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Time Series Analysis Method for Assessing Engineering Design Processes Using a CAD Tool*

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This paper proposes a novel computational approach based on time series analysis to assess engineering design processes using a CAD tool. To collect research data without disrupting a design learning process, design actions and artifacts are continuously logged as time series by the CAD tool behind the scenes, while students are working on a design challenge. These fine-grained data can be used to reconstruct and analyze the entire design process of a student with extremely high resolution. Results of a pilot study in a high school engineering class, in which students solved a solar urban design challenge, suggest that these data can be used to measure the level of student engagement, reveal the gender differences in design behaviors, and distinguish the iterative and non-iterative cycles in a design process. From the perspective of engineering education, this paper contributes to the emerging fields of educational data mining and learning analytics that aim to expand evidence approaches for learning in a digital world.

Keywords: computer-based assessment; computer-aided design; time series analysis; engineering design; engineering education; educational data mining; learning analytics

1. Motivation

Engineering design has been extensively incorporated in the Next Generation Science Standards for U.S. precollege science education [1, 2]. The Technology and Engineering Literacy Framework for the 2014 U.S. National Assessment of Educational Progress includes engineering design as one of the four key skills that need to be assessed at precollege levels [3]. Researchers have developed several assessment techniques. For instance, verbal protocol analysis was used to obtain data from 'thinking aloud' [4, 5]. Latent semantic analysis was used to parse design documentation to characterize designer performance [6]. Timeline analysis was used to monitor students' time allocation to different tasks and their transitions during a design session [7, 8]. These techniques have limitations. For example, the verbal protocol method is intrusive to classroom activities and is weak in capturing non-verbal processes such as perception and intuition that are so important in design [9]. Researchers also found that students did not always put their verbalized knowledge into design practice [10], leaving considerable ambiguity in their performance assessments. The document analysis method has similar weaknesses to those of the verbal protocol method because it, too, is based on analyzing student descriptions of their work, rather than their actual actions. The timeline method was developed to visualize patterns of time usage on different phases, but due to the lack of detailed information about the quality of the design subprocesses in the allocated time, time on task does not always reflect designer performance.

A common disadvantage of these existing methods is that they all require time-consuming data collection and analysis procedures that limit the scale of research. These procedures are often executed manually and the requirement of inter-rater reliability multiplies the work load. Information technology provides a cost-effective alternative. As an important trend in educational research [11], computer-based assessments have been used to study inquiry with interactive media and games [12–16]. But rarely have they been exploited for assessing engineering design, a process that shares some similarities with scientific inquiry but is fundamentally distinct in many ways [17]. We see an exciting opportunity to introduce computer-based assessments into engineering design research. This is possible because computer-based assessments can be implemented within computer-aided design (CAD) tools.

Engineering design is well supported by modern CAD tools capable of digital prototyping—a full-cycle process to virtually explore a complete product before it is actually built. Such CAD tools allow students to take on a design challenge without regard to the expense, hazard, and scale of the challenge. They provide viable platforms for teaching and learning engineering design in the classroom, because a significant part of design thinking is abstract and generic, can be learned through design-

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ing computer models that work in cyberspace, and is transferable to real-world situations. In cases when closing the gap between the virtual world and the real world is required and feasible, a CAD tool can integrate with digital fabrication technologies, such as 3D printers, to allow students to translate their computer designs into physical objects for further learning [18].

For engineering education research, the advantage of moving a design project to an online CAD platform is that learner data can be logged continuously and sorted automatically behind the scenes, while students are solving design challenges. This data mining technique is promising because the logged human-computer interactions and intermediate design artifacts encompass rich information about the quality of learning processes and the evidence of learning outcomes. In a sense, these logged data *reflect* students' design thinking and decision making processes, which are not only regulated by the affordances of the CAD tool such as its user interface and visualization but are also driven by interventions outside the CAD tool such as brainstorming and instruction. To understand the latter, imagine a simple scenario in which students first carry out their design work without any guidance, then stop for an orientation of the project by the teacher, and then carry on their design tasks. It is highly possible that in this case the CAD tool would record a measurable difference before and after the teacher's intervention. This difference in the data logged by the CAD tool can be used to quantitatively study the effect of the intervention.

These logged data include non-verbal, non-textual data that augment other assessment data to provide a more comprehensive and objective picture of learning. For example, to determine if and how students practice iterative designing and systems thinking to search for optimal solutions, we can examine in the design logs the exact types, scopes, time, and frequencies of data-driven inquiry actions students have taken, the numerical results of their investigations through simulated tests, the design rationales students have generated based on their interpretations of the results, the subsequent design actions they have taken as a result of prior inquiry, and the following system performance changes calculated by the CAD software (which can be displayed like game scores to students to guide their design work, too). These kinds of process data with a time dimension can provide evidence of engineering design learning from the perspective of learning progressions [19–21].

This paper is the first of a series of reports about our work on developing, refining, and applying a rigorous computational method for process analysis with the goal to provide reliable analytics and useful visualization for probing into engineering design learning processes on a scale and at a depth unimaginable before. Although this concept-proving research study involved only a small number of high school students, this computational approach is highly scalable and generalizable.

2. Process analytics: Theory and methodology

In this section, we will present a theoretical framework on which our research methodology will be based. This framework considers the dynamic, multifaceted nature of engineering design and aims to define the assessment structures underlying a learning progress from a beginning designer to an informed designer [22] using a CAD tool as both an intervention and assessment system.

2.1 A data mining mechanism based on time series analysis

A complex engineering design process involves many types of tasks and consists of numerous actions that occur sporadically, progressively, iteratively, or even concurrently within the problem space. A CAD tool provides deep design space that is scaffolded by its user interface through which students take actions to shape and test their ideas and designs. Along with the properties and attributes of the designed artifacts that can be calculated dynamically by the CAD tool based on the underlying scientific and engineering principles, the types, timestamps, orders, frequencies, and durations of student actions within the CAD tool provide invaluable insights into the process of engineering design as they accurately reflect the learning trajectories of each student. These longitudinal data can be monitored and collected in the form of *time series*—sequences of data points measured and stored periodically to record the states of an ever-changing designer-design system. In this way, an intervention will leave a measurable trace to its full extent. Assessments can then be viewed as the analysis of a comprehensive set of time series, each representing an aspect of learning or performance over a period of time (Fig. 1).

