Assessing Student Preparedness for Introductory Engineering and Programming Courses

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***Abstract*—Our introductory electrical engineering courses still have high attrition rates which raises the question of how to identify students who may be at risk of failing or withdrawing from engineering courses and programs. We have experimented with two different approaches: one is to develop tests that are deployed early in student engineering coursework, and another is to measure student success in prior math courses. Math preparation is the basis of two of the tests, with one also including logic and algorithmic thinking. Preliminary results indicate that purely math-based tests did not correlate well with success in either an introductory problem-solving and programming course, or a sophomore circuits course. A test that includes logic and algorithmic thinking correlated better, but not as well as prior math GPA. All methods currently suffer from large scatter and relatively small correlation factors.**

Keywords—freshman engineering; engineering education; programming; problem solving; retention.

I. INTRODUCTION AND MOTIVATION

One of the issues confronting instructors of introductory engineering courses is the diversity of student backgrounds and preparedness for a given course. Many factors affect this preparedness, e.g., high school preparation, college level coursework already completed, prior problem solving skills, and prior programming skills. These introductory courses may have no prerequisites, or they are generic, such as “college level algebra”. Despite institutional and instructor best efforts, these courses may have low success rates, leading to low retention and persistence. In our experience, some students are simply not ready for such courses, despite their introductory level. In order to advise students, tailor the instruction, improve the curriculum, and measure student learning, we need instruments that will tell us how well students are prepared for the course.

Nine years ago our Electrical and Computer Engineering (ECE) department replaced a college-wide introductory engineering course with our own course sequence, specifically designed for ECE students [1]. The design of this three-course sequence was based on assessment and feedback from employers and alumni, and addressed four main issues: (i) students had insufficient programming skills, (ii) students had weak communication skills, (iii) students were not introduced to design until upper-division courses, and (iv) we needed to attract and retain undecided and traditionally under-represented groups of students. The overall goals were to include project design and teamwork experience, introduce programming (specifically MATLAB) earlier, stress “soft skills” such as communication, ethics and student success, and to improve student engagement.

In the first course in the sequence, ECE 101, students do a quarter-long hands-on project, such as building a Rube Goldberg machine, to learn the design process, teamwork, and presentation skills. They do lab experiments to learn basic equipment and components, and speakers present an overview of different fields and career opportunities in electrical engineering. In the second course, ECE 102, students learn to develop algorithms and apply computational software tools (mainly MATLAB) to solve primarily simple electrical engineering problems. They do a project using MATLAB programming for data acquisition and control. In ECE 103 they learn software design, algorithms, data structures, and computation using the C programming language. They write C programs to solve intermediate-level engineering problems, and write control code for hardware interfacing projects.

We designed these courses to be engaging and helpful, not to “weed out” underperforming students. However, we see a large percentage of drops and fails, especially in ECE 102 and 103. Retention in engineering majors has been recognized as a complex problem, especially for students not following traditional pathways [2]. In order to improve retention and success, we need to understand our students – is the problem preparation, motivation, college skills, or something else? Some of the challenges come from our non-traditional student population [3]: (i) roughly 60% transfer from community colleges, (ii) roughly 50% work on average 20 hours a week, (iii) they do not follow our advising plans; for example, the average number of credit hours at graduation is about 230 compared to 180 required, and (iv) around 20% are international students who, despite passing an intensive language program, still struggle with English.

This presents the institution as a whole, as well as individual instructors, with a difficult problem in assessing student preparedness for college and for specific courses. One particular challenge in STEM fields is student math preparedness and math placement [4]-[12]. However, math courses also have high attrition rates and the math department at PSU now requires that students either pass a preceding college algebra course or score high enough on the ALEKS online test [13]. If students do not place into Calculus I, they are directed to college algebra or

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lower courses. While this approach has been successful in improving attrition in Calculus I, the remedy of sending students to lower-level math courses is problematic [14][15].

