AC 2012-3933: A FIRST TAKE ON AN INDIVIDUAL DATA GENERATION ASSIGNMENT FOR OPEN-ENDED MATHEMATICAL MODELING PROBLEMS

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I. Introduction

Model-Eliciting Activities (MEAs), a special case of open-ended mathematical modeling problems[1,2], can be exploited so that the inherent complexity and nature of a problem can be harnessed to promote effective learning across a wide variety of learning objectives. MEAs can be used to provide first-year engineering students with opportunities to engage not only in complex and iterative authentic problem solving but also guided problem formulation[3], peer feedback[4], and reflection on team solution progress - all with an overarching emphasis on the development of effective teaming[5] and communication skills.

MEAs, which are a manifestation of the models and modeling perspective[2,6], were introduced into the large required first-year engineering course at Purdue University in 2002.[7] Ten years later, with National Science Foundation support, MEAs have reached relative stability in terms of their design, implementation, and assessment in first-year engineering. This was achieved through a design research perspective[8-14] that guided the development of increasingly better approaches to using MEAs. MEAs are now receiving some recognition as examples of effective engineering learning experiences.[15]

This paper builds on a series of research studies previously conducted by the authors to characterize students' mathematical modeling practices and investigate students' experiences with model-eliciting activities. Of particular interest to this paper is the research being conducted on students' iterative mathematical solutions to an MEA involving decisions with univariate data. This work has looked at students' understanding of basic descriptive statistical concepts[16,17] – where the development of students conceptual understandings of mathematical concepts is the most fundamental benefit of MEAs. Exposure of students' understandings of mathematical concepts is what MEAs were designed to do.[1] Through this research, is has been revealed that when a high quality model requires some quantification of the distribution of the data, student teams have a difficult time moving past looking at only measures of central tendency and variance even with instructor written feedback. To find ways to overcome this, and while trying to stick to the authenticity to engineering practice of the MEA sequence, a data generation step was recently implemented in the MEA sequence as an additional approach to guiding students to see the need for looking at distribution. Students were asked to individually create data sets to further test their team's mathematical model. The particular study described in this paper is a preliminary study in which we seek to understand how students respond to this first implementation of the data generation step. The research question that guides this study is: What elements do students include in their explanations of their data sets?

II. Methods

A. Setting, Participants, and MEA Implementation

The setting for this study is a second semester, required first-year engineering course. This course continues to develop students' engineering problem solving, design, and teaming skills (introduced in the first semester required course) while introducing students to computational tools (i.e. MATLAB and Excel). This course meets for two 110-minute periods each week in sections of 120 students; each session is meant to be highly interactive with minimum lecture. Each period was led by a faculty member and supported by one graduate teaching assistant and four undergraduate teaching assistants. Participants were enrolled in the Fall 2011 offering which had an enrollment of approximately 200 students. The Fall offering of this course is off-sequence of the primary offering of the course. As such the student population is different from the primary offering. The fall offering is populated by a greater proportion of international students, students transferring into first-year engineering from within the university, and students retaking the course for a second or third time than is typical of the primary offering.

Two MEAs were implemented in Fall 2011. This work will focus on the first of these, the *Just-In-Time* (*JIT*) *Manufacturing* MEA. This MEA is about D. Dalton Technologies (DDT), a manufacturer of advanced piezoceramics and custom-made ultrasonic transducers. DDT operates in a JIT manufacturing mode and requires a shipping service to move materials between two subsidiary companies in a timely fashion. DDT is unsatisfied with their current shipping service and needs the first-year engineering teams to develop a procedure to rank a number of alternative shipping companies using a historical data set. This MEA requires students use their knowledge of mathematics and statistics to develop a procedure (mathematical model) to rank shipping companies in order of most likely to least likely able to meet a DDT's delivery timing needs. For Team Draft 1, student teams are provided with a small subset of the data for eight shipping companies in terms of number of minutes late a shipment arrived at its destination (see Table 1). Students are instructed to address ways to break ties in company rankings. For the Team Draft 2 and Team Final Response, teams revisit their procedure (using peer and instructor feedback) and work with the larger historical data set.

