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Characterizing Students' Micro-Iterations Strategies through Data-Logged Design Actions

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Abstract

There has been a drive to incorporate design into K-12 programs in the form of engineering design projects. This presents a unique opportunity to study design cognition from a population that likely has minimal exposure to design. In this study we employ a method of utilizing fine-grained computer logs to capture students' design actions to better understand their design cognition in regards to iteration, which is an understudied but critical component of design. Twenty-seven 9th grade students from an urban high school in New England participated in the *Solarize Your Home* design project where they used Energy3D, a computer aided design platform, to build their home and design several solar array systems for it. Students' computer logs were analyzed for micro-iteration patterns and it was found that 41% of the students engaged in some micro-iterations. These patterns were condensed into four different types: solar panel system capacity testing, solar panel location analysis, solar simulations with panel placements and investigating the suns path across seasons. The paper presents a series of alternative hypotheses and discussion on what these micro-iterations may represent cognitively. Finally the paper concludes on what computer-logged data may be able to assist with on the topic of design learning in K-12.

Introduction

There has been a drive to incorporate design into K-12 programs in the form of engineering design projects to develop students' science and engineering literacy and lay groundwork for some to pursue these fields later[1]. The resulting innovations to K-12 curriculum also present a unique opportunity to study design cognition from a population that likely has minimal exposure to design. Additionally, in contrast to studies with freshman engineering/design students[2-5], K-12 students are situated in a more novice position as they have not yet committed to any form of design higher education. Studying K-12 students may therefore provide great insights into how people learn to think like a designer.

Protocol studies or think-aloud studies are a recognized and well established method for analyzing design cognition and behavior[6-9]. In this study we employ a complementary method of utilizing fine-grained computer logs to capture students' design actions. More specifically, in this study design projects were completed in Energy3D, a professional-grade computer-aided design (CAD) platform with several built-in solar/energy simulation and analysis tools. Energy3D's detailed data schema for logging contains over 150 unique actions from construction actions, simulation and analysis actions to other system control actions[10]. A data-logged approach to studying design has advantages and disadvantages when compared to protocol studies. Data-logging captures a more standardized set of actions that are automatically logged, allowing for a greater number of actors' design processes to be recorded. However, due to its standardization it will necessarily lose some of the rich detail protocol studies provide. Following this, data-logging is best used as a complementary approach to protocol studies.

Design problems are complex and often described as: ill-structured or having components that cannot be fully defined in advance[11-12], navigated through a cycle of problem-solution

coevolution[13] and involving other elements of ambiguity[14]. In light of these attributes of design problems, iteration or looping through parts of the design process is critical for several aspects of design including: developing a better understanding of the problem and constraints, finding new connections in the problem and solution spaces, and improving existing design concepts. Given iteration's importance to design and the limited amount of research that focuses explicitly on iteration[15-16] we select it as fertile ground for testing the efficacy of using data-logging of individuals' design processes as a means to capture students' design cognition.

In this study we hypothesize that students engage in small-scale, micro-iterations, to assist in the development of their design. Our driving questions are: To what extent are there any identifiable micro-iteration patterns in the computer-logged data and if so what kinds of cognitive processes might they represent? This works represents an initial foray into an ongoing project to identify students design cognition and behavior through computer-logged data and how to validate these findings. Identifiable patterns may also hold the promise of being redeployed as feedback for struggling students. The study draws on logged data from 27 high school students who completed a *Solarize Your Home* project where they constructed a model of their home and designed several solar array systems that needed to meet energy and budgetary constraints.

In what follows, past research on iteration, protocol studies, and educational data mining of computer-logged data are reviewed. Next, the context of the study, including learning environment set up, data collected and participants, are reviewed. After this, the methodology and procedure used for analyzing the logged data is described. Finally, the results are presented followed by a discussion and conclusion.

Literature Review

Iteration may be thought of as looping between design activities (at different scales of design) and is often conceptualized as part of design process models[17-18]. In this work iteration is typically modeled at the macro-scale of entire design concept iteration or at a more meso-scale of iteration between design stages. These models make important contributions to our understanding of design, but primarily act as models and do not explore iteration in depth. The limited work that directly examines iteration has studied topics such as the connection between iteration and design performance[19], proposed a framework for types of iteration and their use in new product design processes[15] and analyzed iteration in the context of creative versus routine problems as well as the influence of constraints on iteration[16]. In these studies iteration is typically studied on a meso-scale such as between stages or on a more micro-scale of a small number of design actions. Work by Adams and Atman[19-20] further expound iteration as a goal-directed process with two components: information processing and decisions. In these studies[19-20], freshman and senior engineering students were asked to design a playground. Data was collected in the form of individual verbal protocols and coded with an information processing and decision schema described in Adams and Atman[20]. In closely related work, Adams[21] also distinguished between unresolved and resolved iteration. Resolved iterations follow the definition above whereas unresolved iterations lack a decision activity. This definition and related concepts frame iteration as an intentional (not random) process and may be flexibly

applied at different scales of design. Finally, resolved and unresolved iterations assist in differentiating more or less productive iterations.

Verbal protocol analysis or think-alouds are a research method for eliciting the thoughts and cognitive processes a respondent is undertaking while performing some task[22-23]. In this technique, respondents are asked to think-aloud as they complete some task. Respondents' speech is recorded, transcribed and segmented into smaller units that are analyzed for cognitive processes and behaviors[9, 23-24]. Protocol studies capture a rich volume of data from designers, however the need for a researcher to be co-present to prompt the subject to continue thinking aloud if they fall silent as well as the transcription, segmentation and analysis procedures limits the sample size and requires a heavy time-investment, respectively[2-3, 23].