At first glance, these data may appear to be fairly stochastic. But buried in the noisy data are students' design cognition processes. Time series analysis, which has been widely used in signal processing and pattern recognition [23, 24], can be used to detect meaningful patterns of learner behaviors from seemingly random data. For example, autocorrelation analysis can be used to find repeating patterns in a subprocess. Cross-correlation analysis can be used to examine if an intervention in one subprocess has resulted in changes in another and

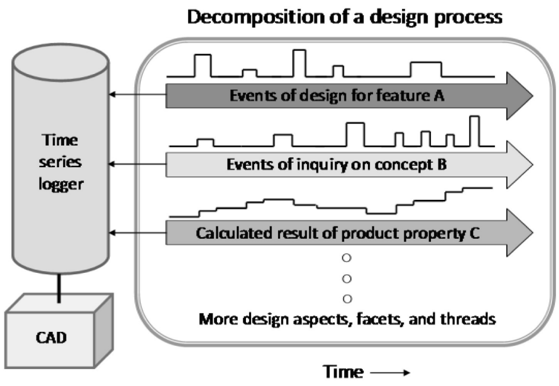


Fig. 1. Engineering design using a CAD tool consists of many human and computing subprocesses that can be monitored as time series. Analyzing these time series would reveal how students learn engineering design from multiple aspects and how different subprocesses are correlated.

estimate how long it has taken for an intervention to regulate a design behavior. Of particular interest is whether cross-correlation analysis can discern and characterize the interplay between an inquiry process about concept B and a design process about feature A, both of which are responsible for the improvement of product performance C (Fig. 1).

2.2 Evidence of design learning from big data

The emerging fields of educational data mining and learning analytics [25] aim to expand evidence approaches for learning and teaching in a digital world [26]. Research in these fields should not be limited to analyzing only Web traffic data generated in online courses such as when the student logs in, which link is clicked, or for how long a video is played. Tracking these generic traffic data is useful for profiling learners, but they provide little direct evidence of deep learning specific to content knowledge or problem-solving skills. This paper represents an effort to broaden the scope of data mining to measure students' abilities to learn inquiry and design in a project-based setting. It presents an example of how evidence of learning may be derived from tracking student exploration *directly within the problem space*. This type of learner data may allow for more meaningful assessments as they are more specifically linked to the content and skill learning goals.

The time series process data can be as fine-grained as the 'atomic' design steps (meaning that they cannot be logically divided further) learners undertake in the problem space, such as an action stored in the undo/redo manager of a CAD tool, or the changes of the individual building blocks of a designed system, including the evolution of a physical property calculated by an analytic module of a CAD tool. Such data can be used to reconstruct and analyze the entire design process of every student with extremely high resolution. Data at this level of granularity possess all the four characteristics of 'big data' [27]:

- *High volume:* A class of highly engaged students can generate a large amount of process data in a complex open-ended project that involves many building blocks and variables.
- *High velocity:* The data can be collected, processed, and visualized in real time to instantaneously provide students with metacognitive guidance and teachers with corrective strategies.
- *High variety:* The data encompass any type of information provided by a rich CAD system such as all the learner actions and artifact properties.
- *High veracity:* The data must be accurate and comprehensive to ensure fair and trustworthy assessments of student performance.

These big data contain a lot of information about the quality of design processes that can yield direct, measurable evidence of learning at a statistically significant scale. Automation of data acquisition and analysis will make this research approach highly cost-effective and scalable.

3. Technology

3.1 Learning and teaching engineering design with Energy3D

This research used a special CAD program, Energy3D (available at http://energy.concord.org/energy3d), which is a free, open-source computer-aided design and fabrication tool that we have developed for children of age 6–18 to make small model buildings (Fig. 2). The program was written in the Java programming language from scratch with the goal to support the teaching and learning of engineering design in the context of sustainable civil engineering. Energy3D provides an easy-to-use 3D graphical user interface for designing model green buildings and assessing their solar energy performances using a virtual heliodon that simulates solar radiation at any given time in any given location. With a What-You-See-Is-What-You-Get (WYSIWYG) user interface that is even more simplified than that of SketchUp, most students are able to master the tool in a short time (15 minutes or so) after watching a tutorial video or a live demo and can quickly design a simple house, a complex building, or even a village. In addition, Energy3D also allows students to 'print out' a design, cut out the pieces, and use them to assemble a physical model to extend learning to the real world. To support this fabrication process, Energy3D automatically deconstructs a 3D structure into 2D pieces and generates a layout of all the pieces on a number

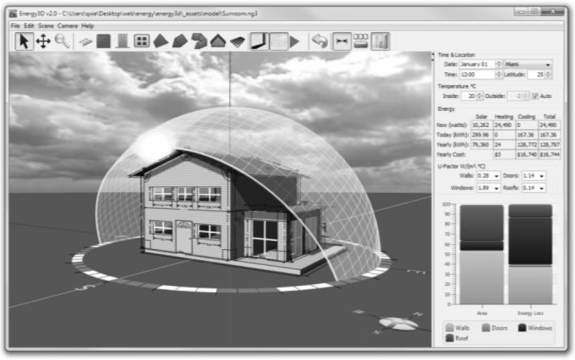


Fig. 2. Energy3D: A special CAD tool for teaching and learning engineering design in the context of building design. Energy3D features a virtual heliodon that simulates the sun path and passive solar heating.

of pages. The entire deconstruction process is animated in the Print Preview so that the user can see the correspondence between the 3D structure on the computer screen and the 2D pieces on the printed paper.