II. Methodology and Data

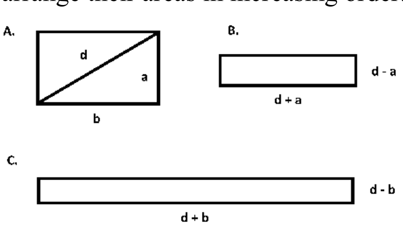
In the past, we have studied prior math achievement as a predictor of success in our introductory courses [16]. However, the correlation between, e.g., prior completion of Calculus I and a grade in our courses, was not as strong as we had hoped. The student level achieved in online math assessment tools (ALEKS) produced similar results. One problem with both metrics is that they only measure the student's ability at some point in the past, possibly many months or even years ago, and in a purely mathematical rather than applied engineering context. ALEKS is also administered at PSU as a "take home" exam. We would prefer to have students take it under supervision and either just before the class starts or during the first week of class. This presents logistical and financial problems because the test can take a long time, and the cost of any customized test may need to be negotiated with the test provider. We have also observed that, in the current online and take-home environment, students do not follow up on their placement results by signing up for appropriate math courses. Instead, the majority of students retake the test within one or two weeks of their first attempt. While this may satisfy the student's desire to immediately take Calculus I, this strategy may result in them being placed in courses that they are not really prepared for.

Given these complexities, we started to look for a relatively simple and reliable way to infer which students are at risk and may need additional help. This search led to a trial of several tests: a simple algebra-based math test obtained from Wright State University [17], a math-algorithmic-logical thinking (MALT) test first published in [18], and a locally developed math quiz for sophomore circuits classes. Below we discuss initial experiences with each of the tests.

A. *Simple Algebra Test*

The original test was set up as a self-efficacy test in which students are asked how confident they are that they can solve a given question. That seemed to be sufficient for advising purposes, but after initial implementation we decided to test if students could actually solve the problems. Fourteen questions cover simple algebra and geometry. For example, the hardest question is one that requires a bit more abstract thinking:

"2. Sally needs three pieces of poster board for a class project. If the boards are represented by rectangles A., B., C., arrange their areas in increasing order. (assume b>a)"



Given that we considered these questions to be simple and straightforward, we did not expect large differences between students' confidence and ability. We have run this test four times: thrice in ECE 101 and once in ECE 102. Tests were administered in class and limited to 45 minutes, and there were no special incentives. Fig. 1 summarizes all four results. Some differences between actual student performance and self-efficacy can be observed, but there is little variation across testing sections. What we found more noteworthy is that the average score was only around 65%. We expected better results given that roughly 65% of ECE 101 students and 80% of ECE 102 students have already passed at least Calculus I. This may be due to students not transferring their math skills to new contexts, inadequate preparation, or lack of motivation for taking the test.

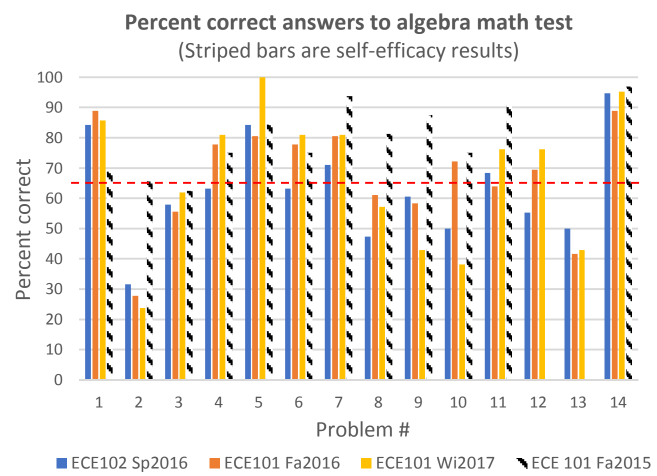


Fig. 1. Percentage of correct answers on algebra math test administered in ECE 101 &102. Striped bars are self-efficacy results, full color are test scores.

