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Data Mining to Help Determine Sources of Difficulty in an Introductory Continuous-Time Signals and Systems Course

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Analysis of historical student performance data in an introductory continuous time signals and systems class

I. Introduction

It is a widespread and common occurrence that students experience a high-level of difficulty with the introductory continuous-time signals and systems (CTSS) course in an undergraduate electrical and computer engineering (ECE) curriculum. While the experience is common, there is not much quantitative data that verifies and describes the challenges to learning that students face. As a result, instructors are forced to wonder if the problem is due to insufficient student preparation and effort or if there is some pedagogical change that will solve the problem. Engineering educators have devoted considerable effort to develop pedagogical techniques in order to teach CTSS courses more effectively. Various pedagogical techniques have been tried, such as the "chalk-and-talk" lecturing style [1], teaching continuous-time concepts before discrete-time concepts [2], or vice versa [3], developing signals and systems concept inventories [4], using MATLAB™ [5-7], instituting hardware-based signal processing laboratories [8], and using LEGO™ MINDSTORMS NXT platforms for signal processing experimentation [9]. Despite all the efforts, conceptual learning of the course content still remains to be a challenge. Without a better understanding of the educational challenges associated with this course, any attempts to improve student learning in this course may not be as effective as possible.

We are beginning a longitudinal study using historical performance data from courses across the curriculum in order to generate a more definitive description of the situation faced by students in a CTSS course. This data was collected at Rose-Hulman Institute of Technology for approximately 800 ECE students in multiple required ECE courses over a period of 10 years from the 2000–2001 to the 2009–2010 academic year. This data is analyzed by looking at the performance of students in the CTSS course relative to other required courses and relative to its pre-requisite courses. The results are presented with respect to multiple variables in order to better understand the influence of different factors on the data. In order to help interpret the results and guide the study, we draw on conceptual learning theories which suggest a tendency of students to focus on procedural rather than conceptual learning [10] and the difficulties that students have using advanced and abstract mathematical concepts in order to model systems and represent physical phenomena [11, 12].

The work described in this paper is only an initial study based on a subset of the data. It is the authors' intent that this analysis be used to motivate and guide future studies of the entire data set and more general studies of student learning with respect to CTSS content. This paper begins with a description of the CTSS course being studied, then provides an analysis of the data in order to quantify the degree of difficulty faced by the students, then relates that difficulty to the students mathematical preparation, and finally summarizes and interprets the analysis.

II. Description of the CTSS Course

In order to better understand the data that is presented in this paper, it will help to have some background information about the course. The course number is ECE300 and the name is Continuous-Time Signals and Systems. Rose-Hulman is on a 10-week quarter system, and

ECE300 has three 50-minute lectures and one 160-minute laboratory session per week. The lab content has primarily consisted of MATLAB™ exercises for the time period of the data set. The pre-requisites for ECE300 include one year of physics, one year of calculus, two courses of differential equations, and two courses of AC/DC circuit analysis with phasors. ECE300 is typically taken in the Fall or Winter quarter of the third year of study while all math and physics courses are typically completed by the Winter quarter of the second year.

The topics covered in ECE300 evolved twice during the period of study. Prior to 2003, ECE300 was the final course in the circuits sequence, and as such included AC Power and phasor analysis in addition to Fourier theory and time-domain analysis of signals and system. From 2003-2009, the focus on circuits was moved to earlier courses so that the entire course content could be devoted to time and frequency domain analysis of signals and systems. During this period the course was more of a traditional signals and systems course covering convolution, Fourier theory, and ending with sampling. At the end of the 2009-2010 academic year, the time-domain analysis of systems including Laplace transforms, convolution, and system properties, was moved into a pre-requisite course, ECE205: Dynamical Sytesm, so that ECE300 could focus entirely on Fourier theory. Even though the course has changed slightly, the focus on frequency domain analysis of signals and systems has remained the central focus of the course.

III. Measuring the difficulty of the introductory CTSS course

The difficulty of this CTSS course relative to others in the curriculum is much easier to determine instead of a measure of absolute difficulty, for which we do not have a calibrated scale. For this study, difficulty is defined similar to the concept of a learning curve, which describes the level of learning achieved for a given amount of experience or effort. In this regard, a higher degree of difficulty would correspond to a shallower curve, meaning that it would take more effort to achieve a given level of learning [13]. Typically the learning curve concept is applied to basic tasks that can be readily improved with practice and measured very quantitatively with response times or other definitive metric. We are abstracting this concept to cover learning of content throughout an entire course and we will only be able to provide very crude measures of effort expended relative to performance achieved.

