A Grand Challenge-based Framework for Contextual Learning in Engineering: Impact on Student Outcomes and Motivation

Dr. Lisa Huettel, Duke University

Dr. Lisa G. Huettel is a professor of the practice in the Department of Electrical and Computer Engineering at Duke University where she also serves as associate chair and Director of Undergraduate Studies for the department. She received a B.S. in Engineering Science from Harvard University and earned her M.S. and Ph.D. in Electrical Engineering from Duke University. Her research interests are focused on engineering education, curriculum and laboratory development, and applications of statistical signal processing.

Dr. Michael R. Gustafson II, Duke University

Dr. Michael R. Gustafson II is an Associate Professor of the Practice of Electrical and Computer Engineering at Duke University. He received a B.S.E. in 1993 from Duke University, majoring in Electrical Engineering and Mechanical Engineering and Materials Science. He continued on at Duke to earn his M.S. and Ph.D. in Mechanical Engineering and Materials Science. His primary focus is on undergraduate curriculum and laboratory development, and he is responsible for the first-year Computational Methods in Engineering course required for all engineering students at Duke University.

Dr. Joseph C. Nadeau P.E., Duke University

Dr. Joseph C. Nadeau is an associate professor of the practice in the Department of Civil and Environmental Engineering at Duke University where he also serves as Director of Undergraduate Studies and ABET Coordinator for the department. He received a B.S. in Civil Engineering from Lehigh University, a S.M. in Civil Engineering from the Massachusetts Institute of Technology, and a Ph.D. in Engineering from the University of California at Berkeley. His teaching and research interests are in the areas of mechanics, structural design, and composite materials. He is a registered Professional Engineer.

Prof. David Schaad, Duke University

David Schaad has over seventeen years of design and engineering experience as a consulting engineer working for various firms including: Parsons Engineering Science, Appian Consulting Engineers and Marshall Miller and Associates.

As part of his experience, Dr. Schaad has: designed waste water treatment systems to address industrial and domestic waste streams; developed designs of storm water control structures and strategies to address water quality and quantity; designed fluid transport systems to replace water supplies impacted by anthropogenic sources; designed fuel transport and delivery systems; developed designs for commercial and residential development; prepared land use plans; developed designs to protect against potential flood hazards; designed and developed plans and specifications for fluid handling systems, waste mitigation alternatives and remedial actions for RCRA and CERCLA sites including active industrial facilities and inactive disposal sites (including NPL sites); conducted feasibility studies by evaluating and analyzing the economic and engineering considerations of multiple design alternatives; obtained extensive experience with innovative remedial techniques (including groundwater extraction and treatment, air sparging, soil vapor extraction, and bioventing).

Current research focuses on sustainable engineering, community development, water and wastewater treatment design, stormwater retention/detention and treatment design, hazardous waste remediation, urban hydrology, constructed wetland and stream restoration design, ecological stabilization, sustainable engineering in land development, water resources, water and wastewater treatment.

He is also the faculty advisor for Duke Engineers for International Development and has led DukeEngage experiences every year since the inception of the program. He has facilitated and/or led trips to Indonesia, Uganda, Kenya, Honduras, El Salvador, Bolivia, and Peru. Representative projects he has worked on include: building a 4800sf Infant and Maternal Health Clinic, constructing a 100ft long vehicular bridge

©American Society for Engineering Education, 2015

over a seasonally flooded river, and installing a 3km long waterline. He was an inaugural member of the Faculty Leadership Council (FLC) of EWB-USA and is a registered professional engineer in 21 states.

Michael M Barger, Duke University
Dr. Lisa Linnenbrink-Garcia, Michigan State University

Dr. Lisa Linnenbrink-Garcia is an associate professor of Educational Psychology in the Department of Counseling, Educational Psychology, and Special Education at Michigan State University. She received her Ph.D. in Education and Psychology from the University of Michigan, Ann Arbor. Her research focuses on the development of achievement motivation in educational settings and the interplay among motivation, emotions, and learning, especially in STEM fields.

©American Society for Engineering Education, 2015

A Grand Challenge-based Framework for Contextual Learning in Engineering: Impact on Student Outcomes and Motivation

Exposure to meaningful, societally relevant applications can increase student motivation and improve learning outcomes. Here, we describe assessment results that evaluate a pedagogical framework based on the NAE Grand Challenges, in which specific engineering concepts are embedded in a societal problem (e.g., "reverse-engineering the brain") that requires students to define problems and apply course content to those problems. Assessment data were acquired from 981 undergraduate engineering students, including students participating in the intervention in an introductory class (N = 576) and advanced classes (N = 59) and control students in introductory (N = 281) and advanced classes (N = 65). Using a multivariate analysis of variance, we tested the hypothesis that the Engineering Grand Challenge Framework (EGCF) influenced students' self-assessments of specific student outcomes (ABET Criterion 3), particularly those related to understanding engineering in a societal/contemporary context. We also evaluated student motivation using well-validated scales drawn from the psychological literature and a structural equation model linking motivation to course outcomes.

The initial multivariate analysis revealed a significant effect of intervention upon student outcome responses considered as a group, and a significant interaction with class level. Significant item-specific interactions were observed for ABET criteria associated with societal context (ABET h), life-long learning (ABET i), and knowledge of contemporary issues (ABET j); in each case, the interaction revealed a greater effect of the EGCF on upper-level students' self-assessments on these criteria. Analysis of student motivation via structural equation modeling revealed a potential role for motivation in shaping course outcomes: for advanced students, the EGCF was associated with significant increases in situational interest (a measure of motivation) that in turn predicted higher ABET scores.

We conclude that EGCF – and, by extension, frameworks that connect engineering content to societal issues – holds promise for shaping student engagement with technical content in a manner directly relevant for national goals for engineering education (i.e., ABET criteria). Moreover, educational research can identify the circumstances in which a particular framework may be most effective (e.g., upper-level courses) and thus guide the allocation of instructor priorities and resources.

