Work-in-Progress: Developing Online Graduate Courses in Electrical Engineering

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A. Introduction

The Department of Electrical Engineering at Stanford University has a long history of teaching large-enrollment master's level and advanced undergraduate courses with broad appeal and applicability. At present twelve such courses are offered, each with annual enrollment of more than 80 students. Another dozen or so courses have somewhat smaller enrollments. These courses are taken by Electrical Engineering students as well as students from other departments within the School of Engineering and the rest of the University. Many of the courses also make up the core of a professional development program offered to working engineers. In order to test the learning efficacy of online education, develop a set of best practices, and provide more scheduling flexibility to students by scheduling multiple instances of a course during the year, the Department proposed to develop online versions of a number of these courses over a three−year period. The proposal was accepted and the "EE Online Program" started in academic year 2012-2013 with course planning and development. Student learning patterns, outcomes, and satisfaction are being measured both quantitatively and qualitatively. This work-in-progress paper reports on the mid-point results of the EE Online (EEO) program.

B. Program and Course Development

The proposed plan for EE Online course development included four courses the first year, six courses the second year, and up to nine courses the third year (all of which already existed in traditional course formats). The initial four courses—applied quantum mechanics, digital signal processing, digital image processing, and convex optimization—were chosen based primarily on the interest and availability of the regular instructors to develop online course materials. All were graduate courses, though at the introductory level, and therefore open to advanced undergraduates.

Funding for the program came from the University's recently created Office of the Vice Provost for Online Learning (VPOL), which had requested proposals from departments that went beyond single-course projects. Each of the four initial courses was budgeted in the range of $35,000 to $50,000 for development of online materials as well as the actual delivery of the course. These amounts included teaching fellow salaries and benefits (advanced graduate students who would assist in teaching the new version of the course) and 200 hours of videographer and editor time at $90 per hour, as well as funds for a teaching assistant who would focus on assessment issues across all the courses. Each course also had its regular assignment of one or more teaching assistants, which were not part of this budget. The faculty involved did not receive extra compensation or release time, even though each spent 200-300 hours or more on course development. (This lack of an incentive may change in the future, as it is a clear obstacle to the participation of faculty, most of whom are already overscheduled. It should also be noted that it was discovered that teaching assistants were very capable of performing the video editing required, and therefore much of the budget for video editing was not needed and could be better spent on increasing the amount of general TA assistance available.)

In addition, there were significant instructional development resources available to each instructor at no cost through the VPOL Office. The Office currently has several full-time instructional designers as well as dedicated teams for media production and for online platforms. A number of classrooms are available that are outfitted with full video capture capabilities and staffed by student operators. A video studio with a green screen is also available for instructor use.

The instructors were given great leeway in how they chose to structure and develop the online versions of their courses, including traditional classroom teaching supplemented with online material, flipped classrooms, tutored online education (of which more below), and a MOOC. In the latter case, the MOOC was to be offered in addition to the regular for-credit course. The University views its MOOCs both as a public service and as laboratories for exploring online teaching and learning—the School of Education at the University has an active learning analytics group with a focus on online learning. But the University has no plans at present for granting credit to non-Stanford students taking MOOCs.

Although instructors were encouraged to experiment with different forms of online instruction, the Department's Academic Affairs Committee (consisting of five faculty, two graduate students, and two staff members) reserved the right to determine when and in which forms (offline, online, blended, etc.) a course would be offered for credit, in order to ensure the overall quality of the EE Department's academic program. In addition, the Department's Associate Chair for Graduate Education took the lead in overseeing the EE Online program.

Three of the initial EE Online courses were offered during the Autumn quarter of 2013: quantum mechanics, digital signal processing, and digital image processing. The quantum mechanics course was taught as a flipped, for-credit course using online video modules and assessment quizzes in place of traditional lectures. It was made available to the public as a MOOC at the same time. The digital signal processing course was also taught in a flipped format, and the digital image processing course was taught in an "online with tutored instruction" format. All three courses assigned offline problem sets.

