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A Controls Approach to Improve Classroom Learning Using Cognitive Learning Theory and Course Analytics

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***Abstract*—** The availability of educational technology and new modes of instruction present unprecedented opportunities for improving the educational effectiveness of engineering courses. This paper discusses a controls approach for developing and improving courses over the span of several semesters using a wide array of metrics to monitor student learning. Changes in course content, pacing, and format were introduced to improve consistency across sections and across semesters in terms of metrics such as student performance and student workload. Results are shown for a course that has an annual enrollment of 1100 students and is taught in a blended/flipped format with online components provided by two MOOCs.

Keywords—blended class, flipped class, analytics, feedback, education, learning theory

I INTRODUCTION

Blended learning is an extension of flipped classrooms, where students watch lecture videos prior to class and come to the class period to work extra problems and homework [1]-[2]. Like flipped classrooms, blended learning makes use of the lecture videos watched before class, but then the class period can be filled with a blend of different activities such as supplemental lectures, hands-on learning with experiments, collaborative learning, problem solving, inquiry-based learning, and student-led instruction. The blended classroom model has much more flexibility in its structure than does a traditional lecture style of teaching, which is fairly rigid in terms of flow of the class and in-class activities, and hence blended learning has the capability of producing much better results if tuned properly.

Applying a controls approach to tuning a blended classroom model requires an understanding of the system model, the control actions that can be employed, the measurements available, and a determination of the desired outcomes or performance metrics. The system model used in this paper is the learning process, derived from research in cognitive psychology on how an individual learns and how human memory works. The performance metrics are student performance and student attitudes towards the subject matter. Historically, instructors use end-of-course student surveys and test performance to improve their instruction. However, end-of-course surveys are taken only once per term and give only coarse-grained data useful for course improvement.

Courses that have a large online component, such as lecture videos and auto-graded online homework, open the option to have much more fine-grained measurements through the use of course analytics – data taken on the students' online usage patterns. Examples of these analytics include video viewership and statistics of online homework completion and correctness. Discussion forums give additional information that can be utilized for course assessment and improvement.

The notion of a "mathematical model" of the system is a logical starting point for any discussion of control. However, due to the complex nature of the learning process, a quantitative model of learning as modeled by differential or difference equations is challenging. Mathematical models of learning date back to the work of Bush and Mosteller [3]. Their model represents the evolution of the probability of learning given a series of reinforcements. Often, learning models focus on the spacing effects [4]. This concept refers to the extensive body of work in cognitive psychology on the timing of testing, review, and the introduction of new material. A good example is Reference [5], where the spacing effects are modeled as a set of constraints that bracket the review of material. Wang and An [6] similarly study the role of the spacing effect in the layout of a learning process.

While accurate models of learning are an important underpinning of the scheduling problem in instruction, we feel that this need is alleviated in the context of a feedback control system. Control action for course improvement is challenging because the involvement of students and instructors means that human factors are part of both the plant model and the control action. Hence, control methods that involve human interactions is appropriate for this system. For example, in the section entitled "Challenges for Control Research" in the Impact of Control Technology Report [7], Egerstedt loosely defines the term "influence" to describe the imprecise control that human operators have over complex systems, as opposed to more mathematically defined notions standardly used in control applications. Control-theoretic formulations are currently lacking for systems with human operators in a control loop, especially ones that use high-level problem-solving methods.

The remainder of this paper describes a control process used to improve a large enrollment, junior-level course taught at Georgia Tech. The next section talks about the application of controls concepts to the learning process. Section III shows how those concepts were applied to the initial development of the course and the course evolution over five semesters. Section IV gives the results over the five-semester time frame.

II CONTROLS FORMULATION

The course that motived the development of this course improvement methodology is ECE3710 Circuits and Electronics taught at Georgia Tech. Prior to Summer 2013, ECE 3710 faced problems with quality, specifically with consistency across sections in terms of coverage, grading, and quality of instruction. This course is taught to non-ECE majors and is required of students from aerospace engineering, mechanical engineering, and materials science engineering. Because the course was considered a service course taught to non-majors, the instructors were selected to be advanced graduate students in order to handle the large enrollment of 400 students per term. A survey of course instructors found that none of the sections covered all the material in the course, with multiple sections missing up to 25% of material. The worst case mismatch of material between sections was 50%. The average GPAs per section of the course ranged from 2.37 to 3.92 during the period from 2004 to 2013.