Studies that employ data mining or seek learning analytics with educational data are a growing area in education research[25-31]. Much of this work relies on educational technology that captures or logs students' interactions with the platform to produce a detailed record of student actions. In the particular area of design learning there is a small but growing body of work drawing on these analytical methods to understand learning in this complex domain[32-36].

At present, many design learning studies in educational data mining examine simple or highly constrained design problems, which makes their resulting data more amendable to many data mining techniques. For example, McComb, Cagan and Kotovsky [32] use Markov Chains, a technique for analyzing transitions between actions, to study students' sequences of actions and their impact on design outcomes. More specifically, for the design task students were asked to work on a team to design a truss with some structural specifications. In the platform, students could take seven actions: adding a joint, removing a joint, adding a member, removing a member, changing the size of a single member, changing the size of all members and moving a joint. From this, they reported several notable connections between actions including most actions with themselves, adding joints and adding members and adding members and removing joints. With a much larger set of actions, detecting connections between any two actions may have become more difficult.

For this study we draw on Adams and Atman's[19-20] definition of iteration and related concepts to guide our analysis. Our focus is on micro-iterations that occur over the course of a small set of actions instead of macro design concept iterations or more meso design stage iterations. As a complement to protocol studies, computer logged design data is used in this study. Computer-logged data does not require a researcher to be co-present during data collection as it is collected through the software, allowing for the collection of more design process data across any population that uses the software. This has the potential to further drive our understanding of design cognition by providing a larger bank of data to examine. Furthermore, as computer-logged data will have a data scheme that delineates what kinds of data is collected, the speed of analysis, comparability of subjects, and potential for greater automation (for example, see[37]) increases, thereby freeing resources for more advanced analytical approaches and allowing for greater comparison of subjects within and across studies. However, as computer-logged methods will rely on these data-schemes, some of the richness of protocol studies will be lost—thus making this approach a complement and not a replacement to protocol studies. Finally, by

eliminating the need for a co-present researcher and opening up avenues of automated analysis, computer-logged methods may also be amendable to assessing design learning for classroom purposes. This potential application of computer-logged design would be similar to stealth assessment[38] where a software system tracks several indicators of students' performance and understanding and provides some evaluation or feedback to students without the need for a formal assessment instrument.

We build on past work with computer-logged educational data and extend this work by seeking out patterns in higher dimensional educational data schemas. Although this specific work does not employ any explicit data mining techniques, it is aimed at defining learning analytics (the micro-iteration patterns) that may prove useful for future analyses.

Design Challenge

In the *Solarize Your Home* project students were asked to create their own home using Energy3D and design 3 different solar arrays to meet their family's energy needs. In this project they were working as solar energy designers with their parents as their clients. The first part of the project more closely resembled a modeling problem: students used Google Earth to find the height, width and length of different components of their house and used this data to construct an accurate model of their home in Energy3D. Data from this part of the project is not analyzed for this paper.

The second part of the project presents students with a design problem: create a solar array system for their home that meets two constraints. The first constraint is that students' solar arrays must meet the annual energy usage of their family. Energy3D allowed students to enter kilowatt hour usage by month. Following this students were asked to bring in their previous year's annual energy bill. For students whose energy bills did not contain raw kilowatt hour information, we assisted them in converting their monthly bills into close approximations. The second constraint is that students' final solar array system must be under a certain budget. To address the possibility of large differences in solar potential across students' homes and provide students an opportunity to explore solar array systems, students were given three budgetary levels to design for: $20,000, $40,000, and $60,000. Budgets were determined solely by the cost of solar panels. Students were given 4 different solar panels to select with solar cell efficiencies ranging from 16-22%, with higher efficiency panels costing more than lower efficiency panels.

While designing, students filled out a design report. The report contained 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 comparative table where students listed the advantages and disadvantages of each design and made a final recommendation.

Energy3D and Data-Logging

Energy3D is a publically available professional-grade CAD software with extensive solar simulations and analytical tools. Figure 1 is an example of a home that can be built in Energy3D. When a student opens Energy3D each of the actions they take from the data schema[10] are logged into a Javascript Object Notation (JSON) file format until Energy3D is closed. JSON is a data

exchange format that is human and machine readable. Energy3D has been used for several different design challenges (e.g., see [36, 39]). For *Solarize Your Home* table 1 displays the most relevant subset of the data schema for this project.

Figure 1 Example of a Home Built in Energy3D

Table 1
Solarize Your Home Challenge Related Data-Logged Actions

Name	Types of Actions	Description
Solar Panel	Add/Edit/Rotate/Remove /Paste	Add and edit panels. Paste places panels next to an existing panel to ease adding multiple panels.
Solar Analysis	Daily/Annual & All/Group/Single Panel	Calculates the solar production for selected panels for a day or entire year
Solar Cell Efficiency	All/Foundation/Building/ Single	Sets the efficiency or conversation rate of solar panels
Daily Energy Graph	Run/Change Contrast	Uses a color gradient (heat map) to display cumulative radiation for an area
Show Heliodon		An aerial display that shows the placement of the sun over the year for a location
Show Shadow		Display shadows for objects in the scene at the current system time
Animate Sun		Move the sun forward in time starting at the current system time
Change Date		Set the month and day in the system
Change Time		Set the hour and minutes in the system

In table 1 the first column displays a category name (if several actions fall under it) or simply the name of the action. Column 2 displays types of the category if there are more than one and column 3 provides a description of the category and its actions or the single action.