3.2 Logging and analyzing engineering design processes with Energy3D

Unlike other CAD tools developed mostly for engineering applications, Energy3D was developed with a vision to provide an open experimental platform that supports a wide range of engineering education research and practices. With this vision in mind, we have accommodated data collection in the software architecture throughout the development process. As a result, Energy3D is capable of recording the full history of designer actions and a complete sequence of product snapshots with an unobtrusive logger that runs in the background. These actions and snapshots can be used to reconstruct the entire design process with all the important details restored for analysis (Fig. 3). The snapshots also store the zoom extent and rotation angle, which preserve the designer's navigation path in the 3D design space, and can be replayed continuously just like running a slide show. Compared with the screencast technology that records student activities in a video format, which requires analysis so labor-intensive that sophisticated computer vision and image analysis software has been proposed to assist the recognition of student actions [28], the reconstructed process is native to Energy3D and can be arbitrarily and closely examined using all the designing functionalities and learning analytics built in Energy3D. This ability to post-process a recorded design process to extract information gives researchers considerable flexibility in data mining. Special data visualization tools have also been developed to render the complicated analysis results from Energy3D's logs, as will be shown in later sections when we present our results.

4. Implementation

4.1 A solar urban design challenge

In sustainable architecture, passive solar design refers to searching for optimal strategies to maximize solar heating on a building in the winter and minimize solar heating in the summer in order to reduce heating and cooling costs of the building. A

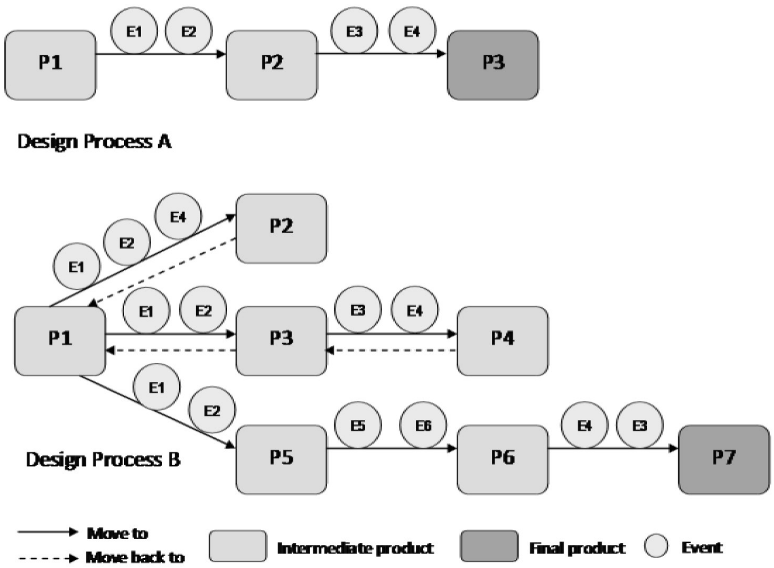


Fig. 3. A schematic illustration of two hypothetical design scenarios in which events and intermediates can be recorded to provide fine-grained details of the design processes. It is shown that the designer in process B goes through more iterations than the designer in process A.

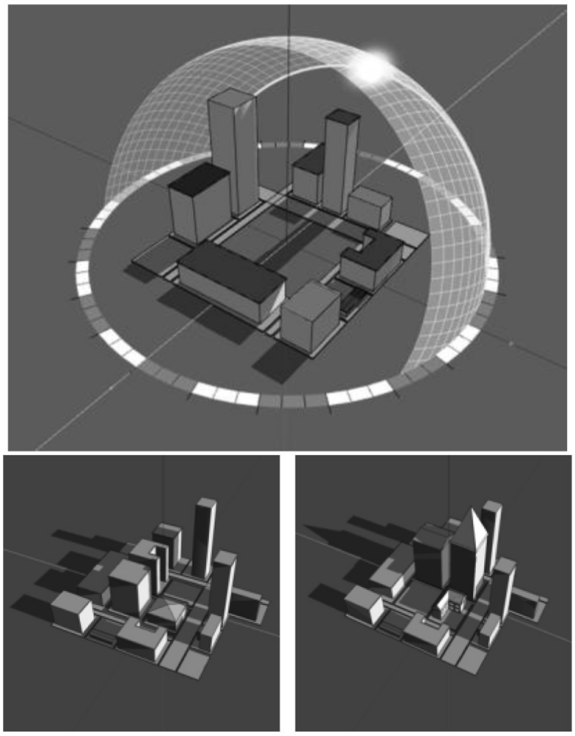


Fig. 4. A solar urban design for an empty city block surrounded by existing buildings. The lower two images represent two possible mock-up designs. The left one is considered to be a better design.

solar design challenge is a typical optimization problem that requires many important steps of engineering design to solve, such as analyzing data, considering constraints, making trade-offs, and optimizing solutions.

For urban design, site layout has a big impact on passive solar heating in buildings as neighboring tall buildings can block low winter sun [29]. Energy3D's heliodon tool can compute, visualize, and analyze solar radiation in obstructed situations commonly encountered in dense urban areas.

The urban design project administered in this study challenges students to use Energy3D to construct a square city block surrounded by a number of existing buildings of different heights (Fig. 4), with the goals and constraints stated in Table 1. The existing buildings, which cannot be modified by students, serve as a type of constraint for the design challenge. This design challenge is an authentic engineering problem as it requires students to consider solar radiation as it varies over a day as well as over seasons and apply these math and science concepts to solve open-ended problems using a supporting heliodon simulation tool. This distinguishes it from common computer drafting activities in which students draw structures whose functions cannot or will not be verified or tested within the drafting software.

This design problem is somehow similar to the playground design challenge used in several earlier studies on engineering design at both college and precollege levels [7, 30–32]. For example, both design problems require students to construct some structures in an empty space; both use some neighborhood settings as design constraints. The solar urban design challenge, however, addresses renewable energy and sustainable buildings that many science teachers are already enthusiastically teaching. Compared with the playground design problem, it is also more closely connected to content requirements in existing precollege science education standards [1]. Therefore, it provides a rich, alternative test bed for research and evaluation on secondary engineering education.