A typical system that suffers from quality and inconsistency in performance can be improved using a controls approach, which is how the revision and adaptations to this course were approached. The course was revised to be taught in a blended format starting in the summer of 2013, where lectures were watched online prior to class. This format allowed for six in-class labs to be added to the course in order to give students hands-on experience. Two MOOCs were developed, *Linear Circuits* and *Introduction to Electronics*, on the Coursera platform to provide the online content of the course. The blended format also offered a more active learning environment for the students. Reference [8] describes the components of the course and its implementation in Fall 2013. Reference [9] shows the positive impact of in-class labs on student learning. The current paper uses a controls formulation to show how such a course can be improved with each offering of the course.

The overall control architecture used to fine-tune the course is shown in Figure 1. This formulation follows that of a common, generic adaptive control strategy [10]. The control procedure is a mixture of control reconfiguration and small, incremental adjustments of control variables. Small incremental changes include pacing of the material, spacing effects, and the number of homework problems given per week. Pacing can be varied in small discrete adjustments. In particular, if the online course material is broken into 90 eight-minute lecture videos scheduled to coincide with 30 class periods over the course of the term, then a particular video lesson might be moved forward or backward one class period to allow more or less time with a particular topic. The number of minutes per class period spent on a particular activity can be adjusted incrementally as well.

Larger adjustments correspond to reconfigurations in the course format or resources. Adding course components, such as adding in-class worksheets and revising or adding video lectures are all course reconfigurations.

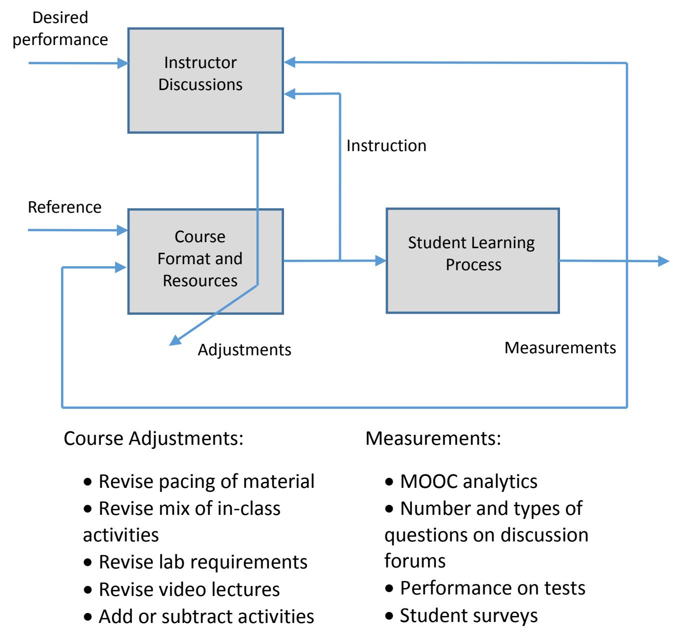

Figure 1: Control formulation of adapting a blended course model from semester to semester.

Desired performance levels and reference values can be selected if an instructor wants to have test scores or final course averages each term to be near a desired value. Another reference value that could be chosen is the *student workload*, defined as the average number of hours per week that the students spend on the course. A credit hour is defined as being the equivalent of one hour of time a student meets with a faculty member plus two additional hours of work [11]. So, a two-credit hour class should have a workload of six hours of work per week.

The measurements referred to in Figure 1 are listed in order of time-scale, with MOOC analytics available for measurements most frequently, such as daily, and student end-of-course surveys being recorded once per term. MOOC analytics useful for course improvement include the percentage of students who watch specific lecture videos, how many times they watched them, and when they watched them. Other information includes the percent of students correct on each homework problem and the number of times that the students had to rework the problem. Online discussion forums can be used for deeper understanding of analytics. For example, the number of posts on a particular topic can be analyzed to identify problematic topics and an analysis of the posts can be performed to determine the source of confusion.