In the online-with-tutored-instruction format used in the digital image processing course, students viewed video modules and worked through assessment quizzes online, while a teaching fellow (an advanced graduate student) offered in-person Q&A times to supplement the videos and regular teaching assistants provided additional help to students. In other words, the main teaching role of the faculty person was via the online videos (although in this pilot version the faculty instructor did hold weekly office hours). In order to compare teaching methods and learning outcomes, this course is being offered in a more traditional format by the faculty instructor during the Winter quarter 2014, and it will be offered again by a teaching fellow in the online-with-tutored-instruction format in the Spring. The quantum mechanics course may also be offered in the teaching fellow format in the Spring or Summer of 2014. The fourth of the initial EE Online courses—convex optimization—is being offered as a regular course with online materials as well as a MOOC open to the public in Winter 2014.

Though the overall program plan called for the development of online materials for six more EE courses for the 2014-2015 academic year, at this point in time it is unclear which and how many EE courses will be included. As mentioned previously, a significant obstacle is the 200+ hours of course development required of the instructor, though we are investigating ways to reduce this time.

C. Surveying Student Perceptions

In order to provide a preliminary assessment of the use of online learning materials, during the Autumn 2013 term we conducted mid-course student surveys for five classes with online components, three of which are part of the EEO Program (applied quantum mechanics, digital signal processing, and digital image processing) and two of which are not (nanomanufacturing and introduction to computer networking). (Because engineering faculty because it allowed us to gather data from a more diverse set of courses, we agreed to extend the service to them.)

The survey sought to gather both quantitative and qualitative information from students, while at the same time not being overly burdensome in terms of the time needed to complete it. Taking the survey was optional, though in one case it counted toward the course participation grade. The survey was online and contained twelve questions (not counting three demographic questions concerning degree-level, year-in-school, and department). Both open-ended questions and choose-a-response questions were included:

1. How are you finding the course so far? What would you like more of? Less of?
2. What do you like/dislike about the online videos?
3. What do you like/dislike about the other online components of the course?
4. What do you like/dislike about the homework assignments distributed so far?
5. On average, how many hours per week are you spending on the online materials (videos, quizzes, etc.)? [A range of possibilities was given from which to choose, such as <1, 1-2, 3-4, 5-8, and so on.]
6. On average, how many hours per week are you spending on the problem sets or other homework assignments? [A range of possibilities was given.]
7. What is your typical practice in terms of the videos and assessment quizzes? [A list of possibilities was given, such as attempting the quiz before watching the video.]
8. When you take an online assessment quiz, are you usually confident of your answers? [A list of possibilities was given, including “usually,” “sometimes,” and “much of the time I am guessing.”]
9. What is your typical practice in terms of the online materials and the problem sets or other homework? [A list of possibilities was given, such as viewing all the materials before starting the homework.]
10. When do you normally start working on the problem sets or other homework? [A list of possibilities was given.]
11. Which of the following support resources have been helpful for finishing the problem sets and other homework? [A list of possibilities was given.]
12. Anything else you would like us to know or that you would find helpful?

We received an average 35% response rate from all courses generally and 40% from EEO courses specifically, as summarized in Table 1 below.

Course	Enrollment (n)	Response Count (n)	Response Rate (%)
QM	82	28	34%
DSP	13	7	54%
DIP	25	13	52%
Nanomfg	41	18	44%
Networking	160	46	29%
Totals	321	112	35%

Table 1. Enrollment, response counts, and calculated response rates for the surveyed courses. (QM = applied quantum mechanics; DSP = digital signal processing; DIP = digital image processing; Nanomfg = nanomanufacturing; Networking = introduction to networking.)

D. Survey Methodology: The Quantitative Data

Using the responses from the "hours-per-week" survey questions, we aimed to better understand how much time students were spending on the individual class components and the class as a whole. For the individual components, we summed up the counts in each weekly time duration range. For the class as a whole, however, we created a range for each responding student by summing the minimum and then the maximum values. If a student reported spending 3-4 hours per week on online materials, 1-2 hours per week on online quizzes, and 3-4 hours per week on paper-based problem sets, the calculated range would be 7-10 hours per week. We then classified each responder's range as low, normal, high, or very high based on the rules outlined in Table 2. For comparison purposes, we compiled historical data for the courses involved from the University's course and section evaluation reporting website. This data went back several years and as far back as 2008 in one case. The results are discussed in Section G.1 below.