The second question was to see if this particular math test could predict student success in ECE 102. In the first case, 22 students in ECE 101 who took the test continued on to ECE 102 the following term. In Fig. 2, we calculated Pearson's $R^2 = 0.0023$ for this case. In the second case, 38 students took the test during the ECE 102 class and we found $R^2 = 0.0044$. Surprisingly, there is no correlation between the test results and final score in the course in either case, making this test questionable as predictor. However, learning about student difficulties with even simple word problems was very helpful.

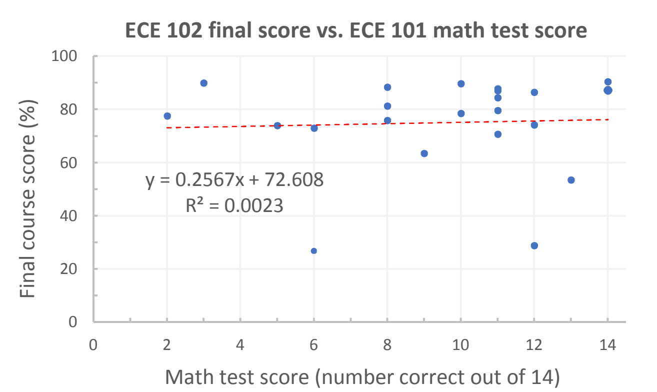


Fig. 2. Final scores used for grading ECE 102 vs. math test scores; test was administered in ECE 101. Sample size N=22.

B. *Math-Algorithmic-Logic Thinking (MALT) Test*

In the second introductory course (ECE 102), we are also concerned about students' abilities to think logically and to develop algorithms and programs. There is a lack of assessment instruments in this area, and we decided to try a set of questions reported in [18]. Because it tests not only math skills but also algorithmic and logical thinking, we thought that this assessment may be better suited to our context than a pure math test. There are twelve multiple-choice questions, four for each area: math, algorithmic thinking, and logic. We have run the test once in Winter 2017 as a pre- and post-test, as described in [19]. The first (pre-) test was done during a lab session and did not have any incentives. The second (post-) test was also done during a lab session but students could earn extra credit, equivalent to one lab session score. In both tests we limited the time to 45-50 minutes. Forty students took both pre- and post-test and are included in this analysis. Fig. 3 presents pre- and post- test results grouped in quartiles. There is a clear improvement in post vs. pre results. As shown in Fig. 4 and Fig. 5, there is a small positive correlation between test scores and the final course score, with $R^2 = 0.12$ for the pre-test and $R^2 = 0.09$ for the post-test. The first value is comparable to what was reported in [19] but lower than in [18]. The post-test correlation is reduced and is smaller than the results in [19]. We currently do not have a good explanation for this finding.

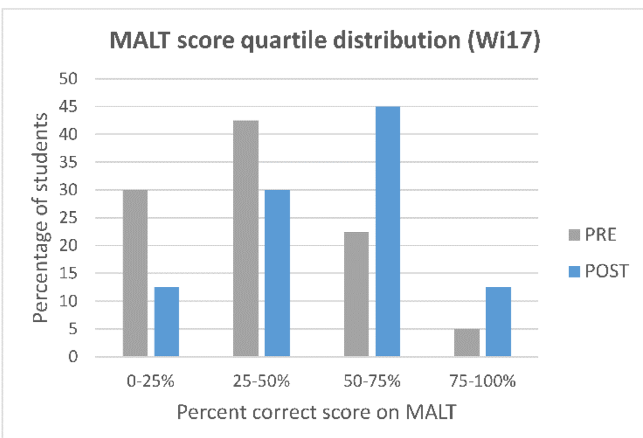


Fig. 3. Percent scores distribution on math-algorithmic-logical thinking test in ECE 102, administered at the beginning (PRE) and end (POST) of class. Sample size PRE = POST = 40.

This test has also been used to examine the extent of student learning during the course [19]. We found that the average improvement in score was around +2 points out of 12. Results of paired t-test for students who took both pre- and post-tests are shown in Table 1. Given that t-value and p-values are very small, we verified that the two means are significantly different. This indicates that students have indeed improved their test scores. However, it is difficult to make the claim that this is solely due to learning in the course, given that there are other potential confounding factors such as student motivation to take the test, or other courses students are taking.