The plant to be controlled, the Aggregate of Student Learning Process, is not a standard type of system in control applications, so the control methodology is not standard. The system under consideration in this paper is not easily defined by a set of traditional differential or difference equations. As mentioned in the introduction, several models of learning exist in the literature. These models are typically associated with a single individual, rather than a classroom-sized group of heterogeneous learners. Indeed, much of this research is motivated by the desire for "individualized learning," or personalized learning environments associated with computer-based learning systems and/or MOOCs. While the models are characterized by inputs, outputs, and constraints, there is to date no effort to apply closed-loop control principles.

III. COURSE DEVELOPMENT AND EVOLUTION

The control formulation depicted in Figure 1 guided both the initial format of ECE 3710 as well as the adjustments that were made semester to semester. The initial course format, analogous to designing an initial control configuration in a standard control application, was based on knowledge of learning theory. Inherent in much of the theory is feedback mechanisms that an instructor might employ to impact learning. Section A includes a discussion of how learning theory was used to design the initial version of the course. Section B gives some details of how the course was adjusted from semester to semester based on feedback.

A. Course Development

The initial format of the revised course was designed to address several learning mechanisms described in Reference [12]: the need for prior knowledge, organization of knowledge, motivation, goal-directed practice, social and intellectual learning climate, and targeted feedback. The principles in this reference were developed by aggregating concepts from a number of different learning theories.

Organization of knowledge and the activation of prior knowledge was achieved in this course through the introduction of a concept map at the beginning of each module. The concept map listed the major topics to be studied in that module and shows the concepts from previous modules that are necessary for the current module. Prior knowledge was activated by introducing real world applications of the material that students may have seen elsewhere. Examples of how the material is used to design and analyze sensors that the students have seen in non-ECE applications helps these non-ECE students relate the material to their own discipline, which also helps to motivate them. Motivation is also addressed from the perspective of the value versus expectancy relationship: students are given very specific and organized procedures to succeed in the course along with an abundance of resources, resulting in high expectancy of success. Also, expectancy is built upon past and current successes at learning or performing a task [13]. From a controls perspective, people often subconsciously examine the rate of change of the error between their desired task performance and their actual performance and may have a negative (or positive) effect on their expectancy if that rate of change is slower or faster than what they anticipated.

Good social and intellectual climate can be achieved through activities that foster student engagement with each other and with the instructor.

Goal-directed practice and targeted feedback are especially interesting from a control systems perspective. Students need a lot of practice working problems in circuits to understand it. This controls perspective on learning is further developed in theories on *self-regulated learning* defined as "an active constructive process whereby learners set goals for their learning and monitor, regulate, and control their cognitive, motivation, and behavior, guided and constrained by their goals and contextual features of the environment" [14]. A standard practice in engineering courses is to have students do weekly homework assignments that are returned a week later. Hence, students get feedback one to two weeks after they have completed a topic, and they have no ability to make adjustments in their approach in order to improve their understanding. The immediacy of feedback was shown to improve learning significantly [15], where personal response systems such as "clickers" were used in a classroom to give feedback in a timely manner both to the instructor and to the students.

In ECE3710, timely feedback mechanisms were introduced into the videos, homework, and in-class activities. The videos were 10-12 minutes long and contained one to three pop-up quizzes on basic concepts that require student action to click on an answer before the video proceeds. The online homework problems are automatically graded with instantaneous feedback of correctness. Getting the "green checkmarks" on their answers builds confidence in their understanding while the "red x's" indicate that they need to adjust their approach and try the problem again. Students have three to five chances to redo each problem with the highest score counting. On average, students in the course attempt each problem approximately twice. Since there is no partial credit allowed on the homework, typical homework averages of 80%-90%, mean that students are getting the homework almost completely correct. Moreover, it shows that students have availed themselves to making those corrections in real-time (that is, the time period during which the topic is being covered in class).