1. **Introduction**

Key challenges for engineering education involve creating and evaluating pedagogical innovations that can improve not only immediate student outcomes but also motivational factors that predict future success. For many students, their engagement with the material and susequent motivation depend on the context in which that material is presented; psychological research shows that if material appears to be directly relevant to a meaningful problem, learning and memory are enhanced.[1] Recognizing that engineering has a critical role to play in major societal problems, the National Academy of Engineering (NAE) has identified a set of *Grand Challenges* (GC). The diverse challenges include reverse-engineering the brain, making solar energy economical, providing access to clean water, and enhancing virtual reality – and solving each will require collaborative work by large-scale and interdisciplinary research teams.[2] The engineers who make significant contributions to such challenges will combine technical training with complementary skills (e.g., communication).[3] Because traditional engineering education emphasizes abstract problem solving as a path toward technical mastery, it does not prioritize those complementary skills – and it may fail to engage students who see engineering as a path toward addressing societal problems.

Over the past few years, we have developed a framework for integrating the NAE GC program into engineering education.[4] This framework has two primary goals. First, it conceives of real-world problems as *integrated components of engineering courses*, rather than as material added to a traditional curriculum. We recognize the importance of many current approaches – capstone design courses, service learning (e.g., the EPICS program[5]), and non-profit internships, among many – each of which provides students with some context for their technical training. But, these typically envision technical training and applications as two stages to be pursued sequentially (e.g., one applies prior technical training while on a service learning internship), limiting their applicability (e.g., in introductory courses). Second, our framework focuses on the role of *context for guiding the learning process.* Using psychological concepts drawn from contextual learning theory,[6-9] it guides students through six defined stages – including initial consideration of societal issues, identification of specific engineering principles, application of related technical content, and evaluation of the structural issues that make up the larger grand challenge. This framework has now been implemented into both lower- and upper-level engineering courses in several majors, and we now have assessment data from almost 1000 students in both test and control courses. These data indicate a potential role for this framework in improving both student outcomes and motivation.

2. **Framework Description**

Connecting core technical content to real-world problems poses challenges for engineering educators. The canonical approach involves identifying a problem that shares structural similarities with a technical concept (e.g., removing noise from a recording by applying filters), but this may not suffice for generalizing that concept to other problems that are not as obviously similar. Conversely, if the gap between problem and concept is too large, it introduces difficulties for both students (e.g., in understanding high-level relationships) and instructors (e.g., in teaching complex interdisciplinary material).

Our *Engineering Grand Challenge*-based framework (or, EGC framework) comprises six stages. Students first consider an overarching GC problem and how it can be represented in a particular engineering discipline (Stages 1-3). Students then learn technical skills that can be applied to a real-world data derived from that same GC (Stages 4-5). Students end by reflecting on the skills required for their problem solving and the relevance of those skills to other aspects of the GC (Stage 6). More details about each stage are provided in the following sections.

Stage 1: Multi-Disciplinary Overview. The course instructor provides an overview of a GC theme, often incorporating information from outside engineering (e.g., a guest technical expert from another field; general-interest or political/economic assignments; an in-class debate). This overview (and the interactions with students) provides the context for the skill development that occurs at later stages – and also motivates the students' initial curiosity about a societal problem.

Stage 2: Definition/Problem Restatement. After the students have considered the larger context for the GC as a group, they then individually reflect on what they have learned and re-define the GC in their own words. The goal is for students to think of themselves as active participants in the solution of the GC, rather than passive observers who watch while others address this societal problem. The instructor guides them to consider what skills they could gain that would help with the GC solution. The way in which this stage is implemented differs across courses and instructors, but it will be common to engage communication skills (e.g., writing a short reflection paper) – which complements the technical skills expressed in the subsequent stages.

Stage 3: Relation of the Grand Challenge to Engineering. Students next evaluate how the Grand Challenge problem is an *Engineering* problem. They draw on their prior experiences as engineers to consider the distinct perspectives engineers bring to problem solving, which makes their potential contributions to the problem clearer – and the problem more manageable. Students complete this stage in a variety of ways, such as using in-class discussions or a formal writing assignment.

Stage 4: Content, Tools, and Techniques. The instructor then presents the relevant course-specific technical content. In most cases, the technical content is drawn from material that would normally be presented in that course anyway – and the mode of presentation will thus depend on the instructor's preference. Importantly, this material can be presented with minimal direct reference to the GC (in this stage).

Stage 5: Application of Course Content to the Challenge. The key connection between the GC material (Stages 1-3) and the technical material (Stage 4) comes as the students complete a problem-solving exercise. Most such exercises will involve hands-on analysis or simulation of data relevant to the GC, followed by reflection on ethical or practical issues raised by the data. For example, the students might be given data related to water quality measures from one location, analyze that data to evaluate the effectiveness of a new filtration system, and then consider whether the filtration system provided a cost-effective solution compared to other alternatives. Connections to experts both within and outside of academia can help with the acquisition of data and the generations of exercises.

Stage 6: Analysis and Reflection. Students end by revisiting the GC and reflecting on how the skills they developed could potentially address the GC – and identifying other needed skills that could speed progress on the GC. They repeat the "define the challenge" exercise from Stage 2; this provides a point of comparison for changes in their perspective because of the exercise. Reflection exercises should also emphasize how engineers contribute in teams, building on skills of others for a common purpose.

3. **Framework Implementation**

The EGC framework has been piloted in four courses – some taught several times – in the 2012-2013 and 2013-2014 academic years. These courses spanned different levels (introductory and advanced), were taught to students from different majors, were either required or elective, and covered very different content. To give a sense of the breadth of coverage, we provide a brief overview of the implementation in the introductory course and then go into more depth about the details of implementation in an advanced elective course.

3.1 Computational Methods in Engineering

Computational Methods in Engineering (EGR 103L) is a required course taken by all first-semester engineering students. The course provides an introduction to computer methods and algorithms for analysis and solution of engineering problems using numerical methods. The concepts and techniques introduced are broadly applicable, thus the course lends itself nicely to the integration of the EGC framework.