Given the definition of difficulty based on the learning curve, we must be able to determine levels of learning achieved with respect to the effort expended. Some possible ways to measure learning include standardized tests, such as concept inventories, and rubrics applied to common exam questions. Measurement of effort put into a course is more difficult to achieve, but some measurements that could be used include the amount of help that students require on homework or how much time is spent studying for a course on a weekly basis. Unfortunately, many of these measurements require a substantial amount of work to collect and even if collected, could be difficult to compare between courses of vastly different content. In contrast, final course grades and GPA are readily available to collect and exist across the curriculum. The authors concede that many factors contribute to a course grade, only one of which is how well the material is learned by the student. However, because we are looking at relative comparisons rather than absolute levels of learning and we are using a large dataset, we are assuming that many of these factors are the same across the curriculum and will get averaged out. Withdrawals in a course are also considered in order to cover the case that students would drop a class at midterm if they are performing poorly in the class. However, the withdrawal percentages are kept separate, because students may drop a class for non-performance related reasons.

The first step in our data analysis is to look at the drop-failure rates for most of the required courses in the ECE curriculum, which is shown in Figure 1. The average drop-failure rate for all of the data shown in Figure 1 is 5.71%. According to Figure 1, the introductory CTSS course has a withdrawal-failure rate that is more than twice the average and higher than any other course in the ECE curriculum. The only course that closely resembles the trend seen in the introductory CTSS course is the first course in electromagnetics (Emag I), which covers electrostatics and magnetostatics. Eliminating the data for the CTSS and Emag I courses, the average failure rate in the other courses reduces to 4.7%.

While experience of both faculty and students suggested that the CTSS course was difficult, the severity of the problem was not known until this data was analyzed. The student performance in the CTSS course and Emag I being approximately 3 times worse than the other required courses suggests that we should pursue solutions to improve this situation. Before these high-failure rates could be attributed to difficult concepts, we wanted to eliminate other factors that could have contributed to the result shown in Figure 1. These factors include individual instructor grading style, textbook used by the instructor, course organization, amount of work invested by a particular student, and student preparation. We would like to address these factors by analyzing the same data set with respect to different variables.

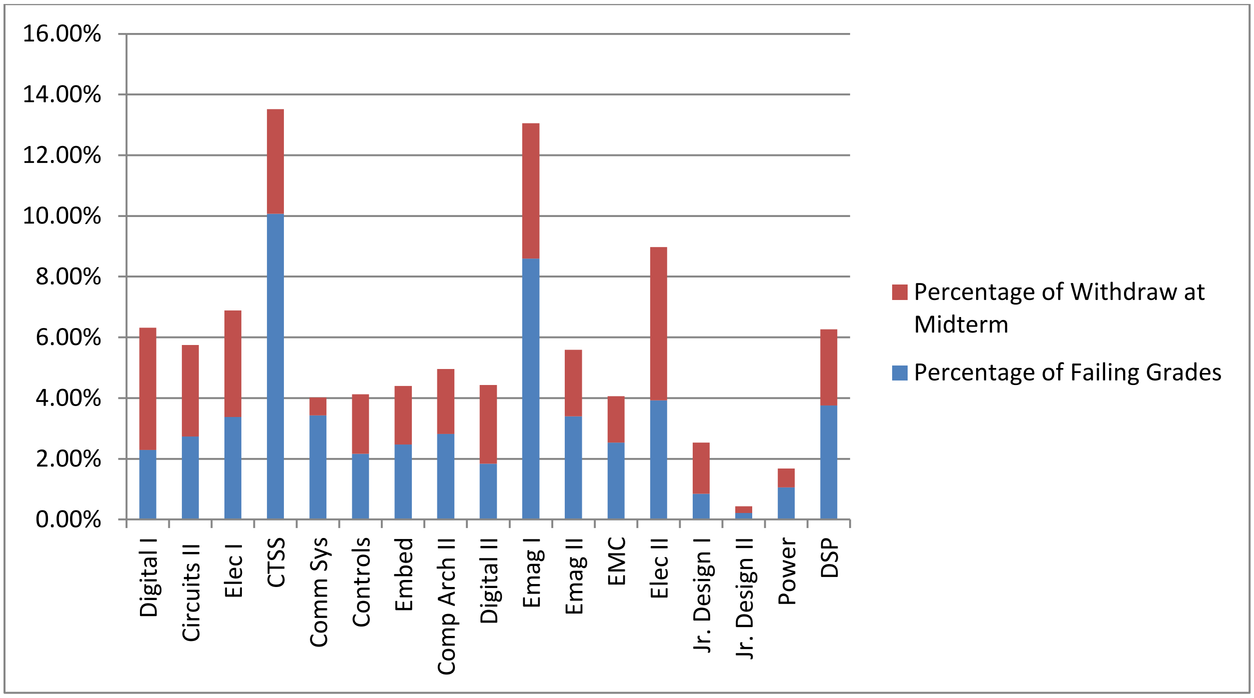

Figure 1: Percentage of withdrawals and failures from the 2000-2010 academic years in most of the required courses in the ECE curriculum

One possible factor that could contribute to the result is if any particular faculty member was more strict in grading, thereby skewing the average failure data. Table 1 explains the answer to this concern by showing only the CTSS data from Figure 1 broken down by eight different instructors who taught this course over the given period. These data show a significantly higher withdrawal-failure rate (18.9%) than the average data shown in Figure 1 when Instructor 1 taught the course. However, for the aggregate data, this higher extreme is offset by the student data from when Instructor 6 taught the course. With these two outliers eliminated from the data set, the average failure rate is 8.8%. The failure rate excluding Instructors 1 and 6 is lower than that shown in Figure 1, but still approximately twice the average of the other required courses and greater than Emag I. The withdrawal rate without student data from Instructors 1 and 6 is 1.7%, which is approximately the same as the data shown in Figure 1. Instructors 5 and 8 each taught only one smaller size section per quarter with each section being in a different year, so we can safely say that the population of students in those sections was possibly less diverse. In contrast, Instructor 6 taught two sections during the same quarter and more likely had a more diverse population.