Participants and Data


```
"Activities": [
{"SolarAnnualAnalysis": {"Months": 12, "Panel": "All", "Solar": {"Monthly": [13.71,15.87,23.15,28.25,31.56,33.96,34.36,32.06,27.72,23.1,13.53,11.6]
, "Total": 8786.43}}},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 477, "Coordinates": [{"x": 21.226, "y": -21.981, "z": 26.673}]}},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 487, "Coordinates": [{"x": 25.856, "y": -15.405, "z": 30.549}]}},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 490, "Coordinates": [{"x": -2.813, "y": 14.68, "z": 30.488}]}},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 488, "Coordinates": [{"x": -6.916, "y": 17.448, "z": 30.461}]}},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 491, "Coordinates": [{"x": 1.291, "y": 11.912, "z": 30.515}]}},
{"Add SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 495, "Coordinates": [{"x": 25.856, "y": -15.405, "z": 30.549}]}},
{"Add SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 496, "Coordinates": [{"x": 21.427, "y": -21.971, "z": 26.73}]}},
{"Solar Cell Efficiency Change for Selected Solar Panel": {"Building": 1, "ID": 470, "Old Value": 0.15, "New Value": 0.22}},
{"Solar Cell Efficiency Change for All Solar Panels": {"New Value": 0.22}},
{"SolarAnnualAnalysis": {"Months": 12, "Panel": "SolarPanel(497)", "Solar": {"Monthly": [18.87]
, "Total": 573.98}}},
{"Add SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 497, "Coordinates": [{"x": -6.363, "y": 18.268, "z": 29.998}]}},
{"Add SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 498, "Coordinates": [{"x": -2.259, "y": 15.5, "z": 30.024}]}},
{"Add SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 499, "Coordinates": [{"x": 1.845, "y": 12.732, "z": 30.051}]}},
{"Solar Cell Efficiency Change for All Solar Panels": {"New Value": 0.22}},
{"SolarAnnualAnalysis": {"Months": 12, "Panel": "All", "Solar": {"Monthly": [19.42,22.49,32.82,40.09,44.91,48.4,48.96,45.62,39.36,32.71,19.16,16.43]
, "Total": 12482.15}}},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 497, "Coordinates": [{"x": -6.363, "y": 18.268, "z": 29.998}]}},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 498, "Coordinates": [{"x": -2.259, "y": 15.5, "z": 30.024}]}},
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{"Solar Cell Efficiency Change for All Solar Panels": {"New Value": 0.2}},
{"SolarAnnualAnalysis": {"Months": 12, "Panel": "All", "Solar": {"Monthly": [17.15,19.69,28.29,33.87,37.84,40.09,40.48,38.24,33.59,28.32,16.78,14.5]
, "Total": 10611.05}}},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 202, "ID": 494, "Coordinates": [{"x": -20.255, "y": -13.742, "z": 19.843}]}},
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{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 496, "Coordinates": [{"x": 21.427, "y": -21.971, "z": 26.73}]}},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 202, "ID": 486, "Coordinates": [{"x": -12.868, "y": -18.725, "z": 19.637}]}},
{"Solar Cell Efficiency Change for All Solar Panels": {"New Value": 0.16}},
{"Solar Cell Efficiency Change for All Solar Panels": {"New Value": 0.16}},
{"SolarAnnualAnalysis": {"Months": 12, "Panel": "All", "Solar": {"Monthly": [11.5,13.1,18.55,21.84,23.83,24.96,25.17,24,21.41,18.44,11.12,9.71]
, "Total": 6802.28}}}
]}
```


Figure 2 JSON Log Pattern 1 Example


```
{
"Activities":[
{"Edit SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 259, "Coordinates": [{"x": 13.356, "y": 8.866, "z": 30.607}]}},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 295, "Coordinates": [{"x": 15.991, "y": 3.863, "z": 30.746}]}},
{"Add SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 321, "Coordinates": [{"x": 15.991, "y": 3.863, "z": 30.746}]}},
{"SolarAnnualAnalysis": {"Months": 12, "Panel": "SolarPanel(259)", "Solar": {"Monthly": [0.28,0.38,0.68,1.02,1.47,1.73,1.77,1.54,1.13,0.74,0.34,0.24]
, "Total": 344.2}}},
{"Graph Tab": "Basics"},
{"Remove SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 259, "Coordinates": [{"x": 13.356, "y": 8.866, "z": 30.607}]}},
{"Add SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 322, "Coordinates": [{"x": 13.516, "y": 8.15, "z": 30.746}]}},
{"Edit SolarPanel": {"Type": "SolarPanel", "Building": 1, "ID": 318, "Coordinates": [{"x": -13.337, "y": 26.941, "z": 26.525}]}},
{"SolarAnnualAnalysis": {"Months": 12, "Panel": "SolarPanel(318)", "Solar": {"Monthly": [0.47,0.54,0.79,0.96,0.93,1.03,1.05,0.95,0.76,0.62,0.37,0.4]
, "Total": 269.87}}}
]}
```


Figure 3 JSON Log Pattern 2 Example

Twenty-seven 9th grade students from an urban high school in New England participated in the study in the spring semester of 2016. All students were in the same physical science class. There were slightly more girls than boys, with 17 girls and 10 boys. The exclusive data source for this study were the JSON log files from Energy3D. Students' data-logs were stored on a USB during their project and collected after the completion of the project.

Figure 2 and 3 above are snippets from two students JSON log files, representing an instance of Pattern 1 and Pattern 2 discussed in the results below. Each action (e.g. edit solar panel) is logged as a separate entry with a set of attributes specific to that action or type of action (in the case of edit solar panel: type, the building it was placed on, panel ID and coordinates)[10]. Additionally, for each action a student takes a year, month, day, hour, minute, and second timestamp is recorded as well as the name of the file students are currently working on. Timestamp JSON values and logged camera actions have been removed from the snippets above to increase readability of the action logs.

Methods

Before describing the analytical procedure several points need to be explicated. First, log files were filtered to only include solar related activities, as listed in table 1. The part of the challenge that involves design relates primarily to these actions so other actions are excluded for this analysis.