In-class quizzes and worksheets are another way of giving practice and feedback to students in a timely manner, as long as the solutions are reviewed immediately after completion. Personal response devices, such as "clickers", are used during in-class exercises and quizzes as a way of recording and reporting the scores immediately. Clickers are also used during lecture to ask students basic concept questions to see if they understand, then the results for the class are tallied to see show students the correct answers, giving near immediate feedback to both the students and to the instructor. In-class labs that test theoretical predictions made in prelabs, and in-class worksheets done collaboratively both give practice and immediate feedback of performance.

B. Course Adjustments

ECE 3710 requires students to view 50-60 minutes worth of online lectures per week and then come to class for 2 hours per week (for a 2 credit hour class). This paper examines the performance over five semesters: Fall 2013, Spring 2014, Summer 2015, Fall 2014, Spring 2015. Enrollments during spring and fall terms range 425-450 and enrollments during the summer terms range 130-150 students.

Constants across all offerings of ECE 3710:

- A lead instructor coordinated the course, and separate section instructors led each section, with section enrollments of 40-50 each.
- The learning management system used for all online materials was Coursera
- All homework assignments are common across sections and are completed online and graded automatically
- Common tests across all sections (except Summer 2014), given at a common time for all students
- 2-minute graded quiz at the beginning of each class on assigned videos
- 6-8 in-class hands-on labs

Specific course adjustments that changed because of MOOC analytics, student performance, or student feedback included small, incremental adjustments as well as configuration changes to accommodate large adjustments. The control changes were made using a rule-based approach. Low test scores on specific topics, low homework scores on specific problems, large number of discussion posts on a particular problem, and difficulty in specific in-class labs triggered adjustments. Also surveys were given that asked students to rate their understanding of topics and also to estimate their average number of hours per week spent on the course, which were both used in making adjustments. A detailed description of the changes made semester by semester is given in [16], which presents a very simplistic control formulation of the problem in comparison to the presentation in this paper. The main goal of the control was to maintain student performance on tests between 70%-80% and to track six hours per week of student workload.

The configuration changes were made to affect the learning mechanisms of (i) the amount of goal-directed practice with timely feedback, (ii) student formative assessment, (iii) organization of knowledge, (iv) motivation (value+expectancy), (v) social climate. The configuration changes along with the associated learning method targeted (i)-(v) are listed below. Additional changes were made to control the desired student workload (vi).

Configuration Changes:

- Summative online quizzes were first mandatory, then made optional, and then eliminated completely (vi)
- Collaborative worksheets were introduced into the classroom (i), (v)
- Specific online lectures were revised and others added (iii), (iv)
- Automated homework problems were broken into smaller parts (ii), (iii), (iv)
- A large bank extra sample problems were added along with video solutions (ii), (iv)

Spacing control and pacing control were performed with the following incremental adjustments in the course.

Incremental Adjustments:

- Pacing control - weekly scheduling of videos
- Spacing control - scheduling tests and labs with respect to subject matter
- Content of the labs
- Due date and time of weekly homework
- In-class mix of time devoted to different activities

Pacing control can be underpinned from the theory of self-regulated learning. One of the fundamental aspects of self-regulated learning is that students devote more time to concepts that they judge to be more difficult. There are two general approaches to explain how students allocate study time. The *discrepancy reduction theory* states that people stop studying an item once they determine that their level of learning meets a preset level. The second approach, *region of approximate learning theory*, suggests that students stop studying a concept once the rate of return falls below a threshold rate [17-18].

Disturbances:

The experience level of the instructors was a significant disturbance. While the lead instructor for the course had extensive experience teaching in a blended course format, the in-class instructors were graduate students, some of whom had never taught a course.

IV RESULTS

A sample of one of the analytics that has been useful for adjusting the course is a plot of the percent of students who watch each video, as shown in Figure 2 for Spring 2015. The lectures that were watched the least, corresponding to the dips in the plot, were lab demos, introductory and summary lectures for each module, and optional videos that gave extra background. If those particular lessons are discounted, then the average viewership for the rest of the lectures in the course is 91%.

These results are obtained in real-time as the semester progresses, so the instructor can see how many students watched a particular online lecture prior to the class period. This analytic was used to adjust the due date and time of the weekly homework, which was done in hourly increments to achieve a good balance between motivation and timely feedback, too early of a due date impacted expectancy while too late impacted timely feedback.