For the past three years (beginning in Fall 2012), the EGC framework has been implement in this course using the GC theme *Make Solar Energy Economical*. This theme was chosen for its accessibility (both technically, as well as the prevalence of data available) and for its broad appeal, given the fact that students majoring in civil, environmental, mechanical, electrical and computer engineering, and biomedical engineering all take the class. Students began by reading several articles that presented the challenges inherent in making solar energy economical from a non-engineering perspective (overview). They summarized these articles in a written assignment (restatement), and subsequently engaged in a discussion of how the course content might be relevant to some of the challenges (relation to engineering). In the lab, students used the methods and algorithms presented in the lecture (content, tools, and techniques) to analyze solar energy data from a collection site in North Carolina (application). Ultimately, they were asked to determine the necessary size of a modern solar panel to power a typical house's energy needs and to evaluate whether such a panel would be cost-effective (analysis and reflection).

3.2 Fundamentals of Digital Signal Processing

Fundamentals of Digital Signal Processing (ECE 381) is an advanced (junior/senior-level) elective for students majoring in electrical and/or biomedical engineering. It is typically taught as a small lecture course (e.g., 20-30 students) with a required weekly laboratory component. The course introduces the theory and applications of digital signal processing, including topics such as sampling and reconstruction, discrete-time transforms (z-transform, discrete-time Fourier transform, and discrete Fourier transform), and the analysis and design of FIR and IIR filters.

The laboratory exercises provide an opportunity for students to apply the theory covered in lecture to more realistic challenges in order to connect that theory to practice. Using both software- and hardware-based exercises, many of the signal processing concepts discussed in the lectures (e.g., designing a system for classifying speech on the basis of vowel sounds) can be illustrated. The potential for applying signal processing concepts to explore a wide range of real-world problems, as well as the varied interests of the students in the course, made this course a natural choice for EGC framework implementation.

In the first year of the EGC framework implementation (Fall 2012), a module based on the Grand Challenge of *Reverse-engineer the brain* was developed and has been described previously.[10] A second module, based on the Grand Challenge of *Making solar energy economical* was initiated in the second year of framework implementation (Fall 2013), and more fully developed in the third year (Fall 2014). The selection of these particular themes was driven in part by the interests of the students taking the course, based on our hypothesis that examples that have personal relevance to the students will have a greater impact. Secondly, we selected these themes in order to leverage local expertise and research interests and to facilitate the connection of signal processing concepts to concrete, problem-driven applications. The data presented in this paper are based on the implementation of the full *Brain* module and the partial *Energy* module in Fall 2012 and Fall 2013. Data from Fall 2014 (full *Energy* module implementation) were not available for inclusion in the analysis.

The following example illustrates how the EGC framework was implemented using the *Energy* theme:

Stage 1 (Overview). Although the Grand Challenge theme focused specifically on making solar energy economical, we decided to broaden the theme in order to more easily connect with an ongoing, interdisciplinary project that was focused on power disaggregation and improving energy efficiency. At the beginning of the project, four goals were presented to the students:

1. To gain a ***multidisciplinary understanding*** of the societal importance of this challenge.
2. To be able to identify ways in which ***signal processing can interact with other areas of expertise*** (e.g., economics, policy, psychology) to make improvements in energy efficiency.
3. To ***apply signal processing tools and techniques*** to investigate a fundamental question about energy usage and efficiency, using real data.
4. To gain a greater understanding of ***how signal processing can inform solutions*** to the challenge, including its limitations, possible fruitful collaborations with other disciplines, and future challenges (including non-technical ones).

In the first assignment, students were assigned three tasks: (1) Read the document "Introduction to the Grand Challenges for Engineering" to familiarize themselves with the NAE Grand Challenges, generally[2], (2) Read the paper "Is disaggregation the holy grail of energy efficiency? The case of electricity" by Armel *et al.*[11] to learn about the use of smart energy meters and disaggregation algorithms to maximize energy savings presented from many perspectives: economical, behavioral, and technical, and (3) Check out the online description of the project led by Dr. Bradbury noting, in particular, the diverse areas of expertise of the project participants.[12]

With this background preparation, students were asked to prepare three questions for Dr. Bradbury, who came to class the following week to give a guest lecture on “Design and Implementation of an Energy Disaggregation System.” This lecture provided an introduction to energy disaggregation, including a discussion of typical patterns of energy usage and the motivation for implementing disaggregation, the hardware used for data collection, the algorithms used for data analysis, presentation of some data that had been collected from on-campus dormitories, and a discussion of some of the policy and privacy implications. Because students were prepared for the lecture with three questions, they were able to readily and confidently contribute to a question and answer session.

Stage 2 (Restatement) and ***Stage 3 (Relation to Engineering).*** The week after the guest lecture which introduced students to the concept of power disaggregation, students completed the first of two laboratory modules related to this project. This first module focused on developing the students’ personal understanding of power disaggregation (the restatement) and establishing a concrete relation between the ideas presented in the papers and by the guest speaker and a real application (relation to engineering). Specifically, students were guided through an exercise in which they built and implemented a system to collect and analyze power waveform data from everyday objects (e.g., incandescent lamp, small fan), as described in Steps 1 through 8 in Figure 1. This exercise not only connected signal processing concepts to the problem, but also integrated knowledge from previous courses (e.g., circuit design and analysis). After collecting data from several items, students were asked to write a report in which they discussed the waveforms, how those waveforms coincided with or varied from their expectations, differences that they observed between the various waveforms and a hypothesis as to why those differences were present, and a discussion of the strengths and weaknesses of the system. Anecdotal feedback from the students indicated that collecting data and viewing waveforms generated by objects they encounter on a daily basis effectively connected the technical concepts to something that the students related to and cared about.