Workload Category	Rule Notation	Rule Statement	Range Example
LOW	$x_{MAX} < 10$	*if the student's reported maximum weekly workload is close to or below the minimum of the expected range*	For example, the student reports 5-8 hrs/week
NORMAL	$x_{MAX} < 13$	*if the student's reported maximum weekly workload is close to or below the maximum of the expected range*	For example, the student reports 7-12 hrs/week
HIGH	$x_{MIN} \leq 12$ & $x_{MAX} \geq 13$	*if the student's reported minimum weekly workload is close to or below the maximum expected range and the maximum weekly workload is above the maximum of the expected range*	For example, the student reports 11-16 hrs/week
VERY HIGH	$x_{MIN} > 12$	*if the student's reported minimum weekly workload is above the maximum of the expected range*	For example, the student reports13-18 hrs/week

Table 2. Categorization of students' reported workload for quantitative analysis.

E. Survey Methodology: The Qualitative Data

To analyze the free-response and qualitative questions on the mid-course survey, we employed primarily low-level coding and pattern matching. Because the data would be used to produce reports for the teaching staff in each course, we analyzed the student responses in terms of (1) course component, (2) component specifics, and (3) student sentiment. Course component refers to the substance of the response we were coding, as when students are referring to online videos or the flipped classroom model, for instance. Component specifics refers to the student reporting a particular aspect of the component, such as the long length or large quantity of online videos. This part of the code is not always present and we included it in our analysis primarily when we began to notice a pattern in the student responses that we specifically wanted to explore. The student sentiment refers to whether the comment is positive or negative. Table 3 showcases several examples of these codes.

Because we were analyzing the data sequentially and not all at once, we developed our coding repertoire as we analyzed more and more student responses. Consequently, we also developed certain codes that are at present unique to an individual course (and thus helpful to the instructor), but we expect that they will become more prevalent as our analysis expands. Using the coded student responses, we not only counted the frequency of individual codes, but also looked for broader patterns within an individual course and across a group of courses. Although we discussed all of these results as we produced the report for each course, we did not explicitly formulate any hypotheses about the broader patterns until we had finished analyzing the data from all courses.

Code	Explanation	Example
Course :: Positive	Comment regarding the overall course that is positive	"I'm enjoying the course--really learning a lot."
Online Videos :: Positive (Transcript)	Comment regarding online videos that is positive, specifically about video transcript	"I really like the transcript that goes along the side."
Online Videos :: Negative (Time-Consuming)	Comment regarding online videos that is negative, specifically referencing the videos' time-consuming nature	"They [the online videos] are extremely long (if you consider that you're replacing one Wednesday class with 3 online videos approximately 25-30mins each at regular speed)."
Course Materials :: Negative (Not Enough Detail)	Comment regarding the course materials that is negative, specifically describing their lack of detail	"The lecture notes on their own are too sparse to be useful for review and reference."
Online Assessments :: Positive (Thorough Explanations)	Comment regarding online assessments that is positive, specifically referencing the thorough explanations to the assessments' answers	"The answers to the quizzes are well written, so, when I truly don't understand a question, I feel like the answer really helps w/ understanding the solution."

Table 3. Samples of codes used for qualitative analysis.

F. Sharing Insights with Instructors

Once we finished analyzing the student responses for a particular course, we produced a report that summarized our key findings for the course teaching staff. The reports include an executive summary, question-by-question brief data breakdown, additional feedback, and screenshots of the survey itself. Throughout each report and especially in the one-page executive summaries, we highlighted any suggestions and recommendations that we felt were relevant for the teaching staff to notice.

G. Trends and Analysis

From the mid-course survey results in the three EEO and two non-EEO courses, we identified three major areas that students are particularly sensitive to and that instructors should be aware of:

- Time usage
- Structure of online assessments
- Offline-online integration

For the EEO classes, we also contextualized these trends through end-of-quarter student course evaluations.

G.1. Student Sensitivity to Time Usage

The most immediate trend noticed from the survey results concerns students' reporting of how much time they spend on a given course. From data gathered across all five courses, we found that on average students spend 3-4 hours per week on online materials/videos, 1-2 hours per week on online quizzes/assessments, and 3-4 hours per week on paper-based problem sets (if they are part of the course). (See Figure 1 below.)

The total time spent outside of class time is therefore 7-10 hours per week. Given that these courses are 3-4 units apiece, this is consistent with the definition of a Carnegie unit, which states that 1 unit of academic credit reflects approximately 3 hours of work per week inside or outside of class. To confirm this conclusion, we calculated the hourly range that each student reported spending on the course overall, and defined that range as low, normal, high, or very high. (See Figure 2 below. Section D and Table 2 above give the definitions of "low," "normal," etc.) For the EEO courses we found that 14% of the responders fit the very high category, and 13% for all five courses. More importantly, more than half of the students in each case responded as experiencing a low or normal workload: 58% for EEO courses and 60% for all courses. From a purely numerical standpoint, therefore, these courses provided a manageable workload for more than 80% of their students.