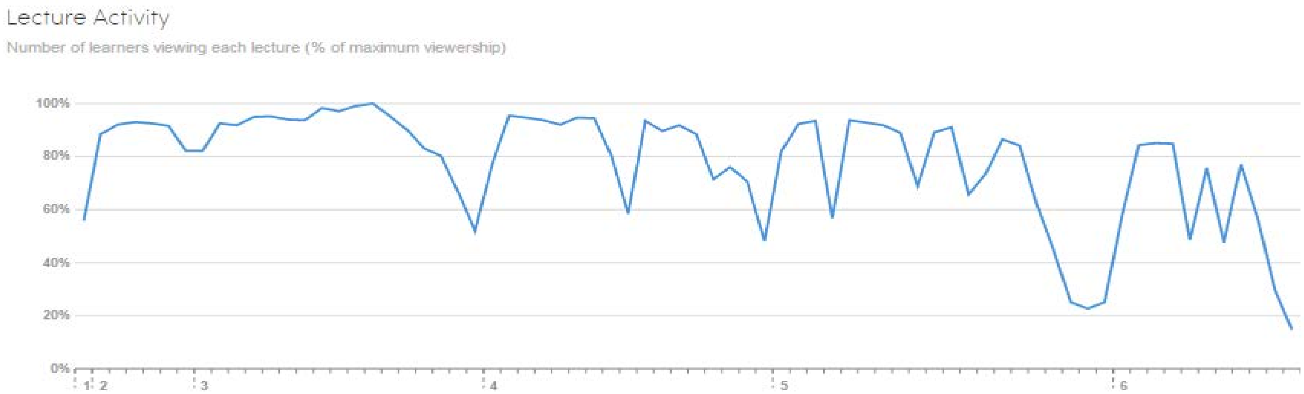

Figure 2: Percent of students who viewed each lecture in the spring semester 2015 as a function of the lecture (listed in chronological order on the horizontal axis and grouped into six topical modules).

A five-semester window of data is shown in Figures 3 and 4 for various course metrics, from Fall 2013 through Spring 2014. The first semester, Summer 2013, was the pilot version of the course and is not included in the plots.

All of the trends shown in Figure 3 are within acceptable ranges, with a reasonable range for average exam scores to be 70%-80% and a reasonable range for average homework grades to be 80%-90%. With the exception of Semester 4, the trends on the homework average and exam average were slightly upward over the first or second terms, stabilizing in the expected ranges. The trends shown in Figure 4 are downward, as desired. A DFW rate (the percentage of students earning a D, F, or withdrawing from the course) below 20% is acceptable, with lower values being better. With the exception of Semester 4, the trend in student workload is approaching 6 hrs/week, the desired value for a two-credit hour course.

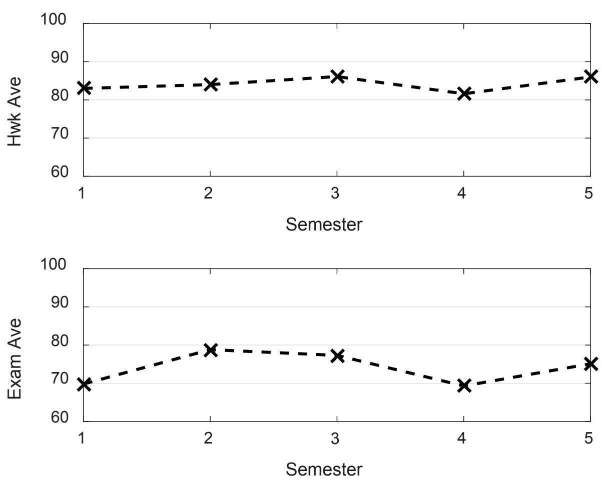

Figure 3: Average number of tries per homework problem, and homework and exam averages plotted over five consecutive semesters.