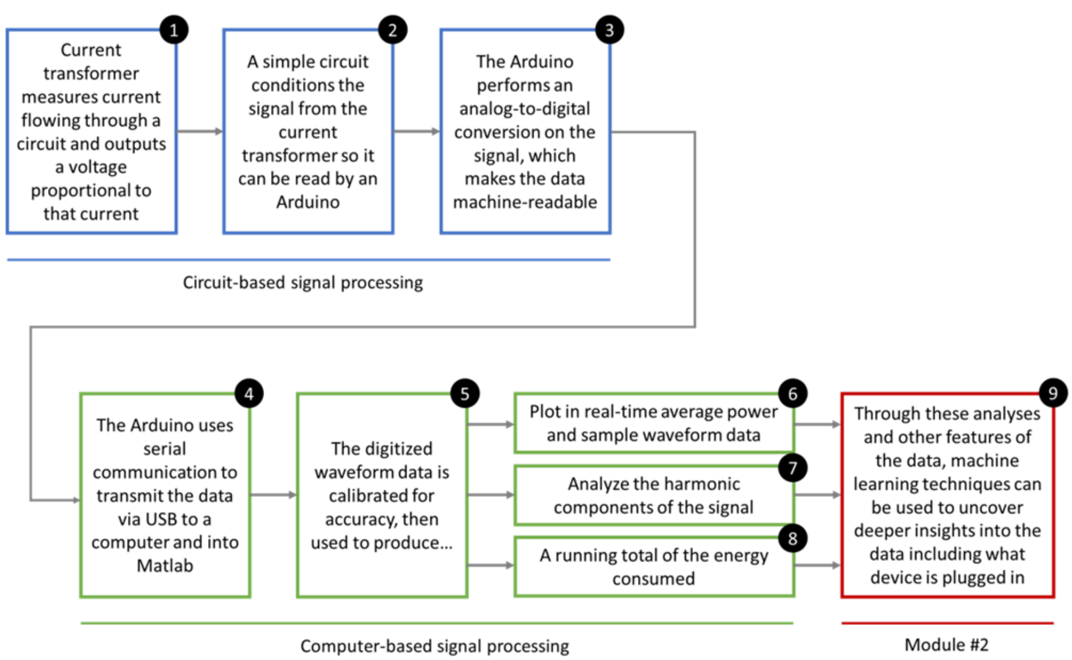

Figure 1 – Flowchart of the design and the components of the 2-part lab module

Stage 4 (Content, Tools, and Techniques). Supporting technical content was integrated throughout the semester. Most of the skills students needed to understand the signal processing within the *Energy* applications were presented in lectures, homework, and laboratory assignments. When appropriate, lectures and assignments made reference to the challenges encountered in developing power disaggregation algorithms (e.g., a discussion of issues related to sampling rate).

Stage 5 (Application). Once a sufficient amount of technical material had been covered in the lectures (Stage 4), the students returned to the laboratory to complete the second module related to power disaggregation. The goal of this module was to have students work with real data, and to use course concepts to design their own algorithm for automatic appliance identification. Students were provided a database with over 500 samples of power data collected from thirteen different household appliances (e.g., refrigerator, computer monitor, lamp, dish washer) and were asked to identify and extract features that could be used to classify an unidentified trace as a specific appliance. Ultimately, students created a confusion matrix to illustrate the performance of their algorithm.

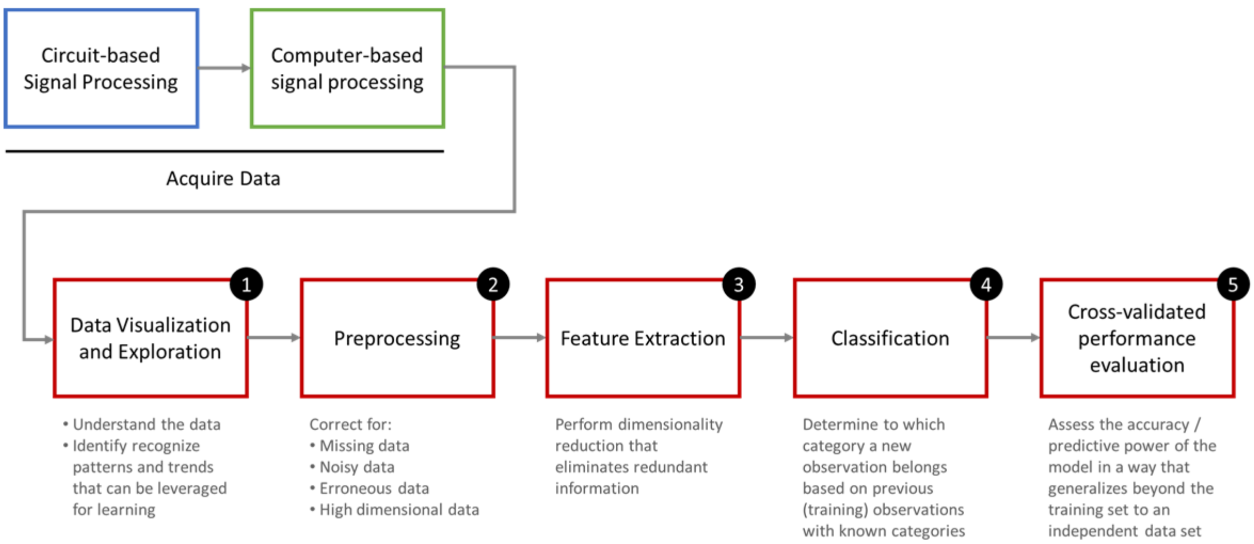

Figure 2. Overview of Module 2: using the acquired data for machine learning.

Stage 6 (Analysis and Reflection). After completing the second laboratory module, students were asked to reflect on what they had done, and to connect this experience back to the bigger issue of energy efficiency. They thought about how power disaggregation algorithms could be used, as well as their limitations. As a class, we returned to some of the non-technical ideas raised earlier in the semester (e.g., privacy issues, policy issues) and discussed how these issues interacted with the technical challenges and possibilities the students observed in the laboratory.

4. **Methods**

4.1 Participants and Procedures

Students who were enrolled in the selected courses were invited to participate in an evaluation study assessing the effectiveness of the framework for supporting student learning and motivation. Assessment data were acquired from 981 undergraduate engineering students, including students participating in the intervention in an introductory class (N = 576) and advanced classes (N = 59) and control students in introductory (N = 281) and advanced classes (N = 65). The introductory course was comprised almost entirely of first-year students, whereas the advanced courses included sophomores, juniors, and seniors. The sample was majority male (62%). The racial/ethnic breakdown of the sample was as follows: 50% Caucasian, 29% Asian or Pacific Islander, 4% African American, 4% Latino/a, 5% Multi-Racial, 2% Other; 6% of the participants did not provide information about the gender or race. Participants were asked to complete surveys in class at the beginning (Week 2) and end of the semester (Week 15) to assess their thoughts and feelings about engineering. The survey took approximately 15 minutes to complete.