As with any MEA, students are not specifically instructed to use particular mathematical or statistical methods. For discussion purposes here, Table 1 provides summary statistics of the data to demonstrate what the student teams should have noticed about the data and referred to when developing their own data sets to further test their mathematical models. Given the data provided at Draft 1, the student teams should have concluded that the mean alone cannot be used to differentiate the shipping companies. The means are all within about 0.1 minutes (not enough to make a practical difference in delivery time), and two of the companies are tied for the lowest mean. No shipping company has the lowest mean and lowest standard deviation combination. The shipping company with the greatest number of on-time (0 hr) deliveries (IHE) also has one of the highest number of late deliveries.

Table1. Number of hours late for shipping runs from Lincoln, NE to Noblesville, IN (sample from complete data set).

Sample Data:	**IHE**	**DS**	**SC**	**UE**	**BF**	**DFC**	**NPS**	**FSP**
Team Draft 1 *(IHE, DS, SC,*	0	1.00	0	1.11	2.53	0.04	2.39	0.91
UE only, N = 255 for each)	1.31	0	7.39	0.90	1.57	0.09	6.21	2.50
Team Draft 2 & Team Final	0	10.49	1.81	0	3.57	0	5.14	0.79
(All shipping companies,	0	0.70	9.00	1.11	5.36	1.42	0.53	1.00
N = 255 for each)	1.73	0.71	4.22	0.84	2.24	1.80	13.97	1.13
	1.92	0.42	0.32	3.31	1.56	1.09	0	1.00
	…	…	…	…	…	…	…	…
Statistics for Data:								
Mean (hr)	1.49	1.51	1.49	1.52	1.54	1.52	1.60	1.60
Standard Deviation (hr)	2.54	2.19	2.25	2.56	1.34	1.55	1.61	1.74
Minimum (hr)	0	0	0	0	0	0	0	0
Maximum (hr)	16.4	10.5	13.0	26.0	9.3	16.2	14.0	14.0
Median (hr)	0.74	0.62	0.65	0.95	1.13	1.13	1.06	1.12
Counts:								
0 hr	100	36	79	14	14	17	1	16
< 2 hr	193	199	196	203	193	197	198	206
> 8 hr	9	9	6	4	1	1	2	6

Note: IHE= Iron Horse Expeditors; DS = Delphi Shipping; SC = ShipCorp; UE = United Express; BF = Blue Freight; DFC = Direct Freight Company; NPS = National Package Service; FPS = Federal Parcel Service

When solving this MEA, student teams must find a way to balance findings with regards to central tendency, variation, and distribution of the data in the context of the problem to develop a procedure to rank the companies. The MEA itself is purposefully created to produce tensions in students' thinking about the problem and push them towards exploring these three characteristics of the data. In previous work, it has been noted that the data alone is not enough for students to "see" that multiple ways of looking at the data must be considered to address the complexity of the problem. Even peer and instructor feedback have been found to be insufficient to guide student teams in productive directions.[16,17]

B. Individual Data Generation Assignment

Between submission of Draft 2 and the Team Final Response (and while waiting on instructor feedback on Draft 2), students were assigned the task of individually developing two data sets to further test their models. The text of this assignment is provided below:

> "The shipping company data sets for the JIT Manufacturing MEA are test cases. They do <u>*not*</u> represent the extent of all possible data sets one might expect to encounter in potential shipping companies. So you need additional ways of testing your solution. Consider the 8 shipping companies that were provided by Ollie Fiji. Create two addition shipping company data sets (yourloginA and yourloginB) each with 100 data points.

> These data sets must, in one or more ways, be different from the ones you have been provided and thus enable further testing of your team's solution to the JIT Manufacturing MEA. Explain how your two data sets are different from the existing 8 data sets and therefore how they further test your solution in ways the other data sets do not."

This assignment was intended to engage students individually in thinking about their team-developed mathematical models and the historical data sets that they were given. Up to this point in the MEA implementation sequence, the students had worked with the provided data as a team. Here is an opportunity for each student to work independently with their team's model and the data, and ultimately bring fresh ideas to the team when completing the Team Final Reponses. The hope was that students would individually review their team's model and think about how the data characteristics of the 8 shipping companies are the same and different from each other and how they don't fill the space of all combinations of data characteristics that could be anticipated.

C. Data Collection and Analysis

All student work on and instructor feedback on students solutions to MEAs is collected through a web-based interface connected to a database.[18] Students entered both their data sets and their explanations through this interface.