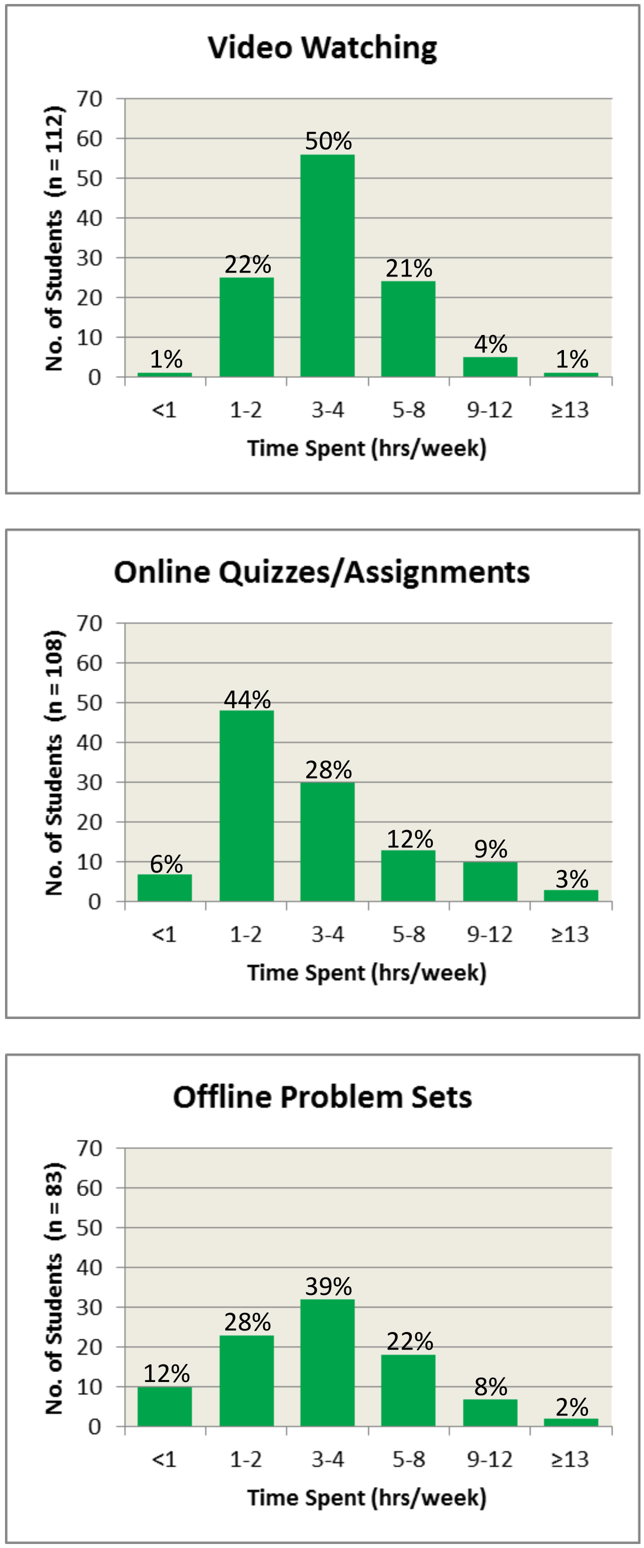

Figure 1. Reported times students spent weekly on online videos, online quizzes and assignments, and offline (paper-based) problem sets.