Second, log files were studied for chains of consecutive actions relating to solar analysis, simulation and solar panel manipulation as listed in table 1. Consecutive chains of actions best represent the students focus at that time and thus form the strongest ground for interpreting students' cognitive state. If a chain is broken, such as a student editing features of their home, any proceeding solar actions would form a new chain. There were two exceptions to this rule. First, camera actions are ignored, since the camera is critical element to navigating Energy3D and systems built in it. Second, a small noise threshold was implemented since students may be drawn to several tasks at any given time. Chains were permitted up to 2 consecutive non-solar actions as part of a solar chain, after 2 non solar actions the chain is considered broken and any resulting actions are considered to be a separate chain.

Finally, to be considered as a potential iteration pattern a chain must involve at least two different kinds of actions (e.g. add solar panel and conduct a solar annual analysis) and must have repetition of a single action or set of actions. This rule was developed to avoid extreme cases of a single action being repeated several times.

Given the volume of actions logged, the open-nature of the design project which allowed students to explore and engage in design in a myriad of ways, and the minimal research on iteration, this initial foray into analyzing students' design cognition through computer-logs embraced an exploratory qualitative methodology. Many qualitative methods seek to develop emergent categories from a relatively unstructured, large volumes of data[40-41]. While the log data is more structured than interviews or observations, the order, frequency, presence or absence of actions may vary substantially by student. Furthermore, the form micro-iterations may take was not known beforehand. Therefore, two techniques for processing qualitative data were employed to identify any potential micro-iterations: data displays and clustering[40].

First, data displays are a collection of visualizations used to summarize and organize qualitative data. In this study a form of data displays called network diagrams were used to visualize the log data. In these network diagrams each action was a node and links from the node showed the preceding and proceeding action. Relevant attributes (see Participants and Data section) of each action were recorded within the node or immediately next to it. Network diagrams assisted in the visual inspection of log files. Second, clustering is a technique for grouping similar observations into patterns. Micro-iterations observed in students' logged data were clustered into a smaller set of common patterns when they had the same or similar sets of actions undertaken in them. For example, if a student placed a panel in a distinct location, used a daily solar analysis on that single panel and repeated these actions (thus constituting a micro-iteration) and another student engaged in the same set of actions but conducted an annual solar analysis, these two sets of observations were clustered under the same common pattern. Observations with the same or

similar sets of actions but variable number of repetitions within them were also clustered together. Using the rules discussed above and these two techniques from Miles and Huberman[40] the data was analyzed through the following procedure.

The process began by filtering the JSON log files through a Python script (available upon request) to only include solar related actions as listed in table 1 with the small threshold for noise described above. The Python script also placed empty entries in the filtered log file to indicate when a chain was broken by other actions. The primary author on this paper transcribed the logged entries into a network diagrams, described above, to allow for visual inspection of potential iteration patterns. A network diagram was made for each log file a student produced (students all had multiple log files as Energy3D creates separate log files after being closed and reopened). Once completed, the network diagrams were inspected for micro-iterations and candidates were transferred to an excel file. These potential micro-iterations were checked against the log files to clarify details and cross-check accuracy of the entries. Twenty micro-iterations were identified through this process.

Lastly, each entry in in the excel file was analyzed for what actions it included and the order of the actions. The rules described above for clustering were used to group the micro-iterations into patterns. This process distilled the total number of micro-iteration patterns down to 4, discussed below in the results.

Results

The analysis revealed four predominant micro-iteration patterns in this sample of data: (1) solar panel system capacity testing, (2) solar panel location analysis, (3) solar simulations with panel placements and (4) investigating the suns' path across seasons. To address the first research question, to what extent are there any identifiable micro-iteration patterns, the frequency of students using these strategies and the frequency of the strategies themselves are reported.

To address the second research question, what kinds of cognitive processes might patterns represent, an exemplar of each pattern is presented in detail, beginning with a description and visualization of the exemplar. In the visualization blue nodes represent actions on solar panels, yellow nodes represent solar simulation related actions and red nodes are unrelated actions that fell within the allowed noise threshold. An arrow encircling a node means that action was repeated and the number in the tip of the arrow indicates how many times it was repeated. Next, variations of the micro-iteration pattern and the general features or configuration of the pattern are discussed. Following this, each pattern is described through Adams and Atman's[19-20] framework and abstracted to a more general form of design activity to assist in their comparability with other design challenges. Finally, since the aim of this study was identifying potential micro-iteration patterns through computer-logged data, we cannot definitively state what was happening in students' minds when they left these traces in the data. Therefore, we propose a series of alternative hypotheses for what these micro-iteration patterns may represent. Ongoing work aims to identify additional indicators in the logged-data and collecting other data sources that may validate or refute these alternative hypotheses.

Student and Micro-Iteration Pattern Frequencies

Table 2
Frequency of Students use of Micro-Iterations

Student	System Capacity	Location Testing	Solar Simulations	Investigate Seasons	Total for Student
A01			2		2
A05	1				1
A09			3		3
A11			1		1
A13	1				1
A16	1				1
A18	1		1		2
A19				1	1
A23		1		3	4
A25	1	1			2
A27	1	1			2
Total Patterns	6	3	7	4	20

Table 2 shows the students (anonymized) who used one or more of the micro-iteration patterns, as well as the overall frequency of each pattern. In total, 11 students or a 41% of the class used at least one micro-iteration while designing. Of those students who used some micro-iteration pattern a little under two-thirds undertook 2 or more micro-iterations, with the greatest frequency by any one student being 4. In terms of the patterns themselves, solar simulation with panel placement and solar panel system capacity testing were the most common with 7, and 6 instances, respectively. The results now turn a fuller description of each pattern.