This assignment was given prior to the last date for withdraw from the course. The work of only those students who were issued a final grade for the course (N = 171) were considered for analysis. Teams of students were randomly selected for analysis to bring the number of students up to a minimum of 34 (20%) of those considered for the analysis. Teams of students were randomly selected rather than individuals to facilitate future analysis that could look at how the individual team members' participation in the data generation assignment impacts the student teams' Team Final Responses to the MEA. Eleven (11) teams of students (or 36 total students) with 3 or 4 members completing the course with a grade were selected for inclusion in this preliminary analysis.

All student explanations were coded using an emergent coding scheme in which categories were created based on a preliminary examination of the data.[19] The themes that emerged in the student responses are the focus of the results.

III. Results

Of the 171 students who should have completed this assignment, 26 (15%) did not. Another 23 (13%) students created 1 or 2 data sets but provided no explanations for their data sets. Of the 36 students who are included in this preliminary analysis, 5 (14%) did not complete the assignment and 6 (17%) provided data sets with no explanations. So, from a completion of the assignment standpoint, the student sample is fairly representative of the class as a whole.

A. Descriptions of Individually Generated Data Sets

Most of these students (31 of 36) described their individually generated data sets. Seventeen (17) described their data sets in very qualitative terms.

> "*The data set1 I created emphasize a situation in which the shipping company has many 0 hour late times but all the late times are extremely big. … And the dataset2 i created emphasize a situation in which the shipping company has rarely any 0 late times…*" [Student 2680]

> "Dataset A: is very unique because there are very small standard deviations from the mean. …Dataset B: there are many delays but very consistent and in the same range." [Student 2736]

> "…*I create two columns data sets which have more non-late data and small late hours number. …*" [Student 2717]

Four students provided a somewhat more quantitative description of their data sets. However, their quantification was often tied to the way in which the data set was generated and not to the resulting data set.

> "*The two data sets were generated following a double sided Gaussian distribution with mean 0. …*" [Student 2750]

> "*… I therefor used Matlab's randn function to create two datasets of positive and negative values with means and standard deviations of five and three each.*" [Student 1547]

Eight students made reference explicit reference to the way in which the generated their data sets. Each of the eight students mentioned random generation of his/her data. In two cases, this was the extent of the description of the generate data.

> "*I found the average of the mean values for each company and the mean of the standard deviation values for each company and use the random number command in MATLAB to generate to random data sets. …*" [Student 1847]

Six students made explicit reference to using either the MATLAB rand or randn function to generate their data.

> "*These data sets are completely random. I used matlab's function rand to calculate them. …*" [Student 2806]

B. Differences Between the Given and Individually Generated Data Sets

Nine students described how their individually generated data sets differ from the eight given shipping company data sets. Three students made only vague reference to the fact that there are differences.

> "…*These two data sets are two completely different situations from those we used before*. [Student 2680]

> "…*Both of the data sets listed below are unlike any of the previous data sets given. …*" [Student 1664]

Five students compared their data sets to those provided but provided no quantification of those differences. For examples:

> "*Set A is different in that it gives late times and early times. Set B is different in that it has one outlier that will make the average seem high for that set.*" [Student 1806]

> "*The first data I provided here is different from the original 6, becasue it has some error data and its standard deviation is quite large*. …" [Student 2697]

Only one student provided quantitative information about the original data sets to show how the data sets generated were then different.

> "*None of the shipping companies are represented for any early times, which should appear as negative times. They all also average roughly ~1.5 and have a fairly low standard deviation. I therefor used Matlab's randn function to create two datasets of positive and negative values with means and standard deviations of five and three each*." [Student 1547]

C. Testing the Model

Twelve students connected the development of the data sets to the testing of their model. Six merely mentioned that testing could be done using the new data or that modifications to their model might result.

> "… *These data sets … can be used to further tests procedures with similar results.*" [Student 1847]

> "… *to prove the effectiveness of our solution and that no matter what dataset, as long as it is under the constraints, our mathematical model can be modified.*" [Student 919]

> "… *These two data sets … will make our model can suit into more situations.*" [Student 2680]

The other six students made more concrete reference to how their model might work with their new data sets.