4.2 Research subjects

The solar urban design challenge was implemented in an engineering/technology class in a public high school in Massachusetts, United States, where engineering and technology education has been part of the state standards [33]. The school has an enrollment of over 1000 students annually. The student population consists of 17% minority, with 11% participating in free and reduced cost lunch programs. A total of 20 students, 4 females (referred to as F1–F4 hereafter) and 16 males (referred to as M1–M16 hereafter), of grade levels 10 and 11 participated in this study. All females and five of the males are honor students. Each student was given a notebook computer (either Windows or Macintosh). They worked individually on the design project for five days (one 90-minute period and four 50-minute periods). Although this research setting might weaken the collaborative part of engineering learning, it ensured that each student had a chance to learn and allowed us to track each individual's work.

Table 1. The goals and constraints of the solar urban design challenge

Goals	Constraints
Three new constructions: (1) a high-rise office building; (2) a high-rise apartment building; (3) a shopping area.	Open space is required.
Maximize solar access for the new buildings.	The sun path in four seasons at the given location.
Minimize obstruction of sunlight to the existing buildings.	The existing buildings in the neighborhood.

4.3 Instructional effects

On Day One, the teacher introduced students to the project and handed out instruction sheets that explained the design project and emphasized the specifications. The researchers gave students a brief demo of Energy3D. Students spent about 20 minutes trying various features and tools of Energy3D and getting familiar with the software. Then the researchers briefly introduced the template with existing neighborhood buildings that students were expected to work on (Fig. 4). Starting from Day Two, students worked independently on the project. Each student was required to complete at least three different alternative designs. At the end of the project, they chose their best designs and wrote a final report to explain the rationale. They were told that they would be graded based on their final reports. In addition, at the end of each class period, they were required to answer a short survey summarizing what they had achieved during the period and what they planned to do for the next day.

4.4 Data sources and analyses

The data sources included CAD logs, student designs, self-reports, classroom observation notes, and post-project interviews. Our research focused on the time series data logged by Energy3D, because only this part of the data can be automatically collected and analyzed. All the other data sources were used in our study to contextualize and validate the time series analysis results.

The CAD actions needed to solve the design challenge are coded in Table 2. The building actions include those steps that are necessary to construct a building. The revising actions are modifications such as reshaping a roof. In addition, students may revisit a previous design. Such actions are classified as switching actions.

Our analyses covered both the design products and processes. We evaluated the best designs the students chose based on how well they met the specifications listed in Table 1. From the time series, we extracted the ratio of building versus revising actions, the number of different designs, and the most frequently performed action for each student. To visualize design processes, we plotted the timelines of the design actions performed by each student throughout the project. As this was an exploratory study, our time series analysis was limited to simple statistics of design actions and artifact properties such as maxima, minima, and averages. More sophisticated techniques such as correlation analysis will be used in future studies.

5. Results and findings

This section presents some preliminary results of our pilot study. These results do not necessarily reveal the exact degree of student learning resulting from solving the design challenge. Instead, the research focus is how they performed over the period of time in which their design processes had been logged. We attempted to identify patterns of design behaviors and occurrences of iterative cycles. Since time series analysis is the key technique used in this research, it may be helpful to get a sense of how the logged time series data look like before further discussion. Figure 5 shows two different types of time series, one for counting student design actions and the other for counting design elements in artifacts, from ten students. More data are available at http://energy.concord.org/research.html.

5.1 Level of student engagement

One of the most obvious information that CAD logging can reveal is how well the design challenge engages students. In a classroom with complicated dynamics, the teacher will not be able to monitor, track, and help each individual student. If CAD logs from every student can be analyzed, aggregated, and shown to the teacher in real time, it would help the teacher respond to a student's needs more timely and accurately when the student is reported to have gone astray.

For example, Fig. 6 shows how the time series of an engaged student (F1) differ from those of a disengaged student (M7). The two students were both engaged in the first day but M7 quickly lost interest in the project and went off-task in the following days whereas F1 maintained a consistently high level of design activity (an interview

Table 2. Coding of 'atomic' actions in Energy3D needed for solving the solar urban design challenge

Construct	Revise	Switch
b1: build a foundation	r1: revise a foundation	o1: Open another design or template
b2: build a wall	r2: revise a wall (resize, delete)	
b3: build a roof	r3: revise a roof (reshape)	
b4: build a window	r4: revise a window (resize, delete)	
b5: build a door	r5: resize a door	
b6: build a floor	r6: revise a floor	
b8: build a sidewalk	r7: revise a building (resize, move, or add)	
	r8: revise a sidewalk	