Pattern 1: Solar Panel System Capacity Testing

This example of Solar Panel System Capacity Testing pattern, depicted in figure 4, starts with a solar annual analysis which reveals that the systems annual kilowatt production is at 8786 kWh. After this, five panels are removed and two added. The solar cell efficiency for one panels is changed to .22 and then this change is applied to all panels. It appears that the student tries to run another solar annual analysis on a single panel, but only a month of data is recorded suggesting they canceled the analysis while it was running. Three more panels were added and solar cell efficiency was set to .22 for all panels. Another solar annual analysis run on all panels shows a spike to 12482 kWh production for the system. Next they remove the 3 most recently added panels and set solar cell efficiency to .2 for all panels. Solar annual analysis is run again showing 10611 kWh production for the system. Next, six panels are removed and solar cell efficiency is set to .16. Finally, another solar annual analysis is run showing 6882 kWh production for the system.

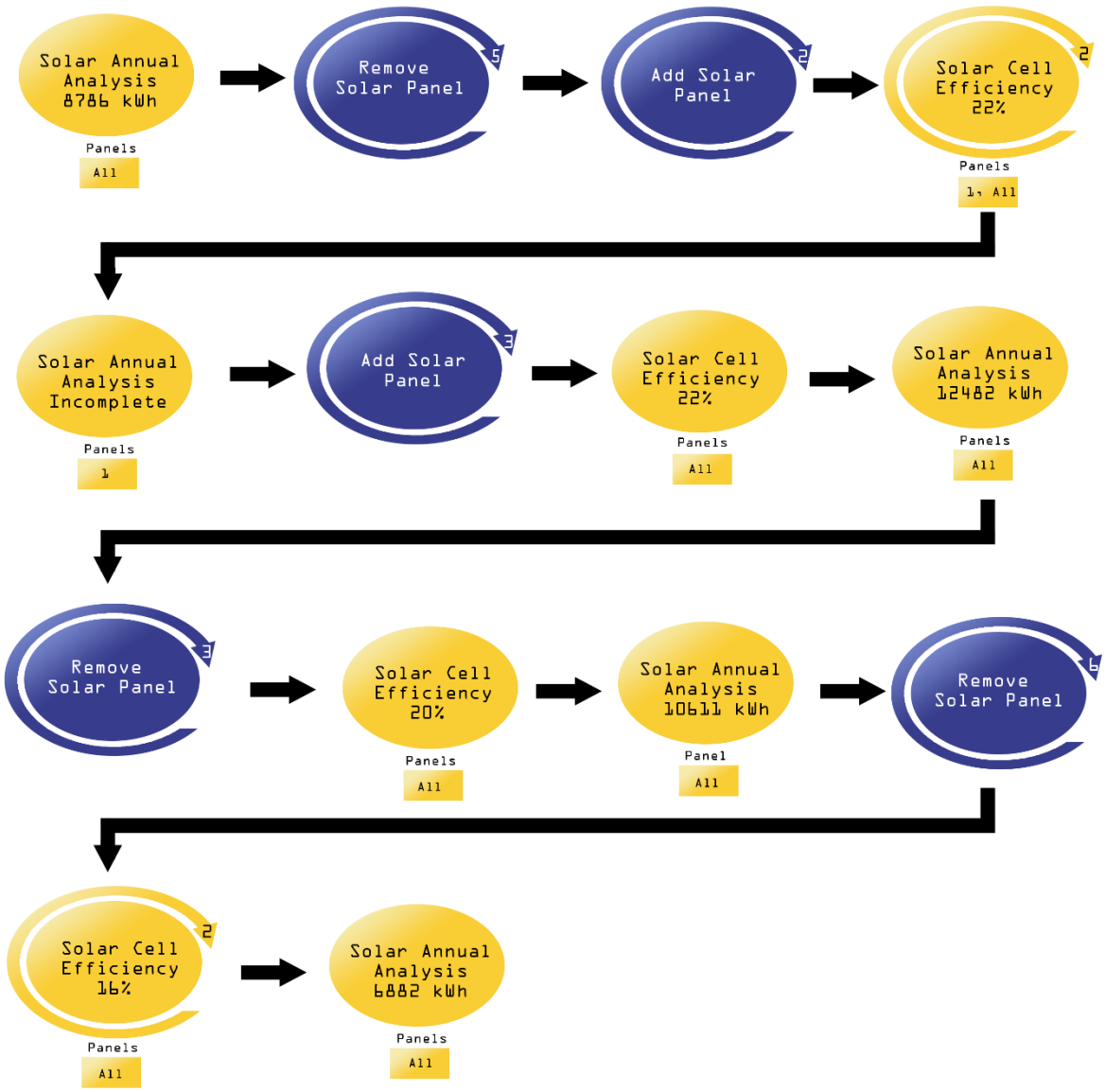

Figure 4 Example of Solar Panel System Capacity Testing Pattern

Some variations on this micro-iteration include: only altering the number and/or location of panels or only showing an increasing or decreasing trend in annual kWh production (as opposed to the rise and fall of kWh production for the pattern described above). As a general configuration, entries in this pattern involved solar analysis of all or a large group of panels, a repetition of testing solar systems and either the addition, editing or removal of panels and/or changes to solar cell efficiency of the systems. Viewed through Adams and Atman's[19-20] framework students engaging in this micro-iteration were collecting and processing information about the kWh production of their system and made decisions about the location and/or the solar cell efficiency of the system. Most of the examples of this pattern appear to be resolved since a set of panels and/or solar cell efficiency is selected by the end of the micro-iteration. On a more

general level of design this micro-iteration appears to resemble system performance testing coupled with modifications.

Lastly, some alternative hypotheses for testing what this pattern may represent include: trying to converge on a design that meets both the production and cost constraints and exploring the potential solar capacity of their home.