The data of individual instructors does show that one instructor taught approximately half of the students in the data set, but the failure rate was not significantly different to account for the increased failure rate of the CTSS course over the other required courses in the ECE curriculum. It is reasonable to conclude that any particular instructor's grading did not cause the higher failure rate.

Table 1: Student failure and withdraw rates for the introductory CTSS course broken down by instructor for the years 2000-2010.

Instructor	Total ECE Students Taught (# Sections)	Failure Rate (%)	Withdraw Rate (%)
1	360 (19)	14.7	4.2
2	159 (7)	12.6	1.8
3	87 (4)	5.7	1.1
4	75 (5)	9.3	4.0
5	60 (3)	5.0	0.0
6	55 (2)	0.0	3.6
7	50 (2)	10.0	0.0
8	20 (2)	5.0	5.0

Another factor that could influence the data in Figure 1 is how a particular textbook or organization of the course influenced student performance. Even though the course description was consistent from the 2003-2010 academic years, the instructors were free to present the material in any order or fashion that best suited their personal style. The same textbook was used throughout an entire academic year, but several different textbooks were used throughout the period. The laboratory content was fairly consistent within one academic year, but tended to gradually evolve as the years progressed. One way to get some idea of the impact of these factors is to look at the CTSS performance on a yearly basis. The same performance data shown in Table 1 is presented in an annual format in Figure 2. This data shows that years 2001, 2002, and 2005 are the outliers. It is of note that, in 2003 the AC power and phasor content was removed from the course and ECE300 became more of a traditional signals and systems course. In addition, instructor 6 taught the majority of students in 2001 and 2002 and none of these students failed the course. That makes the 2005 year a true anomaly for the study. Instructors 3 and 5 were the only instructors who taught during 2005, and they have the next lowest failure rates. If student data from these outlier years are removed from the data set, the failure rate rises to 13%, which is actually much worse than what is presented in Figure 1.

These data suggest that a particular textbook, faculty member, or presentation of course material are not significant contributors to the performance results shown in Figure 1. By eliminating any possible effects of these factors on our analysis, we are suggesting that the results shown in Figure 1 are rather more representative of the difficulty of understanding course content.

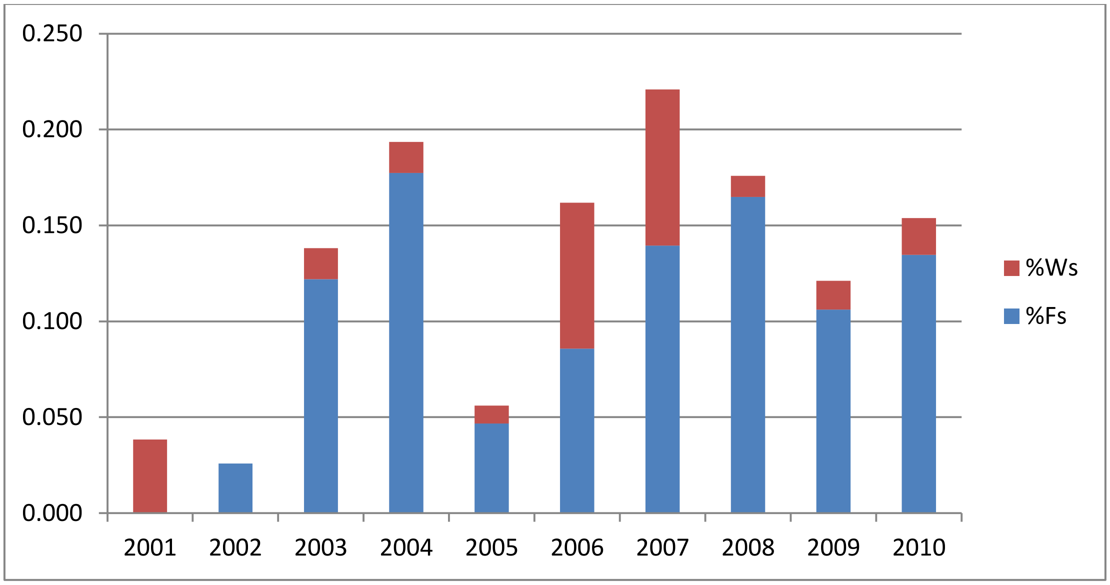

Figure 2: Failure and withdraw rates of students taking the introductory CTSS course broken down by year.