4.2 Measures

In addition to standard demographic variables, we also collected measures of (a) students' self-assessed ability to achieve the outcomes listed in ABET Criterion 3, (b) situational interest in engineering that emerged as a function of the course, and (c) individual interest in engineering as a profession/discipline. These measures, described in detail below, were highly reliable, with Cronbach's alphas above 0.80.

Student Outcomes (ABET Criterion 3). Students rated the degree to which the course increased their ability to achieve the ABET a-k student outcomes. We used students' average score on these 11 items ($\alpha = 0.85$) to examine whether students who participated in the EGC framework obtained higher overall levels of skill development, as indexed by the full set of ABET outcomes (a-k), and whether this increase in skill development occurred via increases in students' interest in engineering. Specifically, we used structural equation modeling (SEM) to test whether changes in situational and individual interest in engineering were associated with higher levels of perceived skill development.

In our second set of analyses, we were interested in whether or not the EGC framework would predict changes in the specific ABET criteria that were directly targeted through the EGC framework. Specifically, we predicted that incorporation of the EGC framework into courses will lead to positive consequences for students' intellectual development, particularly with regard to the broad goal of developing students who can relate technical content to larger societal issues. Thus, we hypothesized that students who participated in the EGC framework would score higher on ABET criteria h, i, and j: awareness of the global and societal implications of engineering, the importance of life-long learning, and understanding of contemporary issues. We tested those predictions using Multivariate Analysis of Variance (MANOVA) using data from end-of-semester surveys given to students in both the control and intervention courses.

Situational Interest (SI). Students' situational interest (e.g., interest that emerges from and is supported by the context) was assessed at the end of the semester using three sub-scales developed by Linnenbrink-Garcia and colleagues.[14] Triggered-SI (4 items, $\alpha = 0.87$) assessed momentary stimulation (e.g., "The professor does things that grab my attention"). Maintained-SI-Feeling (4 items, $\alpha = 0.91$) assessed students' heightened enjoyment of engineering supported through the course content (e.g., "What we are learning in this class is fascinating to me").

Maintained-SI-Value (4 items, $\alpha = 0.86$) assessed the extent to which students perceived a meaningful connection to engineering supported through the course instruction (e.g., "What we are studying in this class is useful for me to know"). We hypothesized that the EGC framework would be especially useful in supporting Maintained-SI-Value given its focus on meaningful, real-world problems.

Individual Interest. Personal or individual interest/value was assessed at the beginning ($\alpha = 0.85$) and end ($\alpha = 0.88$) of the semester using an 8-item scale developed by Linnenbrink-Garcia and colleagues.[14] Sample items include "Engineering is exciting to me" (enjoyment) and "Engineering is practical for me to know" (value). We hypothesized that the EGC framework would support individual interest in engineering, through shifts in situational interest. This hypothesis was tested using SEM.

5. Impact on Student Motivation and Outcomes

Our overarching hypothesis is that the EGC framework – which emphasizes exposure to real-world applications and exercises that encourage active problem solving – will lead to increases in students' motivation and pedagogical effectiveness[15-18] that then ramify into better student outcomes as indexed by ABET Criterion 3. This hypothesis assumes that student learning is most effective when they solve problems in ways that reflect the real-world nature of such tasks[6] – and draws upon research on contextual learning in cognitive psychology and neuroscience.[6-9]

5.1 Student Motivation

To test our hypothesized indirect effect of the EGC framework – that our intervention increases student motivation which in turn influences student outcomes – we used structural equation modeling. This statistical technique involves setting up a multi-stage model describing the relations between variables of interest, followed by evaluation of whether the hypothesized model was well fit to the data. For this analysis, we collapsed across all ABET criteria to increase statistical power; we examine effects on specific criteria in the next section.

We conducted three separate SEM models to examine the direct and indirect effects of the EGC framework (intervention vs. control) on situational interest, individual interest, and ABET criteria (see Figure 3). Each type of situational interest (triggered-SI, maintained-SI-feeling, maintained-SI-value) was tested separately in order to independently evaluate the effects of the EGC framework on these three distinct, yet highly correlated forms of situational interest. For all models, we also tested whether predicted pathways were similar for introductory versus advanced students, using multi-group analyses within an SEM framework. Prior individual interest in engineering, measured at the beginning of the semester, was included as a control in all analyses. As such, we are able to measure how the EGC framework affects situational interest, controlling for any potential differences in individual interest. This approach also enables us to examine changes in individual interest as a function of the EGC framework.

Our first step was to determine whether the model provided a better fit for the data when the path coefficients were free to vary between the introductory and advanced classes. For all three models there was a statistically significant improvement in model fit when parameter estimates