Pattern 2: Solar Panel Location Analysis

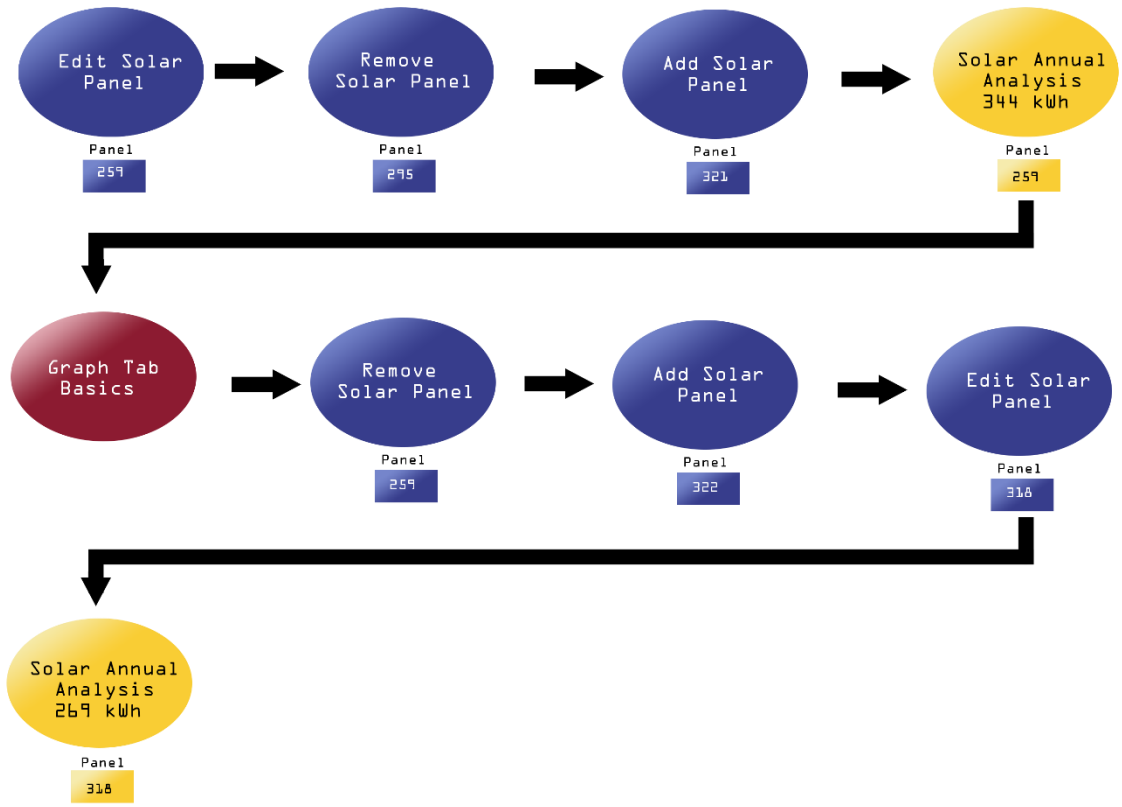

Figure 5 Example of Solar Panel Location Analysis Pattern

This example of Solar Panel Location Analysis pattern, depicted in figure 5, starts with editing panel 259 and then removing and adding another panel. Then the student runs a solar annual analysis for panel 259, finding it produces 344 kWh over the year. Next, the student looks at the Graph tab Basics which contains information like the physical dimensions and locations of panels (a non-solar move that is ignored because it is within the noise threshold). Panel 259 is removed and they add another panel near 259's previous location. Finally, they edit panel 318, which is over 10 feet away from panel 259's location in two dimensions (roughly height and length) and run a solar annual analysis finding 318 produces 269 kWh per year.

Some variations on this micro-iteration include: analyzing daily solar production of panels instead of annual production and varying location and solar cell efficiency for locations. As a

general configuration, entries in this pattern involved the analysis of a single panel, adding or editing panels in unique locations for testing, repetition of locations tested with a single panel and may include the addition, removal or editing of other panels (other than the ones analyzed) and/or alterations to solar cell efficiency. The information gathering and processing actions in this iteration related to solar production of different rooftop locations and the decisions actions related to keeping or removing panels from these locations. Most of the examples of this micro-iteration appear to be resolved since they result in panel placement, although in the case of the example above, some placement may be sub-optimal. On a more general level of design this pattern is similar to analyzing system components under different conditions.

Lastly, some alternate hypotheses for testing what this micro-iteration may represent include: analyzing the solar production of different locations for a to be built system, identifying optimal panel locations for an existing system and leveraging solar panels to better understand the solar science affecting the system.