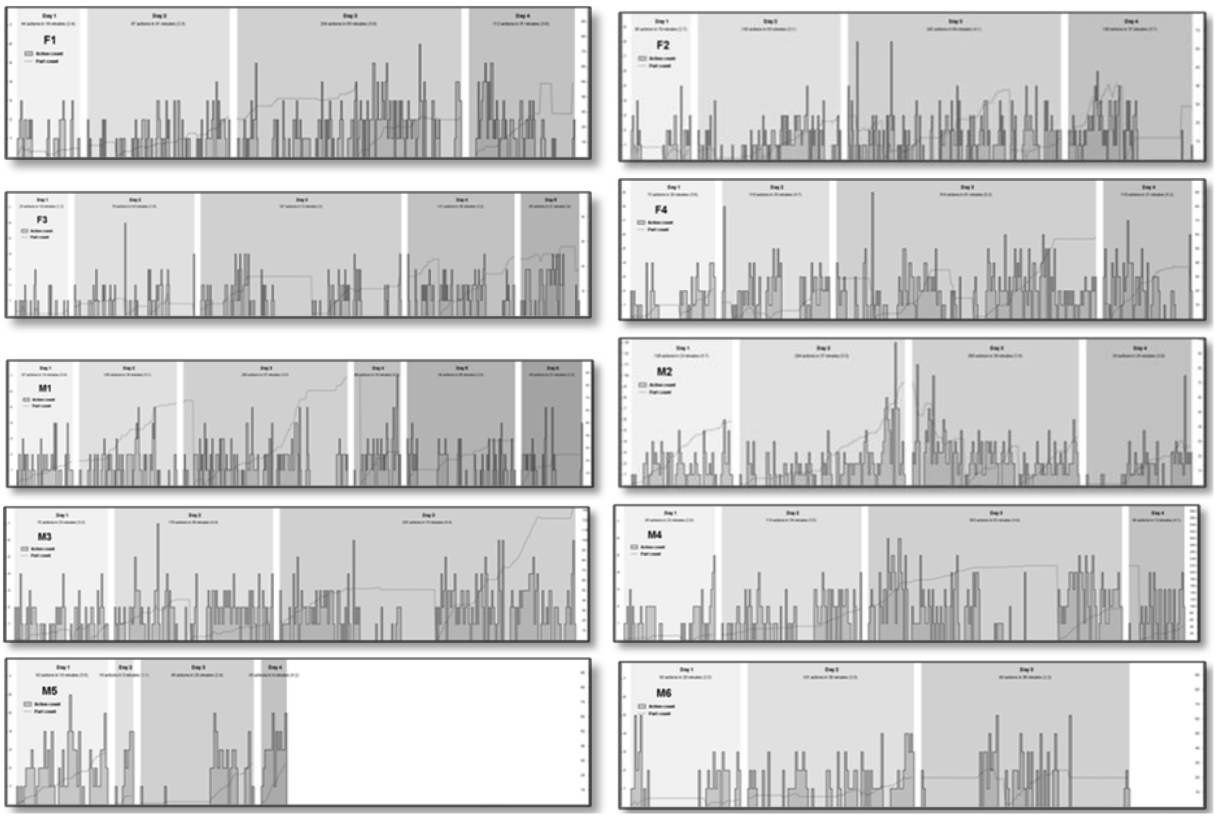


Fig. 5. Two time series across multiple days from ten selected students (four females F1–F4 and six males M1–M6). The Manhattan plots represent the time series that record the number of design actions (see Table 2) taken in a sampling time window (20 seconds). The dashed lines represent the time series that record the total number of building elements in a design, which indicates the complexity of the design.

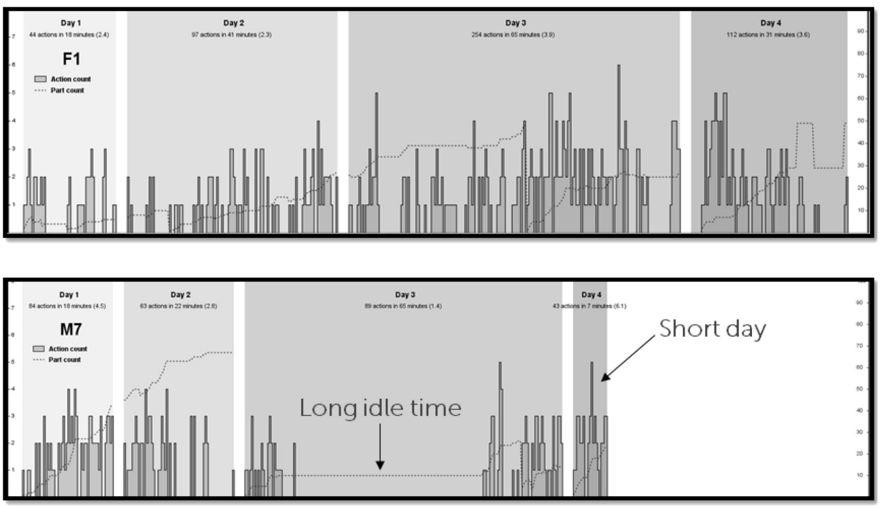


Fig. 6. Time series analysis: A comparison of an engaged student (F1) with a disengaged student (M7). The results conform to our classroom observations.

with her after the completion of the project confirmed that she was constantly searching for better solutions). Similar ineffective behaviors were observed for M5 and M6, as shown in Fig. 5. All these behavior patterns were accurately logged by Energy3D, enabling us to separate the participants into two categories: 'engaged' and 'disengaged.' Our in-depth analyses of design processes focus on eight students (F1–F4 and M1–M4) out of the twenty students, who were identified to be highly engaged by their design logs and confirmed by the classroom observers. For comparison, however, we decided to also include two disengaged students M5 and M6 throughout our analyses.

Table 3. Detailed analyses of student design actions from the logged time series

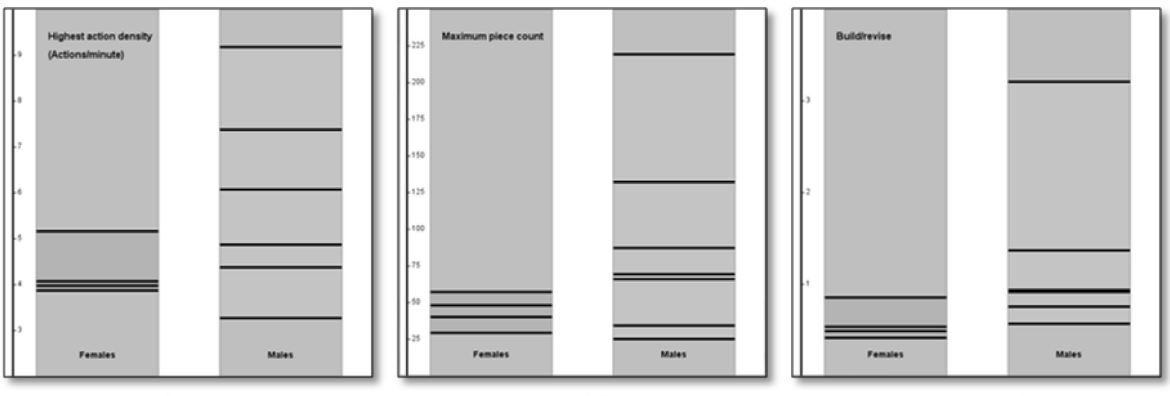
	Total actions	Building	Revision	Ratio of building/ revision	Number of designs	Most frequent action
F1	393	130	259	0.50	4	r2 (revise a wall)
F2	462	163	296	0.55	6	r2
F3	325	97	228	0.43	5	r2
F4	436	202	232	0.87	7	b2 (build a wall)
M1	369	176	190	0.93	3	r2
M2	550	238	310	0.77	5	r2
M3	480	232	245	0.95	3	b2
M4	482	367	114	3.22	3	b2
M5	165	95	79	1.38	4	b2
M6	164	60	104	0.58	2	r2