In order to confidently say that the course content is more difficult than the other required courses, we also have to show that the students are putting forth the same amount of effort in this course as compared to their efforts in the other courses. If the students are performing badly because they are not putting in the same effort as other courses, then the solution is clearer. Even though weakly correlated to a student's effort, the cumulative GPA at graduation is the only value in the dataset that could provide some crude measure of their efforts. The assumption is that the students with a higher cumulative GPA at graduation either put in the required effort in order to earn the better grades or exhibit a higher level of academic ability. Analysis of the data is based on the hypothesis that if the average GPA of a student population is higher at a given performance level in a course relative to another course, then we can say that it took more ability or effort to achieve that level of performance. This hypothesis is based on the assumption that performance levels between courses are equivalent for which we do not have any evidence.

Figure 3 shows the average student GPA relative to a given performance level for a subset of the required courses. The sample group is the same for all courses so the number of students in each group is included to show how the distributions for the average GPAs are changing for each course. The average GPA for the entire population is 3.22/4.0 with a standard deviation of 0.46. A subset of courses was chosen because a complete set of data was not provided for all of the courses and it also helps to simplify the presentation of the data. The CTSS and Emag I courses were chosen in order to represent the traditionally more difficult courses at Rose-Hulman even though Emag I is only taken by the electrical engineering (EE) students. The DSP course was chosen as a representative of the courses that require the CTSS course as a prerequisite and it is taken by most computer engineering (CPE) students whereas the communication systems and Emag II courses are not. The Digital II course is chosen because it is required by all EE and CPE students and is not mathematical in nature.

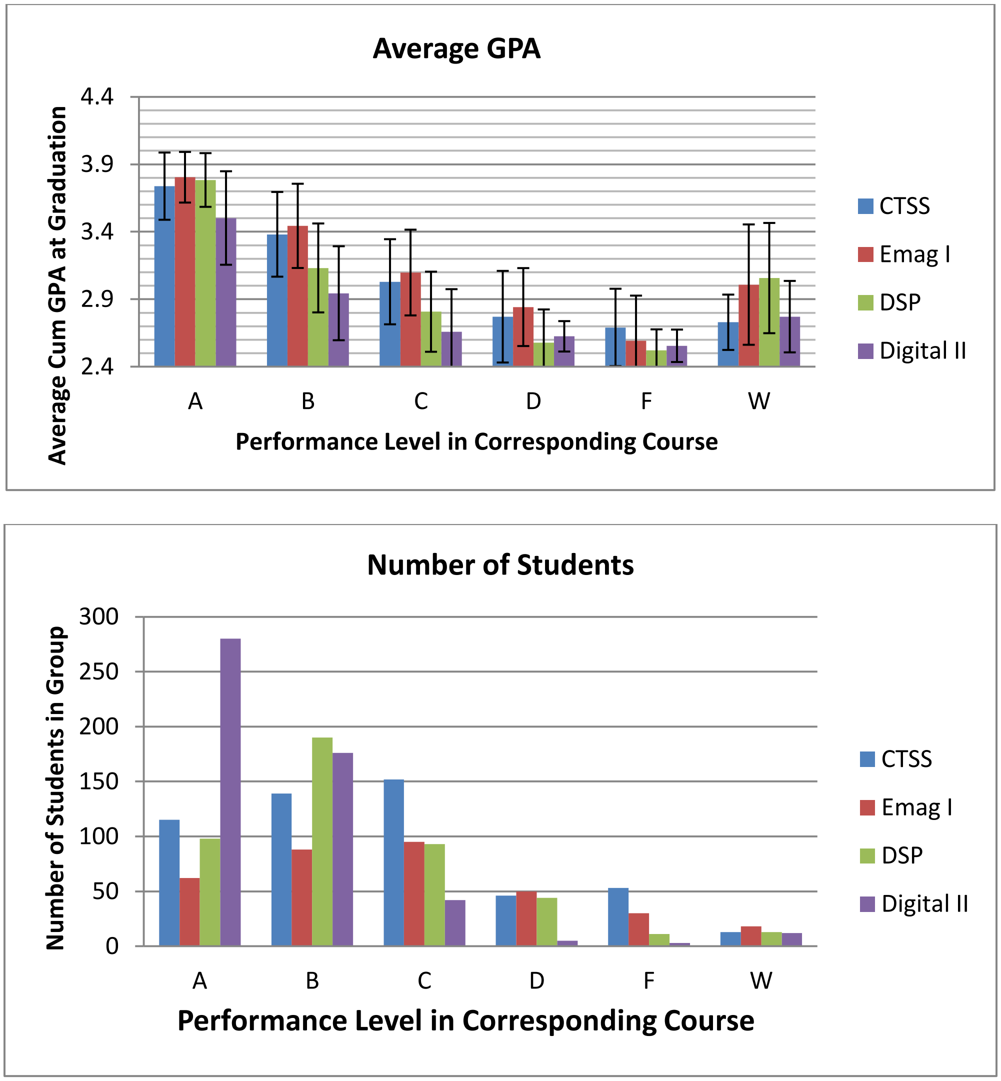

Figure 3: Top plot: Each bar represents the average cumulative GPA of students within a given performance level for a given course. The error bars indicate the standard deviation for that particular group of students. Lower Plot: Each bar represents the number of students in the corresponding group in the top plot. The total number of students in each group is: CTSS=516, Emag I=343, DSP=449, and Digital II=518. The reasons for the different numbers are given in the text.