Pattern 3: Solar Simulations with Panel Placement

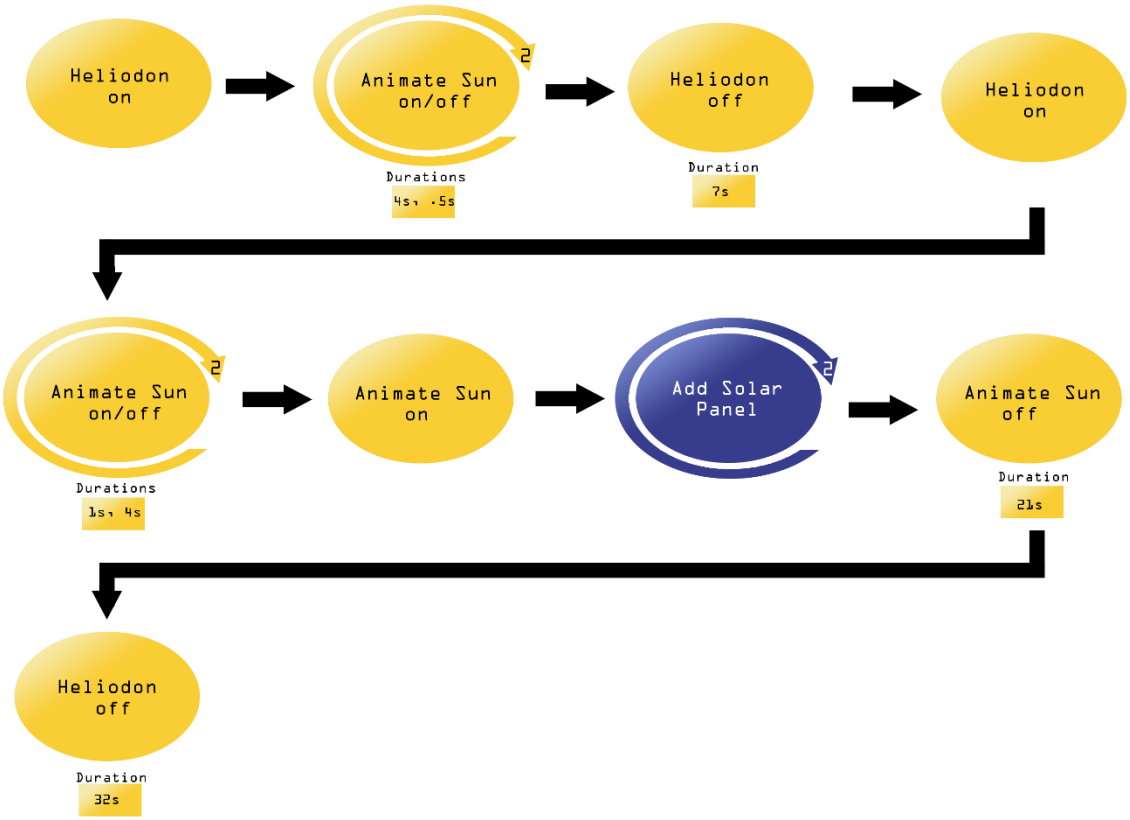

Figure 6 Example of Solar Simulations with Panel Placement Pattern

This example of Solar Simulations with Panel Placement pattern, depicted in figure 6, starts with the student turning the heliodon on. The heliodon shows an aerial curved grid which represents all the locations the sun may radiate from throughout the year relative to a building in a given geographical area. Furthermore, the heliodon shows where the sun is at the specific time and date Energy3D is currently set to. After the heliodon is turned on, the student starts the animate sun

simulation. Animate sun shows the suns movement throughout the day starting at Energy3D's current set time. The animate sun simulation runs for four seconds, and half a second. Each second is approximately one hour of real world time. The student hen turns off the heliodon and immediately turns it back on. Next, they animate the sun for one and four seconds and place two panels while running the animation for a final twenty-one second run. In their final move their turn the heliodon off.

Some variations on this micro-iteration include: turning the shadow simulation on in addition to others, animating the sun continuously without stopping it at specific times, a larger set of operations on panels and several variations where the solar simulation was run without any change or addition/removal of panels. As a general configuration, entries in this pattern involved the use of the heliodon or shadow simulation, the use of animate sun to view sun movement over a day, the repetition of short bursts or longer runs of animate sun and may involve the adding, editing or removal of panels. Information gathering and processing for this pattern revolves around sun location, radiation angle and shadowing. Decisions for this pattern relate to placing panels in locations that maximize solar radiation and minimize shading. For examples of this pattern where there is no panel manipulation or addition/removal, no decision is taken and thus these examples are unresolved iterations. If panels are placed, this seems to suggest the iteration was resolved through a decision about the design. On a more general level of design this pattern is similar to analyzing system components interaction with the natural environment.

Lastly, some alternative hypotheses for testing what this pattern may represent include: using the sun's location to determine promising panel locations, similarly using the sun in conjunction with shadow simulations to find promising panel locations or scientific inquiry into the suns location over the day and radiation/shadow patterns.