The exception in Semester 4 in the results shown in Figure 3 and 4 can be attributed to the equivalence of a disturbance to the system: a variation in the experience level of the instructors. Figure 5 shows the percent of novice instructors, ones who have never taught a course before. Note the spike in Semester 4, where 5 of 9 of the in-class instructors were completely inexperienced. Despite such a large disruption to the course model, the results shown in Figure 3 and 4 are all within tolerances.

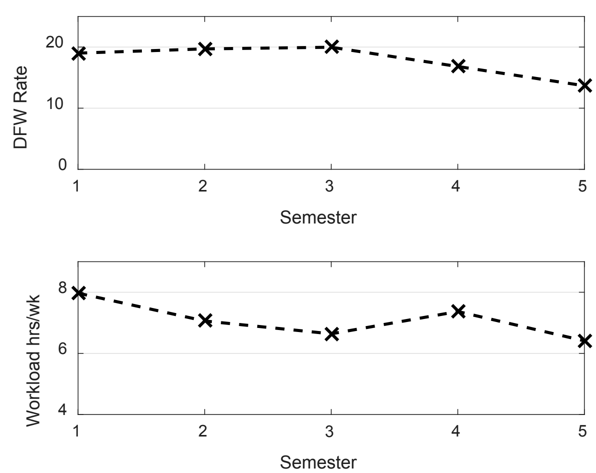

Figure 4: Percent of students who earned a D or F or withdrew from the course and the average student workload in hrs/week plotted over five consecutive semesters.

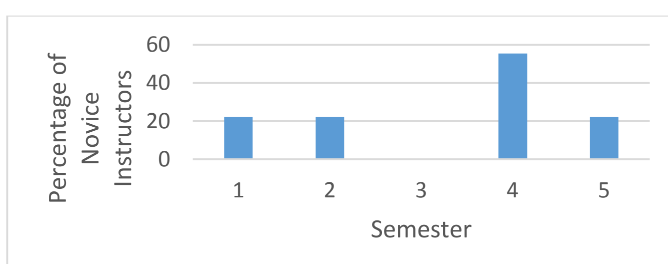

Figure 5: Percent of novice section instructors in each term.

Recall that consistency among sections was an important motivation for revising this course from the traditional lecture format to the blended format. Table 1 gives a comparison of the course statistics from Fall 2012, prior to the revision, and Fall 2014, the fifth semester of the revised course. Both terms had nine sections of the course with enrollments of 40-50 students all taught by advanced graduate students.

While the average GPA for the Fall 2014 course is slightly lower, it matches the average 3.0 GPA for 3000-level courses in the school. GPA can be manipulated by curving grades and skipping topics in the syllabus. While the Fall2012 grades were curved for exams and/or for the final grades, the only curve in Fall2014 was 5 points added to one exam. There were no curves on the final grades, so that A=90-100, B=80-89, C=70-79, D = 60-69. The coverage varied wildly among the sections in Fall2012 while all sections had 100% coverage in Fall2014. The small GPA standard deviation, 0.14, among sections shows significant consistency especially considering that the exams, homework, and labs were common across all sections.

Table 1: Comparison of ECE3710 prior to course revision and 5th semester of course revision.

	Fall 2012	Fall 2014
Number of students	428	436
GPA: average and standard deviation across sections	Ave = 3.32 SD = 0.25	Ave = 2.96 SD = 0.14
Curved grades?	Yes, varied across sections	5% curve on one of 3 exams, no curve on final grades*
Coverage of syllabus	75%-90% (up to 50% mismatch between sections)	100% coverage in all sections

* The exam averages shown in Figure 3 are shown without any curves.

Consistency can also be measured by examining the level of understanding of the various topics in a course. A post survey was given at the end of the term in Fall 2014 asking students to rate their level of understanding of the course topics, from 1=no understanding to 4=solid understanding. The results of this survey are shown in Figure 6, where the topics in the course are listed in order of occurrence from the beginning of the term (on the left) to the end of the term (on the right). The averages for each topic are all within a tight range of each other, from 3.0-3.5 with few exceptions. The first few topics are a review from the prerequisite course and have higher values.