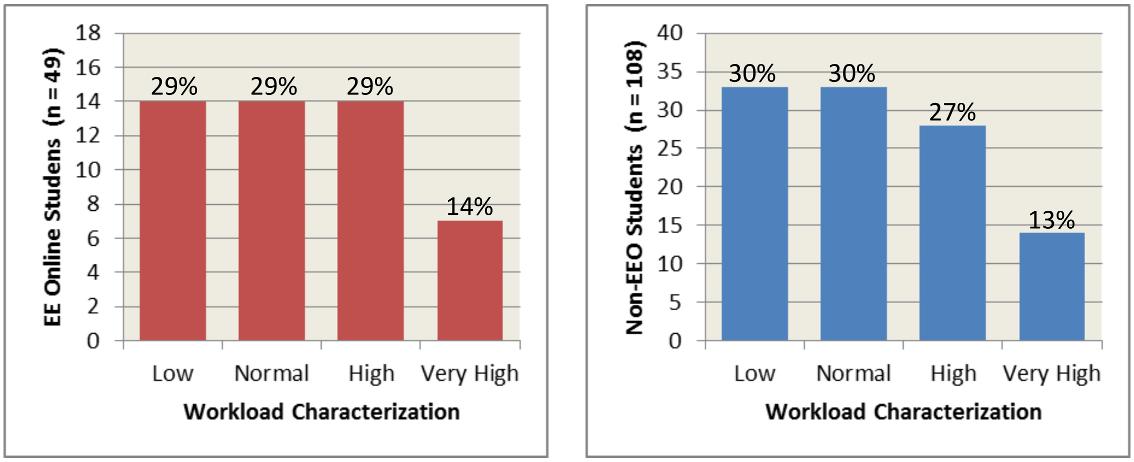

Figure 2. Occurrence of low, normal, high, and very high workloads as calculated from student responses in three EEO courses (left) and two non-EEO courses (right). (Note: Rounding yields a total greater than 100% for the left plot.)

Despite these quantitative results, the subjective experience of the students reveals a different perspective, with students communicating an acute sensitivity to the time spent on a course. In their responses, multiple students specifically referenced how much time they were spending on the online portion of the class. This is not completely surprising, since the average student was spending 4-6 hours per week on the online portions. Given the reported total of 7-10 hours, this represents slightly more than half of the average student's course time.

It is unclear if the online components add time that was not previously used by any offline component or if the student is now simply more aware of this time. Students can see the length of each video, and so they are probably conscious of how much time they spend watching them. The time the students spend online is also strictly delineated by activity: watching videos and answering quizzes. In the absence of these online course components, the students might have still used that time to read textbooks, check notes, and so on. The difference in perception might be that the offline activities are not as explicitly differentiated or that students had no way to consciously track and remind themselves of the time they were spending on them. This is a topic of particular interest that we hope to explore in the future.

The students' general dissatisfaction with the time-consuming nature of these courses is not always that students desire less work. There is a small minority of students who desire less workload so that they can process and elaborate on what they are learning. The following response illustrates this desire:

> "In most classes, I review the material several times, make sure I understanding everything, then explore extensions to what was taught. This is how I learn. There is no opportunity to do so in this course - I simply do not have enough time to do any extra work. The result is that despite spending more time doing stuff for the class, I learn (in a 'retain for longer than the quarter' sense) significantly less than I would in a normal class."

As the same student aptly summarized, the additional workload creates a situation in which the student is "spending twice as much time to learn half as much." The student wanted to spend more time on the course, but not in the structured manner that the teaching staff intended for all students. Although we have seen only a few responses that mention or hint at a similar distinction, it is important to note that by structuring more of a student's time, less time is available for unstructured learning.

G.2. Student Sensitivity to the Structure of Online Assessments

This tension with forced structure also revealed itself in student comments regarding the online and in-video assessment quizzes. In the quantum mechanics course, for example, the teaching staff used multiple-submission as well as single-submission questions. Several students reported an appreciation for the multiple-submission questions, and not only because multiple attempts allow them to get the question right and earn points. As one student explained:

> "I put a lot more thought into an answer if I try once, get it wrong, and then have the chance to get it right than I do if I get it wrong and it becomes immediately inconsequential to my grade."

The incorrectness of the initial attempt prompts further thought, whereas the restriction of a single submission may encourage the student simply to move on.

In addition, many students reported that they thought the online quizzes would be more effective without points attached to them (in those courses where points were given). The students report various reasons for why this is the case, but the following response highlights a common sentiment: "Since we only get two guesses [in this case], there is little room for experimentation and exploration. It transforms a useful learning tool into yet another attempt to grade us." The tension here is whether the quizzes are for the benefit of the students (a "learning tool") or for the benefit of the teachers ("yet another attempt to grade us"). As the student also points out, between examinations, homework assignments, and other forms of assessment, the online quizzes represent "yet another" method by which to grade students.