Analysis of Figure 3 can help to indicate if certain courses are more difficult than the others in terms of effort required to achieve a certain performance level. According to the hypothesis presented earlier, for a given student performance level (A, B, C, …), a higher average GPA for a course would suggest that a given course took more effort or ability on a student's part to achieve that level of performance and is therefore more difficult than the other courses. Looking across the performance levels, the CTSS and Emag I courses consistently have a higher average GPA for a given performance level than the DSP and Digital II courses.

Looking at the "C", "D", and "F" performance groups suggests another important observation. For the DSP and Digital II courses, the GPAs of students at these performance levels are generally consistent within the performance level. For example, the students in the F performance level in these courses are also generally performing at the C or D grade levels with respect to their average GPA. However, for the CTSS and Emag I courses, at least a standard deviation or more of the students are performing a level or two below their typical ability or effort at these performance levels. For example, there are students with cumulative GPAs at the A or B grade levels who are earning C or D grades in the CTSS and Emag I courses. These are not insignificant populations of the students.

The "A" performance group is also a little bit of an anomaly because the CTSS, Emag I, and DSP courses are all at approximately the same average GPA level, and are all higher than the Digital II course. The one thing that the three courses have in common is mathematical modeling.

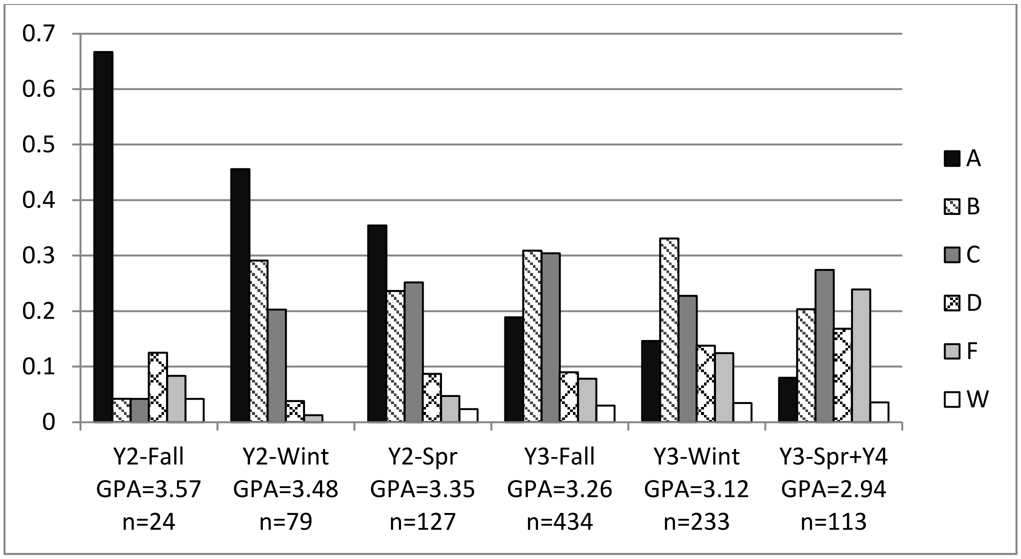

Figure 4: Performance of students in the CTSS course according to which quarter they took the course. Y2-Fall denotes the Fall Quarter of their second year at the school and so on. The Y3-Spr+Y4 group includes those students who took ECE300 during their 4th year because the population was so small. Grade earned is denoted by the legend on the right. The y-axis is the percentage of students within each population earning the corresponding grade. The size and average GPA of each population is noted under the title of each population.

Another factor that could affect student performance is the quarter in which a student takes the course because there may be a particular quarter that is more challenging for students that would cause performance to be worse than it would be otherwise. Figure 4 shows performance data for students taking ECE300 broken down by the quarter in which they took the course. What stands out most in this data is the large percentage of students earning As for the Y2-Fall group and how this percentage decreases for subsequent populations. As mentioned previously and shown in this figure, most students take ECE300 during the Y3-Fall and Y3-Winter quarters. For a student to take the course in the Fall Quarter of their 2nd year, they must have entered the program with most of their math already completed in order to meet the pre-requisites for ECE300 during their Freshman year. The population for Y2-Fall is small and generally composed of students who are ahead of the standard curriculum because they started their freshman year with advanced placement or significant pre-college credit. As expected, the average GPA of this group is the higher than all other groups in this figure. While the percentage of students earning As decreases with subsequently later quarters, it is much more likely that this trend is correlated with GPA than the quarter in which the course was taken. Looking at the other performance groups, the percentage of students earning Bs and Cs is relatively independent with respect to the quarter taken, and the percentages of students earning Ds and Fs seem to be inversely correlated with GPA. These results strongly suggest that performance in the CTSS course is much more correlated to GPA than it is to the quarter in which the course is taken.