5.2 Gender differences in design behaviors

An important thesis for engineering design research involves finding different learning pathways that best support male and female students. Therefore, gender differences in design have been extensively studied. In a meta-analysis of 150 studies, significantly greater intellectual risk-taking was noted in male participants [34]. Notable differences were also found in the design work of male and female UK students: Girls outperformed boys in reflective tasks like investigating and evaluating ideas, whereas boys were better at ideation and development [35].

Our analysis results of CAD logs agree with these earlier findings. Our data suggest that there appears to be a large gender difference in both design products and processes. The main differences are: (1) the male students tended to push the limit of the software and produced complex designs that looked 'cool' but did not necessarily meet the design specifications; and (2) the female students spent more time carefully revising their designs than building new structures and paid more attention to design specifications. Table 3 shows the results distilled from the design action time series.

Figure 7 shows the comparison between female and male students from three design aspects: the highest action density (number of actions per minute), the maximum count of elements in a design, and the ratio of building vs. revising actions. The maximum number of elements in a design approximately represents the complexity of the design. Although a more complex design is not necessarily a better design, it is reasonable to assume that the complexity of a student's design is a rough indicator of the student's risk-taking attitude, because a complex design needs more time investment and may be more prone to fail. The action data (action density and building/revision ratio) approximately measure how reflective students might be in the design processes: A higher building/revision ratio may indicate a more reflective process. Our results show that the female students spent more time revising their designs than the male students (who spent more time on adding new elements or new features). As a result,



(a) (b) (c)

Fig. 7. The comparison between female and male students in terms of: (a) highest action density (i.e. number of actions per minute), (b) maximum element count, and (c) the ratio of building vs. revising actions. Each line in the graphs represents a student's data point. In each graph, the lines for females and males are drawn separately in two bands. The left and right bands represent the ranges of data points from the females and males, respectively. All three graphs show a similar trend of gender difference: On average, male students inclined to perform more actions, add more elements in a design, and spend more time on building than on revision.

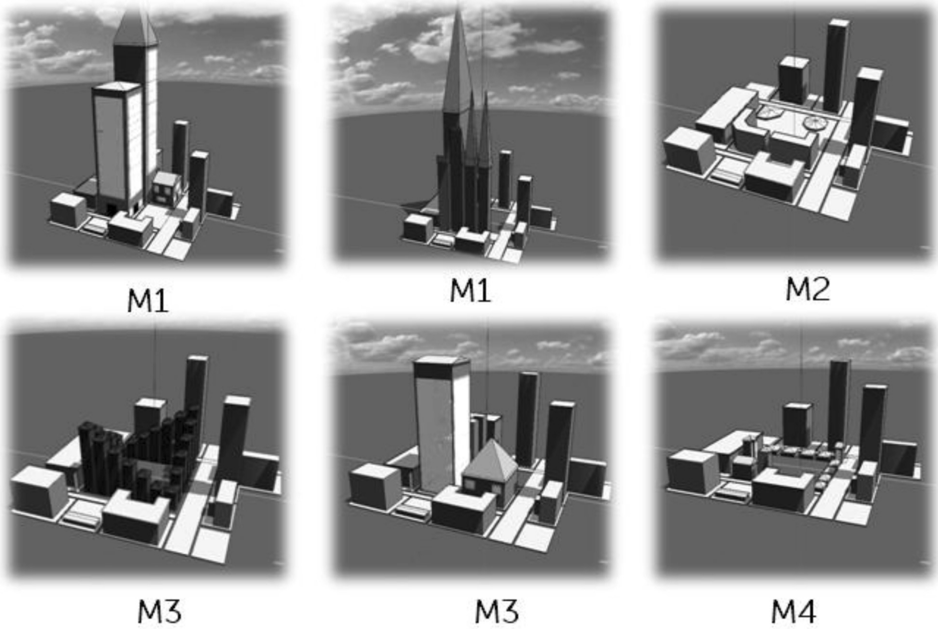


Fig. 8. A few alternative designs from male students that were not chosen as their best designs, indicating the variety of options these students had explored.

the artifacts of male students appeared to be more complex and diversified (Fig. 8).

It is interesting to note that, for this particular group of students, this increased complexity and diversity, however, came at the expense of failing in meeting the specifications. Figure 9 shows the self-picked best designs of the eight selected students. Interestingly, none of the final designs from the male students met the specifications listed in Table 1. For example, in M3 and M4's designs, most of the new constructions were in the shadow of existing tall buildings to the east. All of M1's designs were huge skyscrapers that were out of scale. M2's final design, on the other hand, did not include any high-rising buildings required by the specifications. In contrast, the self-picked best designs of the female students observed most of the specifications. This result may be striking, but not surprising, as it actually agrees with previous observations [35].