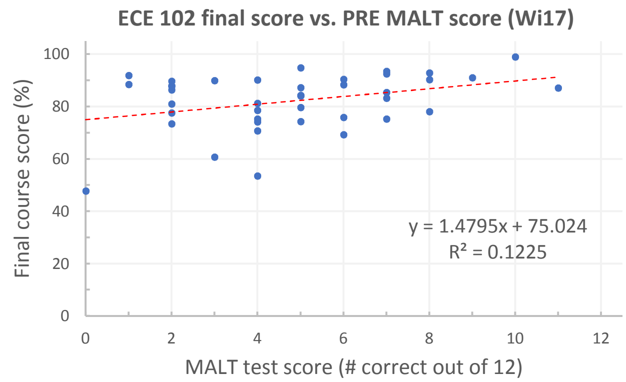


Fig. 4. Final course scores in ECE 102 vs. number of correct answers on MALT test administered at the start of the course. Sample size N=40.

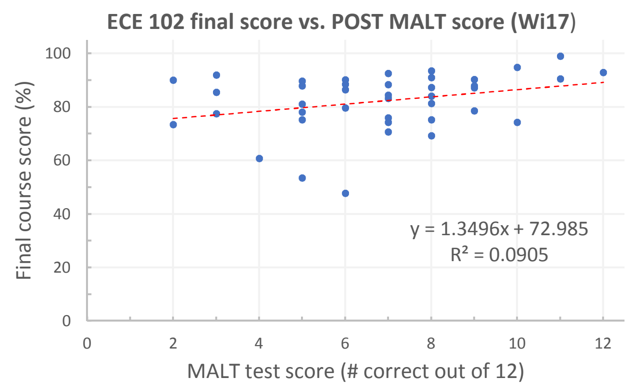


Fig. 5. Final course scores in ECE 102 vs. number of correct answers on MALT test administered at the end of the course. Sample size N=40.

Table 1. t-Test analysis of student scores on MALT test in ECE 102. MALT administered at start and end of course.

	PRE (/12)	POST (/12)
Mean	4.825	6.8
Variance	6.712179	5.958974
Observations	40	40
Pearson Correlation	0.537603	
Hypothesized Mean Diff.	0	
t Stat	-5.15508	
$P(T \leq t)$ two-tail	7.67E-06	
t Critical two-tail	2.022691	

C. *Math Test in Sophomore Circuits Courses*

In our sophomore circuits class, we tested preparedness by giving students a simple math quiz at the beginning of the year, and comparing their scores on the math quiz with their average score on three circuits exams. The math quiz included mainly basic calculus problems, but also some algebra, complex numbers, and simultaneous equations. Contrary to our expectations, we found weak correlation between the math quiz and circuits exams in the first quarter of the circuits sequence, as shown in Fig. 6. Sample size was N = 58 and $R^2 = 0.05$. Furthermore, by the end of the second quarter, there was no correlation at all. Whatever math skills were lacking at the beginning of the year, students seemed to manage to catch up by the second quarter.

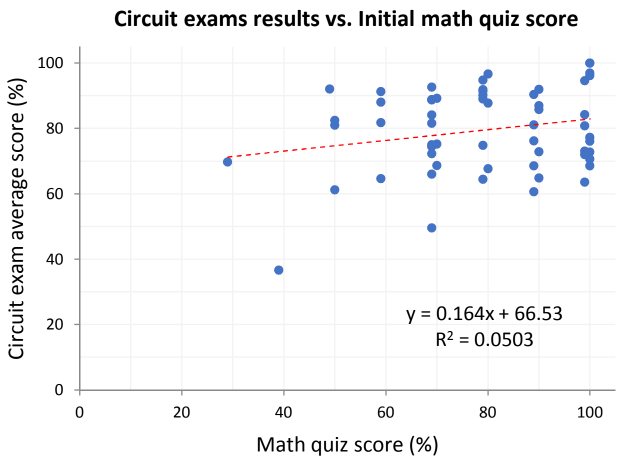


Fig. 6. Average of scores on three exams in sophomore circuits class vs. score on initial math quiz.