Another common complaint across most of the courses was the poor wording and lack of clarity in the questions. Although the questions were perceived to be clear and straightforward by the instructors, many students felt otherwise. Students seemed to notice every grammatical and syntactic inconsistency. They also noticed any inconsistency between the crafted questions and the material presented in the video. Commenting on this mismatch, one student wrote that students can "easily spend at least the amount of time it took to watch the video (or more) answering quiz questions." Several students from across multiple courses reported having to rewind videos, reference texts, and even search elsewhere online to be able to answer the quiz questions. The result is that, as another student wrote, "[I] spend so much time trying to get the question right that I lose sight of what's really important, the material." Students in most of the courses also requested more comprehensive explanations to the quiz answers, in order that they might become better opportunities for learning.

G.3. Student Sensitivity to Offline-Online Integration

The various types of mismatch and inconsistencies in online assessment are indicative of a broader and deeper need for online-offline integration. Simply put, the online and offline components in a course need to fit together. On one hand, the online components must complement the offline ones (which, in the case of these courses, came first). On the other hand, the online components cannot render the offline components (such as class time) superfluous. One student summarized the situation well in noting that the course was in danger of becoming "just a really time consuming TV show as opposed to a fun class." From our data, it seems that even if students viewed the offline and online components positively, unless the two integrate well with each other, the overall experience becomes negative. The quality of integration is at least as important as the quality of the components.

Probably the most significant point of misalignment centered on homework and other forms of assessment. Expressing a sentiment we found across most of the courses, one student wrote that "it sometimes feels like the treatment [in videos] is too simple for us to do the homework." This mismatch, compounded by other previously stated problems such as poor wording, can result in students feeling that "the course staff doesn't put as much detail into the course material as they expect out of the students" (especially when the course does not have a textbook).

G.4. Overall Student Evaluation of the Courses

Apart from the mid-course survey through which we collected student responses, students also filled out university-administered end-of-term course and section evaluations. From these, we found that students rated all three EE Online courses above the School of Engineering mean for the Autumn 2013 term. Technological and pedagogical experimentation, therefore, does not necessarily imply negative student rating of the course and its instructor. On the other hand, of course, this does not mean that turning an offline course into an online-offline blended one automatically produces an above-average student rating. In the case of one EEO course, for example, the end-of-term evaluations produced the highest rating in the history of the course since 2008. For another course, however, there was a drop in the course rating from the prior year's course, although it still remained above the School of Engineering average. Unsurprisingly, one significant factor leading to more negative student evaluations was a mismatch between instructor-communicated course expectations and the actual student experience, such as when the online videos and assessments took much more time than advertised.

H. Analysis of Video Usage

We are also currently analyzing the details of student viewing behavior in the digital image processing course. The video player and data collection system that the course employed is an internal system developed by the Stanford Center for Professional Development. The system allows the collection of data on a variety of behaviors, including usage of the pause/play and speed changing buttons, jumping from one segment to another (whether forwards or backwards), and the day of week and time of day when students viewed the videos the most frequently.

We have found several preliminary patterns in our analysis. For example, significant changes in viewership behavior occur when videos exceed a certain length. Viewership begins to drop at the 3-4 minute mark and even more so when the 5 or 6 minute mark is reached. To explore viewer behaviors at the levels of individual videos, we are isolating time segments of significance (e.g., very high or very low viewership) and correlating them with the content, and presentation of the content, in the video at that point. We are also examining the sequence of interaction. What did student X do right after watching video Y? What did student X do after answering quiz A? After watching video Y, did student X go straight to quiz A? And after answering quiz A, did the student return to video Y? The aim is to explore which videos and which parts of videos receive higher viewership, and why, as well as to connect viewership data to quiz/assessment data.

I. Analysis of Learning Outcomes

At this point in time (March 2014), the analysis of learning outcomes from the EE Online courses is still in process. We are using the digital image processing course, in particular, to compare the efficacy of the online-with-tutored-instruction method (described in Section B above) with a more traditional lecture-based class. During the summer of 2013 the faculty instructor for the course spent 200+ hours developing short online video modules and associated assessment quizzes for the course material. The structure of the course was designed to cover all of the material during the first seven weeks of the ten-week quarter, with weekly offline homework assignments. During the final three weeks of the quarter students work in small teams on projects. A take-home midterm exam is given in week 9. There is no final exam. The final course grade is based on final project 40%, midterm 30%, homework 20%, and participation 10%.