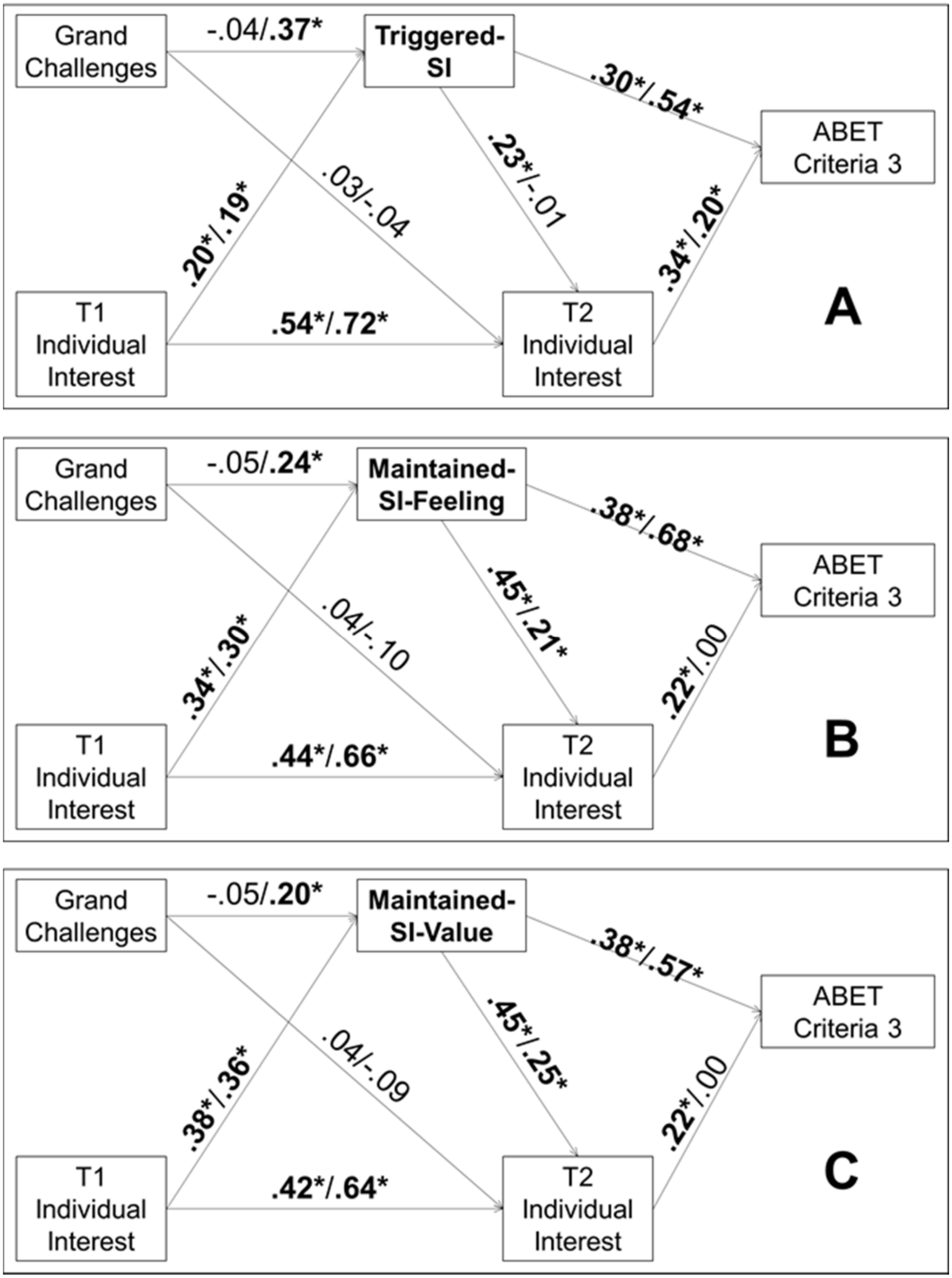

*Figure 3. Path models for interest development. Model A: χ^2 (4) = 12.520, p = .014, RMSEA = .070, CFI = 0.99; Model B: χ^2 (4) = 15.842, p = .003, RMSEA = .082, CFI = 0.989; Model C: χ^2 (4) = 19.811, p < .001, RMSEA = .095, CFI = 0.986. All paths were allowed to vary between introductory (first value on each line) and advanced classes (second value on each line). Path coefficients are all standardized. Statistically significant paths are indicated in bold (*p < .05).*

were free to vary (Triggered-SI model: $\Delta\chi^2$ (2) = 19.975, p < .001; Maintained-SI-feeling model: $\Delta\chi^2$ (2) = 13.430, p = .001; Maintained-SI-value model: $\Delta\chi^2$ (2) = 11.676, p = .003). These results suggest that the effects of the intervention and its downstream consequences in terms of changes in interest and ABET criteria varied significantly between the introductory and advanced classes. Thus, we employed a multi-group SEM for the analyses reported below. The model fit for all three situational interest models was acceptable (Triggered-SI model: χ^2 (4, n = 873) = 12.520, p = .014, RMSEA = .070, CFI = 0.990; Maintained-SI-feeling model: χ^2 (4, n = 873) = 15.842, p = .0032, RMSEA = .082, CFI = .989; Maintained-SI-value model: χ^2 (4, n = 873) = 19.811, p = .0005, RMSEA = .095, CFI = .986). The final results for both introductory and advanced students across the three SI models are depicted in Figure 3.

For students in introductory classes, the EGC framework did not alter student motivation; instead, students who had high individual interest at the start of the course experienced higher levels of situational interest in the course and maintained a high individual interest later in the course. Both situational interest and the change in individual interest were in turn associated with higher ratings on the ABET criteria. Given that there were no significant effects of the EGC framework on situational or individual interest, it is not surprising that there was no significant indirect effect of the EGC framework on either changes in individual interest or ABET criteria. Thus for the introductory students it appears that students' entering level of interest rather than the EGC intervention supports interest development and perceived skill development.

For students in advanced classes, we found that the EGC framework predicted higher levels of all three forms of *situational interest*, which were in turn associated with higher ABET scores. There were also significant indirect effects of the EGC framework on ABET for all three situational interest models. Additionally, both of the maintained forms of situational interest predicted changes in individual interest among the advanced students, although Triggered-SI was not a significant predictor. As expected the EGC framework had a significant indirect effect on changes in individual interest through both maintained-SI-feeling and maintained-SI-value. Thus, relative to the no-treatment control participants, advanced students in classrooms where the EGC framework was implemented experienced gains in both motivation and skill development.

5.2 Student Outcomes

We used Multivariate Analysis of Variance (MANOVA) to evaluate the effectiveness of our EGC intervention. We included both the intervention status (control vs. intervention) and the level of classroom (introductory vs. advanced) as independent variables in the model, and the ABET criteria (a-k) as dependent variables.

We first evaluated whether there were effects of the intervention and/or classroom level on responses to the overall set of items (i.e., running a multivariate test across all dependent variables). We found a significant main effect of intervention ($F(11, 943) = 13.302$, $p < .001$), a significant main effect of class level ($F(11, 943) = 12.960$, $p < .001$), and a significant interaction ($F(11, 943) = 3.240$, $p < .001$). This significant multivariate effect provided justification for analyses of item-specific (i.e., univariate) effects.