> "*A has data points all under our the outlier that we chose so no penelty will be assigned to it. B has data points all over the outlier we chose so it will only recieve the penalty*."
> [Student 1857]

> "*Dataset A: is very unique because there are very small standard deviations from the mean. In such a case where standard deviation has not been given much importance, It would be interesting to see how this issue is dealth with. Dataset B: there are many delays but very consistent and in the same range. It often requires extra ordinary analytical skills to understand why a specific pattern is being followed in a dataset (i.e anaylzing data with no outliers).*" [Student 2736]

> "*Data set 1 is an exaggerated BAD shipping company. They have terrible shipping times and they aren't even consistent. In our model this company should end up in last place. Data set 2 is an exaggerated GOOD shipping company. They have GREAT shipping times and they are very consistent. In our model this company should end up in first place.*"
> [Student 1685]

D. Relationship to the JIT Context

Four students made reference to the concepts of Just-in-Time Manufacturing. This impacted how the students created their data sets.

> "*…the second data set … also has some negative values, which affect just in time inventory placement.*" [Student 2658]

> "*The real data set I believe should not be too exaggerate. The companies should usually arrive on time and don't have so many late hours. If they do never arrive on time, no companies would hire them. Therefore, I create two columns data sets which have more non-late data and small late hours number. . These two sets of data are more reality I think.*" [Student 2717]

IV. Discussion

What is most revealing in the student responses to the individual data generation assignment is what is missing – quantification. The students provide very vague or at best qualitative descriptions of the data sets. The students rarely or poorly quantified the nature of the eight provided historical data sets, their two newly developed data sets, or the differences between the provided and created data sets. This is not entirely a surprising finding. During the early implementations of MEAs, there was a persistent struggle to get student teams to present quantitative results from applying their model in their memos back to the task supervisor. This has had to be explicitly developed and encouraged as a habit-of mind appropriate for engineers through specific student instruction with MEAs and the assessment strategy. Similar instruction and assessment strategies will need to be developed around this assignment to encourage quantitative descriptions of the data sets and their differences.

What is also missing is any significant discussion of how their models will be tested further by their data sets. It was anticipated that students would write about (1) how their model would/should rank these new data sets with respect to the other 8 data sets, or (2) how these new data sets would require specific changes to their models. It does not appear that many students revisited their models when thinking about the data sets they were developing – as few even made reference to their models. Or if they were revisiting their models, they stuck to creating data sets that varied in measures for which they were already accounting. So, say their model focused on mean to rank the shipping companies; then they might be creating new data sets with means that are different and ignoring other data characteristics. This can only be verified by looking at the teams' Draft 2 models and the responses to this assignment in combination. This is beyond the scope of this paper, but is a planned next step.

It is encouraging that a few students kept the context of the problem in mind when developing their data sets. Students had individually explored some JIT manufacturing concepts during a context setting step in the MEA sequence. While only two students explained that they included negative values in their new data sets because the practice of JIT includes the reduction of storage space, many more students included negative values in their actual data sets but failed to explain why. Whether this is an artifact of their method to generate date or an intentional feature of their data sets will need further investigation.

Students focus on the method of data generation is an artifact of the first-year engineering course in which they are learning MATLAB. One assignment during this MEA sequence had the students generate a random Gaussian distribution and perform basic statistics on the data set. This may have led some students to believe they needed to discuss the use of this tool. It is somewhat evident (through the lack of quantification of the nature of the data sets) that many students did not understand that rand creates a uniform distribution between 0 and 1 (a distribution type perhaps worth creating and testing over a wider range) and randn creates a normal distribution.

V. Conclusion

This preliminary study sought to understand students' responses to a data generation step in the MEA sequence. It was hoped that this assignment would encourage students to individually review their teams' Draft 2 model and think about data sets that would be useful for testing their models in ways the instructor provided data did not. Students' responses lacked quantification – students did not reveal that they had computed the basic data characteristics of the instructor provided data or their new data. If the difference between the instructor provided and student generated data were articulated, this was done in very qualitative terms. In addition, students rarely connected their generated data sets to the functionality of their teams' models.

Next steps include revising the individual data generation assignment to include instruction for the students emphasizing quantification and connections to the model development. More explicit wording of what is expected in the response will also have to be provided to the students.

Future research will focus on quantification of the student generated data sets themselves and how these actually compare to the instructor provided data sets. Further, there will be investigation into the connections between Draft 2, the student responses to this assignment, and the impact of this assignment on the Team Final Response. Finally, these analysis were will be repeated on the student responses to the next iteration of this assignment.