In reference [16], a similar plot to Figure 6 for another course, ECE2040 Circuits (the course for ECE majors) is shown. The same lead instructor for ECE3710 in Fall 2014 taught a section of ECE2040 using the same resources and blended classroom model for both courses. The post survey for the blended ECE2040 course showed the same tight range of student level of understanding across all topics as is displayed in Figure 6. During that same term, two other sections were taught using a traditional lecture approach, with the same post survey showing a dramatic fall-off in understanding for the later topics in the course in comparison to the relatively constant levels shown for the blended course. Since the later topics are more challenging than the earlier topics, it makes sense that many students would be less confident in their understanding. Another common phenomena is that instructors often speed up their pace in the last weeks of a semester in order to cover the material. The consistency in student level-of-understanding across topics was achieved in the blended model by rigorously adjusting the pacing of the topics from term to term (giving more time to the more difficult topics) and by taking the topics that showed the least level of understanding and adapting the corresponding course materials.

V. SUMMARY

This paper demonstrates a controls-based strategy for improving learning effectiveness. The methodology is applied to a course in circuits with large enrollments, over 400 students in per term. The overall strategy is an adaptive controller where the plant is the learning process, the measurements are the course analytics, student performance, and student surveys results. Large control actions require a reconfiguration of the course format and resources while small control actions are accomplished by the pacing and spacing control.

The results indicate that the course has evolved over five semesters to one where the student performance as measured by exam and homework averages is within acceptable ranges, and the student workload is starting to track the desired number of hours per week appropriate to the course credit. In addition, consistency in student performance and course coverage across multiple sections and across multiple terms is achieved within very tight bounds. Student ratings of their understanding of the different topics in the course all fall within very tight bounds of one another.

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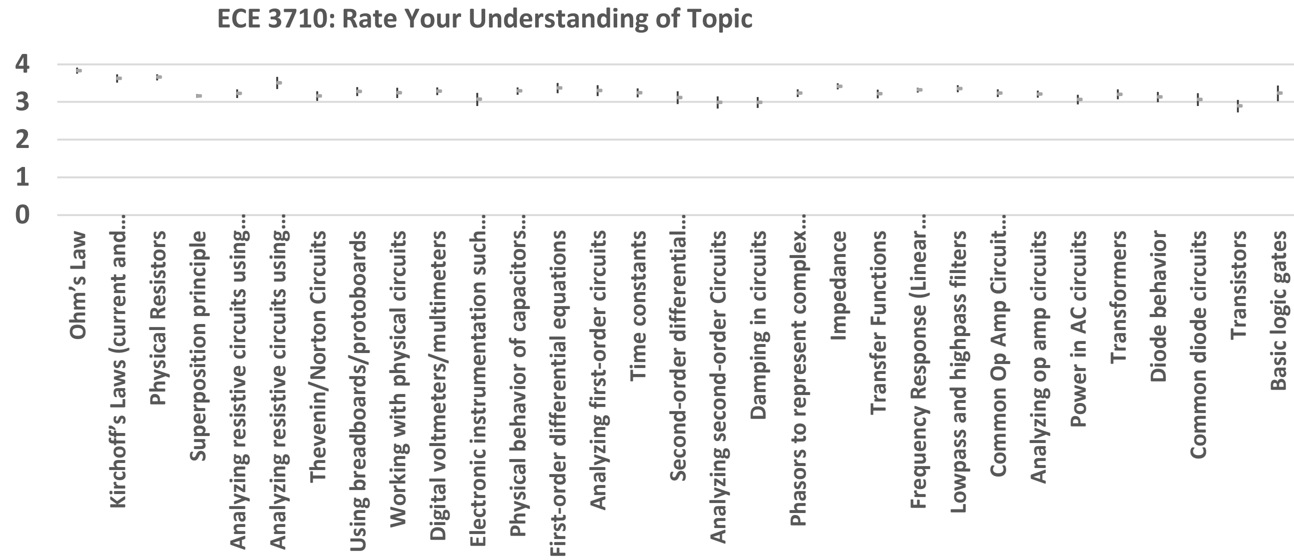

Figure 6: Post survey results of course topics displayed in order of occurrence in the course (left to right). Rating is from 1=no understanding to 4 =solid understanding. 95% confidence intervals and mean shown for each topic. N = 310.

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