Our most striking results involved interactions between intervention and class level. We found significant interactions for five of the ABET – a, f, h, i, and j – with statistics as follows: a ($F(1, 953) = 6.201$, $p = .013$), f ($F(1, 953) = 7.202$, $p = .007$), h ($F(1, 953) = 12.343$, $p < .001$), i ($F(1, 953) = 7.033$, $p = .008$), and j ($F(1, 953) = 6.368$, $p = .012$). Four of these criteria – f, h, i, and j – had a similar pattern of results. In each case, the intervention had no effect or a small effect on the ratings students in introductory courses, but had a particularly positive effect on the ratings of the ABET criterion for students in advanced classes (see Figure 4). The only different pattern was observed for ABET criterion a, for which the intervention had no effect on students in introductory classes and a negative effect on students in advanced classes (i.e., it decreased advanced students' beliefs that their class helped them to "Apply knowledge of math, science, and engineering."

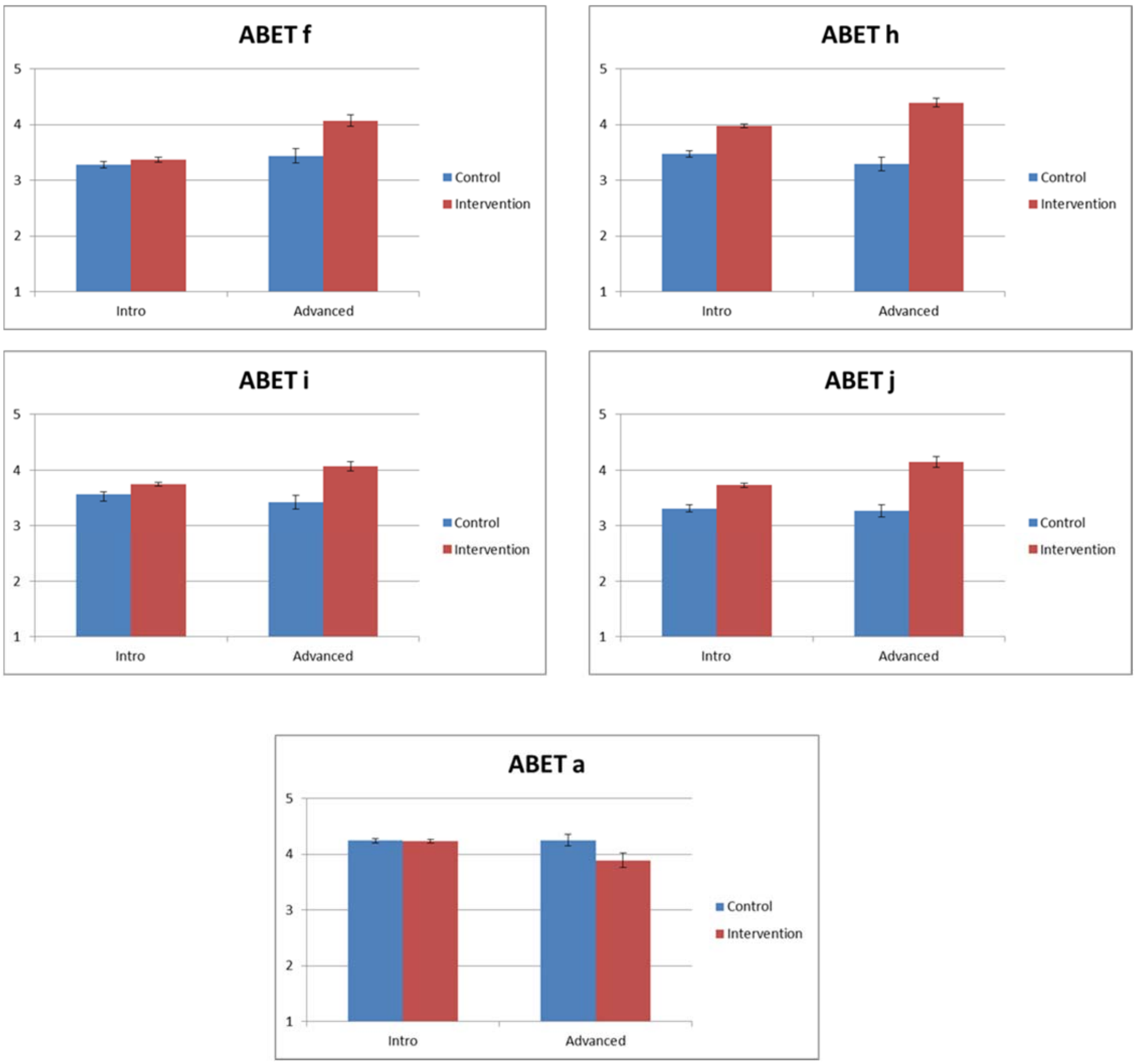

Figure 4. Impact of intervention and class level on students' ratings of ABET criterion f: "Understanding of professional and ethical responsibility", h: "The broad education necessary to understand the impact of engineering solutions in a global and societal context", i: "Recognize the need for engaging in life-long learning", j: "Knowledge of contemporary issues", and a: "Apply knowledge of math, science, and engineering".

We also found a positive main effect – and no interaction with class level – on ABET criterion g. Students in the intervention classes reported significantly higher scores on this criterion – "communicating effectively" – than students in the control classes ($F(1, 953) = 18.056$, $p < .001$). And, we found several main effects of class level, such that introductory students reported higher ratings for ABET criteria b and k, and advanced students reported higher ratings for ABET criteria c, d, and g – independent of any effects of the intervention. Because these last effects could depend on idiosyncratic features of the classes, we do not consider them further.

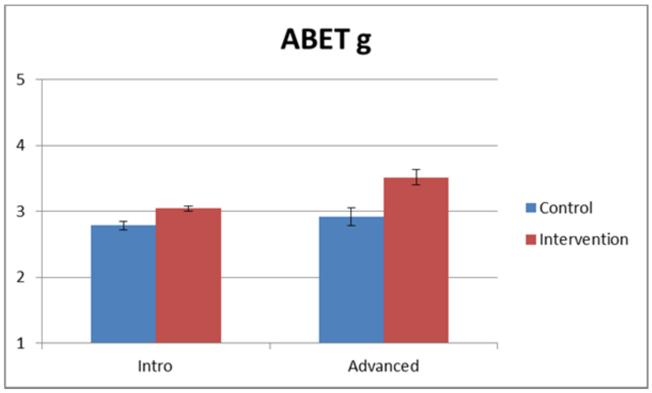

Figure 5. Impact of intervention and class level on students' ratings of ABET criterion g: "Ability to communicate effectively".