The results presented in this section strongly suggest that the CTSS and Emag I courses are more difficult than other courses within the ECE curriculum more because of the course material itself as compared to other possible pedagogy and student related factors. The fact that five different instructors have taught the CTSS course material to varying levels of students each with their own pedagogy, and textbook and did not achieve any significant changes in student performance suggests that the way to resolve this difficulty is based more in how students conceptualize the topics covered in this course than how the course material is presented or at what academic level it is presented. Although the accelerated students are doing better in this course than the other students, the results presented in this section help to guide further studies to determine the sources of the learning difficulties in this course. The authors discuss their hypothesis about the possible reasons for difference in students' performance levels in the conclusions of this paper.

IV. Analyzing the role of math and modeling preparation on performance in the CTSS course

The previous section showed that both the CTSS and Emag I courses share similar performance results, it is not a huge leap to connect the two courses by their heavy reliance on mathematical theories and models. This led the authors to analyze the role of mathematical preparation of each student with respect to their performance in these courses. Furthermore, the lack of mathematical preparedness leading to poor performance of students in these courses was cited numerous times in discussions with faculty from other universities in various academic settings during the period of data analysis for this study. Perhaps, it is mathematical ability that explains the performance results from the previous section and separates the higher performing students from the lower.

The historical data set discussed previously did not contain the performance data for the required math and physics pre-requisite courses. Therefore, another data set was gathered that contained student performance for the years 2002-2012 for math and physics courses in addition to some of the ECE courses. The data sets are presented as box plots in Figure 5. Each set of box plots represents the group of students who earned the same grade in the CTSS course. These plots illustrate how students within each groups performed in other courses. The particular courses included for this comparison help to illustrate both how the students were prepared and how well they were able to apply the CTSS material in follow-on courses. The physics courses are an indication of how well the students learned to use modeling to understand physical phenomena. The second calculus course is intensive in infinite series and is where students first encounter the Fourier series. In differential equations, the students begin to see the modeling of physical phenomena with mathematics. The Dynamic Systems course is a special case because it contains only a subset of the students after the year 2010 year. In an attempt to improve the performance in the CTSS course, after the 2009-2010 academic year, the CTSS course was split into two courses at Rose-Hulman. The first course, Dynamic Systems, covers all of the time domain and transient analysis of signals and systems, while the second course, CTSS, covered only the frequency domain analysis. It is included here because it became the direct pre-requisite for the CTSS course and so that the total CTSS material would be consistent across the dataset. Communication Systems and Discrete-time Signal Processing (DSP) are courses for which the CTSS course is a pre-requisite. The first electromagnetics course does not depend on the CTSS course, but is also included to see if the same group of students performed similarly in both courses.