Another observation is that all the four female

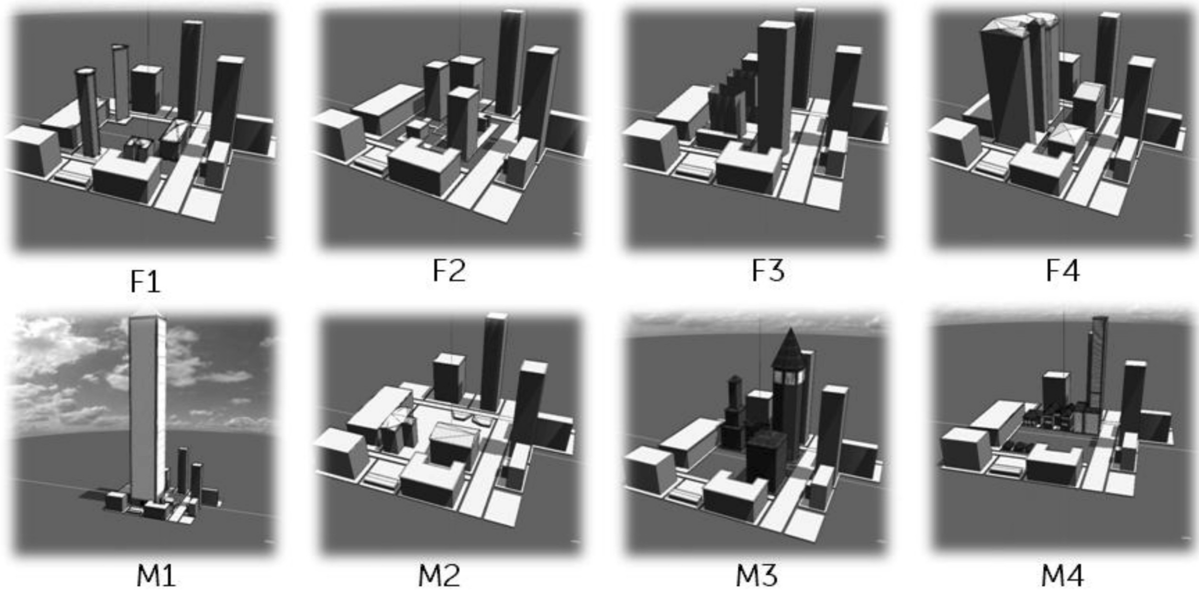


Fig. 9. The best designs from eight students, chosen by the students themselves from at least three different designs each student was required to complete.

students chose their last complete designs as their best designs whereas none of the four male students (M1–M4) did. This means that the design processes of the female students were somehow convergent whereas the design processes of the male students were somehow divergent. One reasonable explanation of this difference is that, at the end of the project, the male students were still exploring the design possibilities so they were not sure that their latest designs would be the best ones. The next subsection about design iteration may provide evidence of this difference from the time series data.

5.3 Evidence of design iterations

Iterations are fundamental subprocesses in engineering design. It is the iterative cycle of design that offers the greatest potential for applying science knowledge in the classroom and engaging in engineering practices [2]. Detecting iterative cycles in student work, therefore, is an important part of engineering performance assessment. A design process without any sign of iterations could indicate premature design fixation [36, 37] and poor learning quality.

There are many different forms of iterations. Students might ask what-if questions and run

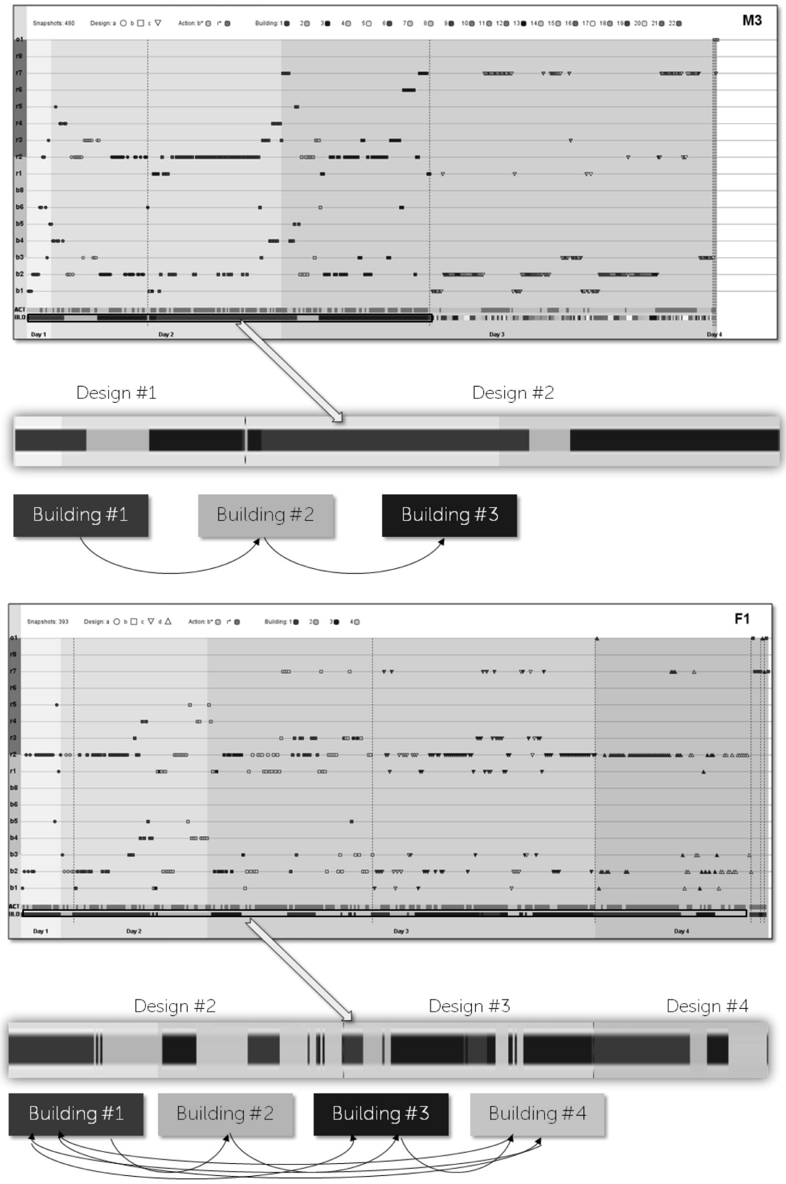


Fig. 10. Non-iterative design behavior (student M3) vs. iterative design behavior (student F1) identified from the CAD logs and visualized in a colored timeline graph that indicates the switching of design actions performed on different buildings. The colors represent different buildings in the designs. The colored timelines are projections of actions displayed in the dotted charts above onto the axis of buildings. (For full-sized, colored versions of these images, please visit http://energy.concord.org/research.html.)

thought experiments in their minds before taking real actions. CAD logging can only capture those iterations that have been translated into actions. A CAD program that provides inquiry tools to spur the design-build-test iterative cycle [38], such as the heliodon simulator in Energy3D, can potentially create an abundance of opportunities for actions, which in turn generates an abundance of student data for research. One type of iteration in the solar urban design challenge involves modifying multiple buildings iteratively based on the solar interplay among them. A modification of one building may affect the solar heating on another and vice versa. This kind of 'domino effect' in the design problem requires students to think about their designs as a system consisting of interacting elements, not just a few isolated individual elements that can be handled separately and linearly.

