of the modeling and simulation features in Energy3D on guiding engineering design. The field tests used the Solarize Your Home Project, which challenges students to design rooftop solar energy systems for their own home buildings. Participants' experiences with the project were overall positive, with 26 out of 33 survey responders indicated that they would recommend it to others. The analysis of their design journals suggested that students learned science concepts and understood design parameters from simulations and used evidence provided by simulation-based analyses to justify their design decisions. The comparison of the process data from a high-performance design and a low-performance design by two different students reveals how simulation-based analyses informed and regulated their design processes. It is evident that the first student's frequent use of analytic simulation tools was responsible for the higher performance and the second student's lack of using them was responsible for the lower performance.

Despite these encouraging results, the sample size of this study is relatively small, potentially limiting the generalizability of the conclusions. Nevertheless, as we are planning field tests of much larger scale in the near future, these initial results can serve as baseline and guidance for developing better data mining algorithms and improving formative feedback generators. Our future work will include investigations of the effects of formative feedback compiled from modeling, simulation, and data mining results, which are currently difficult to separate in students' learning outcome and process data. The research scope of this study will also be expanded to cover the affordances of computational design, which represents exciting developments in the CAD industry based on modeling, simulation, and artificial intelligence [27,30].

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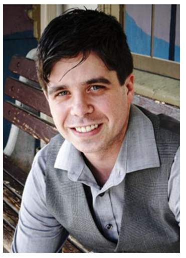
C. Xie has 18 years of experience in STEM innovations. He has created a series of scientific and engineering simulation tools used by over a million people and authored over 40 research papers. He is the main developer of the Energy3D software showcased in this paper. Since 2009, he has served as the Principal Investigator of 12 projects funded by the National Science Foundation and General Motors. His computational fluid dynamics simulation software Energy2D has been used in 16 papers published in the field of science and engineering research. He is currently spearheading two citizen science projects, the Virtual Solar Grid and the Infrared Street View, which aims to engage students and the general public in research on energy science and engineering.



C. Schimpf is a Learning Analytics Scientist at the Concord Consortium. He has a PhD in Engineering Education from Purdue University where his dissertation research explored the use of a game-based learning environment to assist students' in developing design collaboration and ideation abilities. A major strand of his current work focuses on developing and analyzing learning analytics that model students' cognitive states or strategies through fine-grained computer-logged data from open-ended technology-centered science and engineering projects.

J. Chao is a learning scientist with extensive research experience in technology-enhanced learning environments and STEM education. She completed her doctoral and postdoctoral training in Instructional Technology and STEM Education at the University of Virginia. Her past research experiences ranged from fine-grained qualitative mental process analysis to large-scale quantitative and longitudinal investigations. She is currently focusing on learning analytics research in open-ended domains such as engineering design and scientific inquiry. With insights in learning sciences and a strong, computationally oriented mindset, she hopes to utilize learning analytics to investigate important questions with unprecedented granularity and generate actionable knowledge for the design of technology and curriculum.

S. Nourian has a PhD in Computer Science with extensive background in computer graphics. He has 2 years of experience as a lecturing professor and over 8 years of experience in the industry. He is also the founder and creator of Runiter Graphing Calculator 3D software application which has been downloaded by over half a million people worldwide. He was a main developer of Energy3D until 2017.

J. Massicotte is a co-principal investigator on the next step learning project. She has 8 years of experience in energy education and program management in industry. She directed the award-winning Sustainable Energy Education Drive that mobilized environmental science clubs at 18 schools. She holds an MS in Resource and Administration from the University of New Hampshire and is a Building Performance Institute (BPI) certified analyst.

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