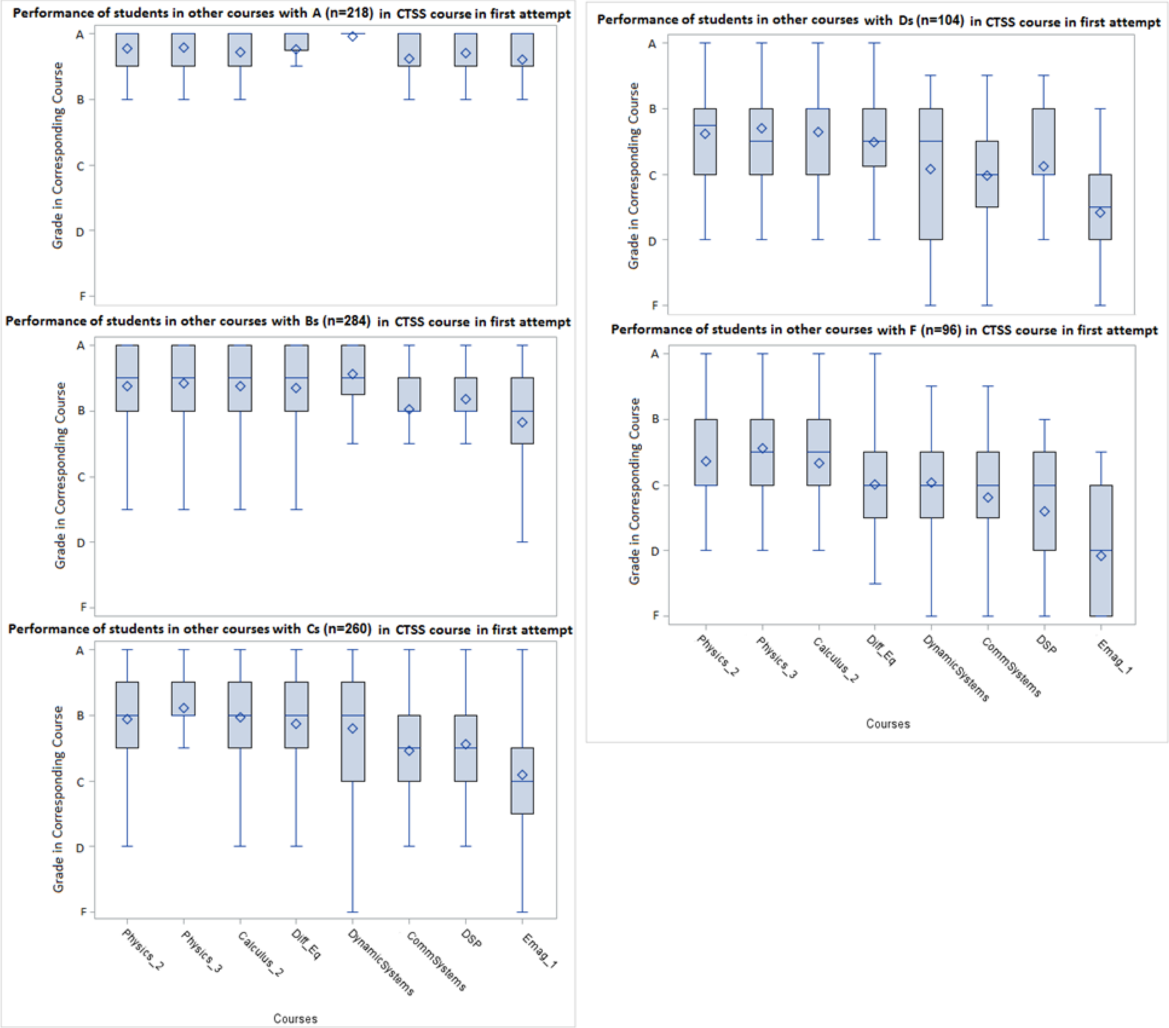

Figure 5: Box plots showing grades earned by students (grouped according to their grades in ECE 300) in some other courses.

One observation of this data shows that, in the population of students who earned penalty grades (D or F) in the CTSS course, the median grades for calculus, physics, differential equations, and dynamic systems are all C or better and in some cases much higher than a C. This means that more than 50% of the students earning penalty grades in ECE300 are performing relatively well in their preparatory courses. Note that there were no students who failed these courses because Rose-Hulman has an unlimited grade replacement policy for all courses at the freshman and sophomore level (200 level), for which all of these pre-requisite courses apply. If a student did replace a grade, it is assumed that their understanding is commensurate with their final performance and most students who grade replace do so with a C rather than an A or B. This is consistent with the observation from the data in Figure 3 which showed that many students are performing below their average in the CTSS course.

One factor that can influence the ability of students to use their mathematical preparation is the amount of time that elapses between when they finish the math sequence and when they take the CTSS course. The differential equations sequence is especially relevant because the students are exposed to Fourier series and complex numbers in these courses and these are the last required math courses that the students take. Perhaps those students who earned As and Bs in differential equations and then a penalty grade in ECE300 took ECE300 many quarters after the math courses. The performance data for ECE300 is presented with this perspective in Figure 6. Because there is no strong trend in these data, they suggest that student performance in the CTSS course is independent with respect to when the students take ECE300 relative to their mathematics preparation.

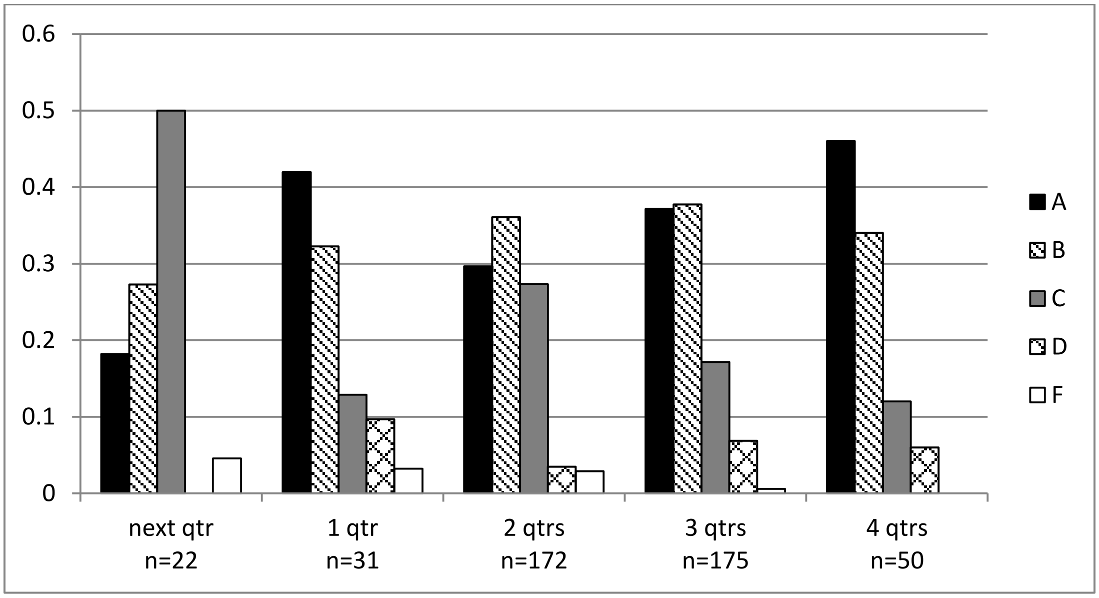

Figure 6: Performance in ECE300 for the sub-group of students who earned As or Bs in Differential Equations. The y-axis is the percentage of students in each group who earned the corresponding letter grade. The data is organized according to how many quarters elapsed before the student took ECE300. “1 qtr” means that there was one quarter in between their completion of Differential Equations II and ECE300. The sample size and average GPA are given for each group.