Figure 10 shows the compressed dotted chart plots of design actions from two reconstructed design processes ('compressed' means that we have removed the time gaps in the graphs to render a compact view of the timelines in order to save space). A dotted chart shows the spread of actions over time by plotting a symbol for each action [39]. The chart has four dimensions: The horizontal axis shows time, the vertical axis shows action type, the color of a symbol represents the object the action is applied to, and the shape of the symbol represents an alternative design solution. These high-dimensional data can be projected onto a selected axis that measures a facet or unfold a thread of the design process, as shown in the call-out parts of the two images in Fig. 10.

As illustrated in Fig. 10, the case of M3 shows no iteration—the student just designed one building after another without stopping for reflection and investigation. In the last day of his project, he even created an extremely complex design that had a total of 22 new buildings, completely ignoring the design criteria. He probably was aware that this last design would not pass because he did not select it as his best design. By comparison, the case of F1 shows significant iterations in design #2 and #3. Having gained experience and insights, she came to the decision of what her last design #4 should be and she did not hesitate to zero in to it, which she then picked as her best design.

The following are the scripts transcribed from the recorded interviews with M3 and F1, respectively, conducted a few days after the completion of the project. The interviews somewhat explain why there were such differences in their design behaviors.

Interview with M3: '*The most thing that I focused on is this building and the windows. With the windows on all sides of it, it will always be able to get some sunlight, because I know the green space is more open, and the skyscraper is over there and the green space is on the opposite side. So in the afternoon and middle of the day, the green space will be under the sunlight. The skyscraper won't cast a shadow on the green space.*' [This student did not mention in the course of the interview that he had considered the interplay among buildings.]

Interview with F1: '*I revised using the heliodon. I moved the buildings according to the heliodon. For example, this building is facing a different direction, so when the shadow is on, it completely blocks one of the surrounding buildings. Also I realized that because my building is so large, the front of it would completely be in the shadow. So because of it, I was able to resize it and make it a smaller building. So that even though there's still a little shadow, but it is not completely covered by the other one. Let me show you this. See this building is huge. Right now it is covered because it's in August. Then when it's in January, it's not covered any more. Because of the heliodon, I was able to see it. In the winter, it's not covered, but in the summer, I guess it's OK to be covered because it's hot outside. You don't want the sun to be on the building anyways.*'

6. Discussions

6.1 Future work

This paper lays out a theoretical foundation for our future research on engineering design and raises many new questions. For example, finding iterative cycles is only the first step to analyze engineering design processes. The more important question is how to stimulate iterations for meaningful learning. Future research on the mechanics of design iterations should identify triggers that can prompt students to revise their designs from new directions or spur them to add new features to their designs. We are also planning research and development that will allow our CAD tool to capture the full cycle of engineering design. This is possible if a CAD tool is used to assist and implement the entire design process that includes problem scoping, ideation, experimentation, evaluation, and communication [7].

Our future goals include finding ways to: (1) computationally gauge the extent and effect of inquiry actions in a complex engineering design process that involves structure-function relationships and data-driven decision-making, and (2) computationally measure the volume of the design space explored by a designer [40] to find evidence of the student's development of divergent-convergent thinking that is critical to creative designing [41]. In the long run, these data mining techniques will demonstrate the feasibility of automatic analysis of student design processes in real time, which is important to the ultimate development of dynamic, adaptive feedback in intelligent tutoring systems for scaffolding the learning of engineering design.

6.2 Limitations

Time series analysis of engineering design learning processes requires that the design challenges be based on CAD tools. Even though we try to integrate CAD extensively into the full engineering design process, there may still be certain subprocesses and aspects of engineering design that cannot be easily supported and captured by a CAD tool, such as the designer's knowledge [42, 43]. It is also legitimate to demand a way to distinguish the learning of the CAD tool per se (especially when the CAD tool is too complicated for students to master in a short time) from the learning of the more important and transferable engineering content and skills that the CAD tool is intended to teach. Despite these limitations, the time series analysis represents a promising step towards a more rigorous methodology for performance assessments of engineering design at large scales.

Another limitation is that user data logging is currently not widely supported by CAD tools. This is understandable because most CAD programs have been developed for professional engineers to solve engineering problems, not for educational researchers to conduct research. This series of work aims to explore the values of data mining within CAD tools using our own Energy3D CAD program as an example. The process analytics we are spearheading could result in robust designer modeling [44] that may eventually spur other CAD developers to consider incorporating data mining into their programs to increase the system intelligence for improving user experience, boosting user productivity, and stimulating user creativity.

7. Conclusions

This paper demonstrates that the time series analysis of CAD logs can reveal student patterns and gender differences in engineering design that have been observed in earlier studies using traditional assessment methods. This research technique provides potentially more reliable performance assessments because a CAD tool offers a highly interactive learning environment with compelling computer graphics that can entice students to devote more time and explore more ramifications. For as long as students are engaged, they will likely produce enormous quantities of learning data that can be automatically collected and analyzed to provide objective evidence of learning and suggest effective strategies to improve learning. This unique integration of computer-aided design and computer-based assessments provides a powerful technology that serves learning, assessment, and research goals at the same time with maximal efficiency.

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