The course was offered during the Autumn 2013 quarter via the OpenEdX platform using the online-with-tutored-instruction method. Students watched the online videos and then took short assessment quizzes (1-5 questions) that tested their understanding of the material. There were 80 quizzes (one for each video) and a total of 199 questions, and most of the questions were multiple-choice or true-false. Taking the quizzes counted for a student's participation grade in the course, but the actual performance on the quizzes did not count for or against a student's overall course grade. The instructor and two TAs for the course held regular office hours, and the TAs also conducted weekly problem sessions related to the homework. An online discussion forum was set up using Piazza.

The course is being offered again during the Winter 2014 quarter by the faculty instructor using a more traditional lecture format (though with some time devoted to in-class exercises). Students were again required to take the online assessment quizzes for their participation grade, but watching the online videos was optional, given that the material was covered in class. (Though most students did watch the videos, at least in part.) Class attendance was required and counted in the participation grade. The quiz questions were identical for each quarter (aside from one or two corrections).

Final results are still pending for the Winter 2014 course. But a preliminary comparison shows minor differences between the outcomes of the Autumn and Winter versions. For the online course in Autumn, the average homework score was 84% (n = 26 students), while for the more traditional course in Winter it was a very high 96% (n = 24). But midterm exam results were more similar: 83% for Autumn students and 87% for Winter students.

For both courses, the student performance on the online assessment quizzes was much lower than expected. The quiz questions were intended to be relatively straightforward in most cases, assuming that the student watched the associated video (and paid attention). Yet the average quiz score was 45% for the online Autumn course and 43% for the traditional Winter course. (These figures include a correction to take into account the possibility of student guessing on the multiple-choice questions; raw averages were still low, however: 63% and 61%, respectively.) Possible reasons for these low scores, besides student inattention, include the common occurrence where experts underestimate the difficulty of a question for novice learners in a field, the inadequacy of the video modules to explain the material well enough, and/or poorly formed questions and answers.

In addition, a multiple-choice pre-course test was given to all students to establish a baseline for the knowledge of the incoming students and at the end of the course a second test (essentially identical to the first) was given. Results for these tests from each quarter will provide another way to compare the learning outcomes of the two instructional methods. (Post-course test results for the Winter 2014 course are not available yet.)

Given just the two course offerings at this point and the relatively small number of students, we cannot draw statistically rigorous conclusions. But our primary goal is to check whether the online-with-tutored-instruction method in introductory EE graduate classes can produce learning outcomes that are approximately equivalent to a more traditional face-to-face class with some online elements. The tentative conclusion is that it can. Clearly more iterations and fine-tuning are required. But given the preliminary results, it seems viable to offer students more flexibility by scheduling multiple instances of a course throughout the year without having to have the faculty instructor be directly involved in all of them. (It also allows the possibility of the faculty member not being involved in any of them, of course. But whether that is desirable or not is another question.) If it is important to students to take a course with face-to-face interaction with the instructor, then they may enroll in the course during the term in which the instructor is directly involved. On the other hand, if scheduling flexibility is a higher priority for them, then students would have the option to take it during another term via the online-with-tutored-instruction method.

A secondary benefit of the online-with-tutored-instruction method that should be mentioned is the opportunity it gives to advanced graduate students to gain teaching experience beyond that of the typical TA experience.

J. Conclusions

At this point in the development of the EE Online program, we have identified three major areas that students are particularly sensitive to and that instructors should be aware of: extra requirements on the students' time, the structure of online assessment exercises, and the integration of the online and offline components of a course. There are more moving parts in a blended course compared to a typical traditional course, and managing student expectations and then delivering on those expectations with a well-integrated online-offline pedagogy is a crucial skill in online and blended instruction. Instructors should also keep in mind that for many students, as for instructors, online and blended instruction is a new experience, and they sometimes need to learn how to learn differently, and it is hoped, more effectively. Graduate students and advanced undergraduates tend to be set in their study habits, and therefore change does not come easily.

Given the preliminary and roughly equivalent results from the two offerings of the digital image processing course, one using the online-with-tutored-instruction model and the other a more traditional in-class model, it is concluded that the online-with-tutored-instruction approach shows promise for allowing departments to schedule more instances of a course than a regular faculty member would normally teach. The initial requirement of time and resources is not inconsiderable, however, and appropriate incentives for faculty members to make the investment should be considered. But in the long run the increased flexibility for the department and for students may make the investment worthwhile.