Pattern 4: Investigating the Sun's Path Across Seasons

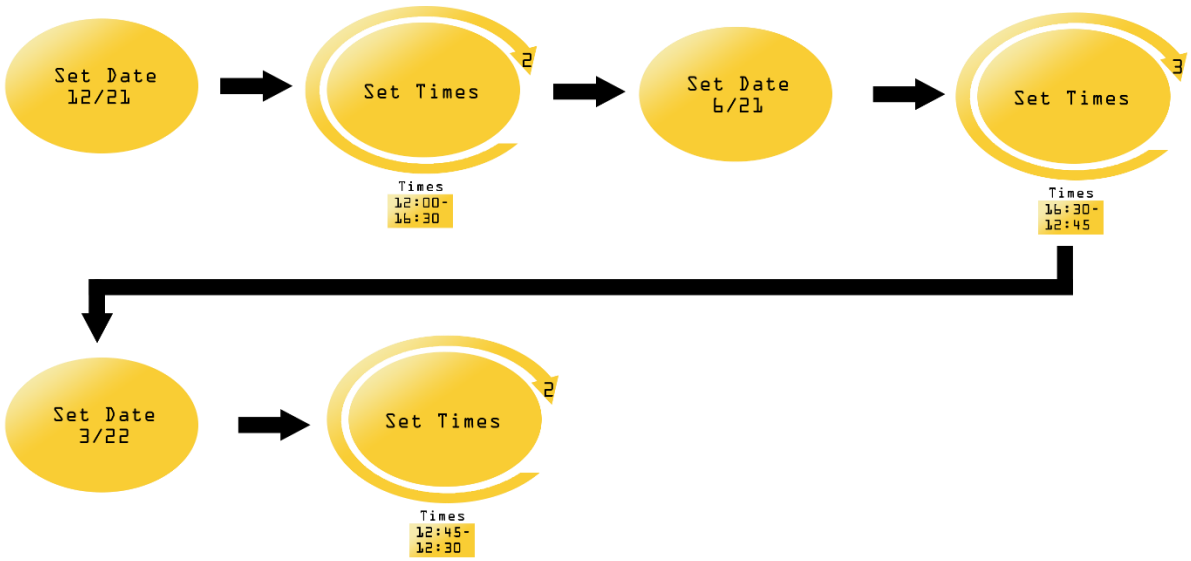

Figure 7 Example of Investigating the Sun's Path Across Seasons Pattern

In this example of the Investigating the Sun's Path Across Seasons pattern, depicted in figure 7, it is important to note the heliodon is on, but that specific action happened earlier in the chain before the student exhibited this specific micro-iteration. In their first action the student set the date to December 21st (winter) and then set the time to 12:00 PM and 4:30 PM. Next, the date was set to June 21st (summer) and the time was varied 3 times between 4:30 PM and 12:45 PM. Finally, the date was set to March 22nd (spring) and the time was varied 2 times between 12:30 PM and 12:45 PM.

Variations on this pattern include cycling through some of the seasons more than once and analyzing a consecutive set of months instead of seasons. As a general configuration, entries in this pattern involve the use of the heliodon, setting the date to different seasons or months, adjusting the time at set dates and the repetition of changing date and time as set of actions. Information gathering and processing for this pattern relate to sun locations over months, seasons and time of day and radiation angles. Decisions involved with this micro-iteration are not apparent, no examples identified displayed any changes to students' design. Therefore, this micro-iteration pattern appears unresolved in this sample of students. On a more general level of design this pattern appears similar to analyzing environmental systems in isolation of a designed system or its components. Such actions may relate to an early problem scoping/information gathering stage of design.

Lastly, some alternative hypotheses for testing what this pattern may represent include: inquiry into the location of the sun, radiation angles and how these concepts vary over seasons, months or times of day, analyzing sun locations over seasons/months to identify promising locations for panels and as an extension or follow up to other patterns that examine daily sun patterns.

Discussion

In addressing the first research question, results from this study show that a moderate amount of this sample of novice designers engaged in micro-iterations as part of their design process, 11 out 27 or 41% of the class. Students who engaged in micro-iterations did so at modest levels, nearly two-thirds—63% —exhibited two or more instances of one or more of the micro-iteration patterns identified in this work. Although its frequency was modest, the findings on micro-iterations suggest a not insubstantial amount of novice designers may engage in small-scale iterative cognitive strategies to develop their design, consistent with our hypothesis.

In addressing the second research question, the results' detailed discussion of each of the 4 patterns identified here—(1) solar panel system capacity testing, (2) solar panel location analysis, (3) solar simulations with panel placements and (4) investigating the suns' path across seasons—begins to illustrate that micro-iterations can assist a designer in exploring the design space and modifying/improving their design. For example, many of the observed micro-iterations that were grouped into one of the 4 categories involved both information about the design components itself as well as the environment in which it was situated. Therefore, from one of these patterns a designer may iterate to gather information and understanding about aspects of the design itself or the environment. Furthermore, for those patterns that involve design components, a designer can iterate over multiple configurations or aspects of a particular component to modify or improve

the design. For some of pattern 3 that only involved simulation analysis and all of pattern 4, as observed, there were no design components in the chain, however through these micro-iterations it is still possible to gain information and understanding from the environment that affects a design.

In light of these micro-iteration patterns potential as cognitive strategies for design space exploration and design modification/improvements and findings that novice students often exhibit fewer iterations or transitions in the design process[2-3, 14, 42], these patterns may hold promise as forms of feedback for novice designers. Feedback about potential micro-iteration strategies could take several forms. At a basic level, teachers guiding students through a design project could offer just-in-time feedback about micro-iteration strategies to assist struggling students. Looking ahead to artificial intelligence systems in software, feedback related to micro-iteration strategies could be offered after a system (with data-logging functionality) monitors a student struggling to develop their design[36, 38].

Finally, turning more broadly to design cognition, the results of this study suggest iterations exist as a spectrum, ranging from micro-iterations composed of a few repeating explicit actions, to meso-iterations of bundles of actions within or across design stages[15-16, 19] to macro-iterations of an entire design concepts[17]. This work also opens questions as to whether more experienced designers may also engage in similar kinds of micro-iterations as identified in this study and what the relationship between micro-iterations and other scales of iteration may be.

Conclusions

This paper hypothesized that high school students who engaged in a design challenge would exhibit micro-iteration patterns throughout their computer-logged actions and then sought to generate hypotheses for future work about what these actions might represent. It was found that 41% of the students engaged in some pattern of micro-iteration and that of these students, 63% engaged in 2 or more micro-iterations. Four patterns were identified: (1) solar panel system capacity testing, (2) solar panel location analysis, (3) solar simulations with panel placements and (4) investigating the suns path across seasons. Three of these patterns were predominantly resolved iterations that involved students interacting with simulation or analytical tools in conjunction with altering their designs. Designers using one of these patterns may gain information about the designs components or environment and/or modify/improve their design through the micro-iteration. Examples from the final pattern (4) showed no resolution to the iteration, however this micro-iteration pattern may help with understanding of the environment that affects the design. Ongoing work aims to build upon these findings by collecting more student data that may contain more micro-iteration patterns and using additional indicators from the logged-data and other data sources to validate or refute the hypotheses generated in this work.

Computer-logged data for design projects holds great promise toward two ends. First, for novice designers, like K-12 students, computer-logged data may help elucidate their design cognition on a fine-grained, easily comparable level and grant insight into how people learn design. Second, identification of these patterns in computer-logged data may be leveraged by students, teachers

or through software systems themselves as forms of feedback or heuristics that can use to assist students in traversing a design space and modifying their designs.

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