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Bibliography

1. Lesh, R., Hoover, M., Hole, B., Kelly, A., & Post, T. (2000). Principles for developing thought-revealing activities for students and teachers. In A. E. Kelly & R. A. Lesh (Eds.) *Handbook of research design in mathematics and science education* (pp. 591-645). Mahwah, NJ: Lawrence Erlbaum.
2. Diefes-Dux. H. A, Hjalmarson, M., Miller, T., & Lesh, R. (2008). Chapter 2: Model-Eliciting Activities for engineering education. In J. S. Zawojewski, H. A. Diefes-Dux, & K. J. Bowman (Eds.) *Models and modeling in Engineering Education: Designing experiences for all students.* Rotterdam, the Netherlands: Sense Publishers.
3. Salim, A. & Diefes-Dux, H. A. (2009). Problem identification during Model-Eliciting Activities: characterization of first-year students' responses. *Proceedings of the Research in Engineering Education Symposium, Palm Cove, QLD, Australia.*
4. Fry, A., Cardella, M. E. & Diefes-Dux, H. A. (2011). Student responses to and perceptions of feedback received on a series of Model-Eliciting Activities: A case study. *Proceedings of the 118th American Society for Engineering Education Annual Conference & Exposition), Vancouver, B.C., Canada.*
5. Moore, T., Diefes-Dux, H. A., & Imbrie, P. K. (2007). How team effectiveness impacts the quality of solutions to open-ended problems. *International Conference on Research in Engineering Education (ICREE)*, Honolulu, HI.
6. Lesh, R. & Doerr, H. M. (2003). Foundations of a models and modeling perspective on mathematics teaching, learning, and problem solving. In R. Lesh & H. M. Doerr (Eds.), *Beyond constructivism: Models and modeling perspectives on mathematics problem solving, learning, and teaching* (pp. 3-33). Mahwah, New Jersey: Lawrence Erlbaum.
7. Zawojewski, J. S., Diefes-Dux, H. A., & Bowman, K. J. (Eds.) (2008). *Models and modeling in Engineering Education: Designing experiences for all students.* Rotterdam, the Netherlands: Sense Publishers.
8. Brown, A. L. (1992). Design experiments: theoretical and methodological challenges in creating complex interventions in classroom settings. *The Journal of Learning Sciences and Research*, *2*(2):141-178.
9. Cobb, P., diSessa, A., Lehrer, R., & Schauble, L. (2003). Design experiments in educational research. *Educational Researcher*, *32*(1):9-13.
10. Collins, A. (1992). Toward a design science of education. In E. Scanlon & T. O'Shea (Eds.), *New Directions in Educational Technology* (pp. 15-22). New York: Springer-Verlag.
11. Collins, A. (1999). The changing infrastructure of education research. In E. C. Lagemann & L. S. Shulman (Eds.), *Issues in education research: Problems and possibilities* (pp. 289-298). San Francisco: Jossey-Bass.
12. Edelson, D. C. (2002). Design research: What we learn when we engage in design. *The Journal of the Learning Sciences*, *11*(1):105-121.
13. Kelly, A. E. (2004). Design research in education: Yes, but is it methodological? *Journal of the Learning Sciences*, *13*(1):115-128.

14. Lesh, R. (2002). Research design in mathematics education: Focusing on design experiments. In L. English (Ed.), *International handbook of research in mathematics education* (pp. 27-50). Mahwah, NJ: Lawrence Erlbaum.
15. Litzinger, T. A., Lattuca, L. R., Hadgraft, R. G., & Newstetter, W. C. (2011). Engineering education and the development of expertise. *Journal of Engineering Education, 100*(1): 123-150.
16. Carnes, M. T., Cardella, M. E., & Diefes-Dux, H. A. (2010). Progression of student solutions over the course of a Model-Eliciting Activity (MEA*). Proceedings of the 40th ASEE/IEEE Frontiers in Education Conference, Washington, DC.*
17. Carnes, M. T., Diefes-Dux, H. A. & Cardella, M. E. (2011). Evaluating student responses to open-ended problems involving iterative solution development in Model Eliciting Activities. *Proceedings of the 118th American Society for Engineering Education Annual Conference & Exposition, Vancouver, B.C., Canada.*
18. Verleger, M. A. & Diefes-Dux, H. A. (2010). Facilitating teaching and research on open-ended problem solving through the development of a dynamic computer tool. *Proceedings of the 117th American Society for Engineering Education Annual Conference & Exposition, Louisville, KY.*
19. Patton, M. Q. (2002). *Qualitative research & evaluation methods*. Thousand Oaks, CA: Sage Publications, Inc.