Perhaps a stronger relationship between math preparation and performance in ECE300 is not when or what students learn but how they learn math. Those students who focus on the procedures and algorithms can memorize enough to do well in the math courses, but do not fully understand the concepts they are learning. For example, they can solve a differential equation, but do not fully understand the concept of the derivative as the slope of a function. It is these students who can earn As and Bs in the math classes but penalty grades in ECE300. If cumulative GPA is an indication of a student's ability to understand concepts as well as procedures then this conclusion is supported by another observation. The students who performed well in Differential Equations and also earned As in ECE300 had an average GPA of 3.75, while those who performed well in Differential Equations but earned penalty grades in ECE300 had an average GPA of 3.08.

Looking at the data for the Communication Systems and DSP courses in Figure 5 shows that the median grades for these courses is higher than the performance of the students in the CTSS course. Both of these courses depend on the CTSS course as a pre-requisite. Despite performing poorly in the CTSS course, the students are able to perform better in the follow-on courses. This can be explained by the possibility that the first exposure to the CTSS material is insufficient for many students to learn the mathematical concepts at a higher level. When seeing the material again in the follow on courses and in a different context, they are able to understand the concepts.

V. Summary and Conclusions

In this study, we analyzed a large historical dataset of ECE students in order to validate the difficulty that students are facing in the introductory CTSS course and to get an idea of how the students' preparation in pre-requisite courses is related to their performance in the CTSS course. For this analysis, difficulty was defined as the level of understanding achieved based on the amount of effort required to achieve that understanding. The analysis suggests that the CTSS course is in fact one of the more difficult courses relative to other required courses at the target institution. Furthermore, the same students who are performing poorly in the Emag I course are also performing poorly in the CTSS course, but are not performing as poorly in the pre-requisite math and physics courses. While the data and analysis are particular to Rose-Hulman, discussions with faculty at other schools indicate that the difficulty of the CTSS course is much more widespread. Through this paper, it is one of our goals to encourage faculty at other schools to collect and share similar data as presented in this paper. The long term goal is to develop a better understanding of common learning problems within different learning conditions that students are encountering in CTSS courses.

Both the CTSS and Emag I courses require students to understand mathematical cocncepts and apply them in different contexts. Simple procedures and algorithms cannot be memorized and applied to a limited set of situations because changing one variable of a problem can completely change the context. The analysis presented in this paper has led the authors to hypothesize that those students who focus on procedural rather than conceptual knowledge struggle the most with these courses. An example between the two forms would be to find the Fourier series coefficients of a single sinusoid. Using procedural knowledge, a student might try to integrate the function multiplied by a complex exponential to find the coefficients. Whereas, using conceptual knowledge, a student would recognize that a sinusoid is already a Fourier series and get the coefficient directly from the amplitude and phase of the sinusoid. These two forms of learning are consistent with the idea of students taking a deep versus a surface approach to learning.

We are currently performing a number of activities in order to test this hypothesis and develop pedagogy that can help to improve students' conceptual understanding of CTSS course contents. In order to better understand the students' thought processes, we are conducting student interviews in which students "think out loud" while solving CTSS problems similar to those presented in textbooks. At present, only preliminary interviews have been conducted in order to evaluate the interview protocol. The results from these preliminary interviews do support our hypothesis, and we hope to present more sophisticated results in the near future.

The analysis presented in this paper showed that many of the students in the CTSS course are performing below their usual performance level as indicated by their cumulative GPA. This result suggests that it may be possible for carefully designed pedagogy and curricula to have a significant impact. In light of our hypotheses, the goal of designing pedagogy should be to encourage students to take a deeper approach to learning in order to develop conceptual understanding. There are many sources in the literature that describe methods that faculty can use to encourage this development in students as described in [10]. To strengthen students' conceptual understanding, we are developing hands-on application-oriented activities at Rose-Hulman that can provide personal experiences with the CTSS concepts [14]. Students are then required to explain these experiences in short answer questions that can only be explained with conceptual understanding. These questions are counted as part of the laboratory assignment grade.

The fact that student performance is similar between the Emag I and CTSS courses suggests that the studies we are conducting can have a broader impact within the ECE curriculum in particular and engineering curriculum in general than just for CTSS courses. Determining more effective ways to help students to take a more conceptual approach to learning concepts taught at a higher academic level will impact a wide range of studies even beyond engineering.

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