D. *Overall Math Preparation*

In our previous study [16], we found that the grade point average that students achieved in all of their prior math courses was a slightly better predictor than the grade attained in the most recent math course taken. We repeated this analysis for the three cohorts of students taking ECE 102 in Winter and Spring 2016 and Winter 2017 quarters. Results in Fig. 7 show a scatter plot of course grades vs. prior math GPA scores. Given that around 80% of students have already passed Calculus I, there should be a reasonable amount of prior math grades available for GPA calculation. Details of the procedures are given in [16]. In addition, we attempted to adjust the grades to remove effects of differences in mean course grades between sections, but the final results differed very little. Overall sample size was N = 164 with $R^2 = 0.2$. This indicates somewhat better strength of correlation compared to other math tests, but it is still relatively weak. This result is also better than in our previous study when $R^2 = 0.09$ for N = 201 was found.

III. Discussion and Conclusions

We have started our search for a practical, useful, valid, and reliable test of student preparedness with high demands and expectations, but this task has been more difficult than anticipated. One of the issues is that designing a good test is a challenging and time consuming task [2] and there are many confounding factors that can limit usefulness of such tests. So far, our research has revealed:

- Results of a simple math test administered in freshman ECE courses revealed a lower than expected level of math preparedness, but
- the same test does not correlate with eventual success in our ECE 102 course.
- A test that combines math skills with algorithmic and logical thinking seems to be somewhat better predictor of eventual course success, and

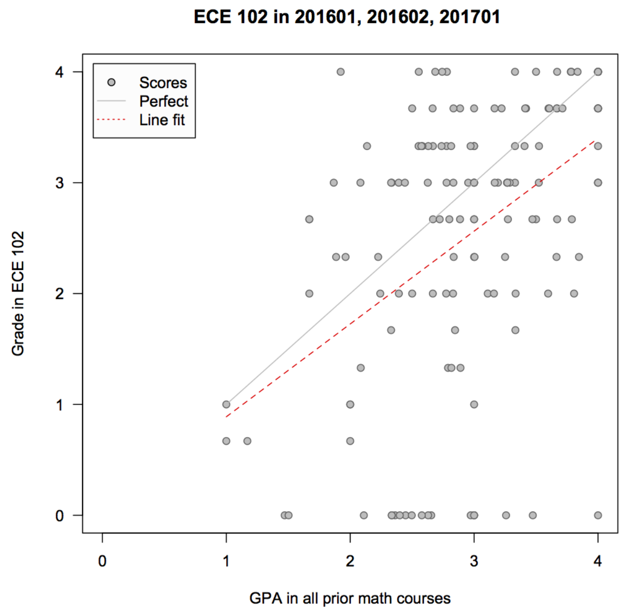


Fig. 7. Grade in ECE 102 vs. GPA in all prior math courses taken. Three course offerings with total N = 164 students and $R^2 = 0.2$.

- the same test can be used to demonstrate gains in student learning.
- Overall math GPA in prior coursework is, so far, the best predictor of success, but
- it is puzzling that students who have successfully completed college level math courses, many including Calculus I or above, cannot solve relatively simple math, algorithmic, or logical problems.

Based on these findings, we will focus our attention on using a combined math-algorithmic-logic thinking (MALT) test as our primary means of identifying at-risk students. We will continue examining students' prior math GPA as an additional indicator. Once we feel confident in these results, we will examine instructional or curricular options. For example, it may be beneficial to set up a separate section for at-risk students or to extend the coursework over two quarters instead of one. The MALT test may also offer us a means of testing the effectiveness of instructional interventions. We should also point out that simple math tests like we attempted to use have uses other than predicting student success. For example, such tests can be used to activate prior student knowledge that is needed in the course. However, such tests would have to be more focused on the course-specific math needs.

Our work needs to be improved in several directions, including: a) more consistent application of testing procedures, b) increased sample size, and c) examining student performance among sophomore and upper-division students to examine development of student learning.

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