6. **Conclusions**

Our EGC framework has now been implemented in engineering classes across a variety of levels and majors – now totaling over 600 students across 2+ years. By comparing data from those students to well-controlled baseline data from students in similar courses taught by the same instructors, we could systematically evaluate whether that framework influenced student motivation and, in turn, student outcomes measured via ABET criteria.

Using structural equation modeling, we found that the EGC framework did increase student motivation which then led to positive effects on student outcomes – but only in upper-level courses. Using a MANOVA that examined effects of class level and intervention, we found that the EGC framework did have positive effects on several ABET criteria – again, specifically in upper-level courses. We emphasize that our EGC framework did not lead to a generalized increase in student motivation across courses and students; instead, the framework increases the motivation for some students (particularly in upper-level courses) but does not alter motivation or outcomes for other students. A key direction for future research will be specification of those circumstances in which the EGC framework has maximal effect – recognizing that no intervention is likely to benefit all students or to have equal effects across all courses.

Our results demonstrate the potential advantages of connecting upper-level engineering content to engaging real-world problems, particularly with regard to training engineering students who can interpret, apply, and communicate technical concepts. The EGC framework does require planning by the instructor; most notably, attention should be paid to the exercises that set up the grand challenge and to the summary discussions, since those elements are not typical parts of engineering courses. In recent years, as our instructors have gained more experience with the EGC framework, they have introduced the EGC content earlier in the semester – often laying the groundwork for subsequent discussions and projects. In that way, the EGC framework becomes more than just an ad hoc exercise dropped in the midst of other content, serving instead as a framing device for the entire course.

Acknowledgements

This work was supported by NSF grant #DUE-1141073 and with funding from The Lord Foundation of North Carolina.

Bibliography

1. Nairne, J.S., Thompson, S.R., and Pandeirada, J.N.S. (2007). Adaptive Memory: Survival Processing Enhances Retention. *J. Experimental Psychology: Learning, Memory, and Cognition*, 33(2), 263-273.
2. "Grand Challenges for Engineering", engineeringchallenges.org, 05 April 2015, <http://www.engineeringchallenges.org/File.aspx?id=11574&v=ba24e2ed >
3. *Educating the Engineer of 2020*, Washington DC: National Academies Press, 2005, National Academy of Engineering.
4. Huettel, L.G., Gustafson, M.R., Nadeau, J., Schaad, D., Barger, M., and Linnenbrink-Garcia, L. (2013, June). A Grand Challenge-based Framework for Contextual Learning in Engineering. 2013 Annual Conference of the American Society of Engineering Education.
5. Coyle, E.J., Jamieson, L.H., and Oakes, W.C. (2005). EPICS: Engineering Projects in Community Service. *International J. of Engineering Education*, 21(1), 139-150.
6. Karweit, N. (1998). "Contextual learning: A review and synthesis", in A.M. Milne (ed.), *Educational reform and vocational education* (pp. 53-84). Washington, DC: U.S. Department of Education, Office of Educational Research and Improvement, National Institute on Postsecondary Education, Libraries, and Lifelong Learning.
7. Caine, R.N., and Caine, G. (1997). *Education on the edge of possibility*. Alexandria, VA: Association for Supervision and Curriculum Development.
8. Lave, J. and Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge, UK: Cambridge University Press.
9. Bransford, J.D., Brown, A.L., and Cocking, R.R. (1999). *How People Learn: Brain, Mind, Experience and School*. Washington, DC: National Academy Press.
10. Huettel, L.G., Gustafson, M.R., Nadeau, J., Schaad, D., Barger, M., and Linnenbrink-Garcia, L. (2014, June). Evidence for the Effectiveness of a Grand Challenge-based Framework for Contextual Learning. 2014 Annual Conference of the American Society of Engineering Education.
11. Armel, K.C., Gupta, A., Shrimali, G., and Albert, A. (2013) Is disaggregation the holy grail of energy efficiency? The case of electricity. *Energy Policy,* 52 (2013), 213-234.
12. "The University as an Energy Laboratory: Design and Implementation of an Energy Disaggregation System", bassconnections.duke.edu, 05 April 2015, <http://bassconnections.duke.edu/project-teams/university-energy-laboratory-design-and-implementation-energy-disaggregation-system>

13. Huettel, L.G., Brown, A.S., Coonley, K.D., Gustafson, M.R., Kim, J., Ybarra, G.A., and Collins, L.M. (2007). Fundamentals of ECE: A Rigorous, Integrated Introduction to Electrical and Computer Engineering. *IEEE Trans. Education, 50(3), 174-181*.

14. Linnenbrink-Garcia, L., Durik, A. M., Conley, A. M., Barron, K. E., Tauer, J. M., Karabenick, S. A., and Harackiewicz, J. M. (2010). Measuring situational interest in academic domains. *Educational and Psychological Measurement, 70,* 647-671.

15. Shuman, L.J., *et al.* (2002). "The future of engineering education," in *Proc. 32nd Annu. Frontiers in Education Conf.*, Boston, MA, Nov. 2002, vol. 1, pp. T4A-1–T4A-15.

16. Olds, B., and Miller, R. (2004). The effect of a first-year integrated engineering curriculum on graduation rates and student satisfaction: A longitudinal study. *J. Eng. Educ.*, 93(1), 23–36.

17. McLellan, J. H., *et al.* (1996). Using multimedia to teach the theory of digital multimedia signals. *IEEE Trans. Educ.*, 38(3), 336–341.

18. Munson, C.C. (1995). "Elements of a new Electrical Engineering curriculum at Illinois: A shift from circuits to signal processing," in *Proc. IEEE Int. Symp. Circuits and Systems*, Seattle, WA, vol. 1, pp. 1Sf–4Sf.