AC 2010-190: REGRESSION MODELS FOR PREDICTING STUDENT ACADEMIC PERFORMANCE IN AN ENGINEERING DYNAMICS COURSE

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Regression Models of Predicting Student Academic Performance in an Engineering Dynamics Course

Abstract

Prediction of student academic performance helps instructors develop a good understanding of how well or how poorly the students in their classes will perform, so instructors can take proactive measures to improve student learning. Based on a total of 2,151 data points collected from 239 undergraduate students in three semesters, a new set of multivariate linear regression models are developed in the present study to predict student academic performance in Engineering Dynamics − a high-enrollment, high-impact, and core engineering course that almost every mechanical or civil engineering student is required to take. The inputs (predictor/independent variables) of the models include a student's cumulative GPA; grades earned in four prerequisite courses: Engineering Statics, Calculus I, Calculus II, and Physics; as well as scores earned in three Dynamics mid-exams. The output (outcome/dependent variable) of the models is a student's final exam score in the Dynamics course. Multiple criteria are employed to evaluate and validate the predictive models, including R-square, shrinkage, the average prediction accuracy, and the percentage of good predictions. A good prediction is defined as the one with the prediction error of ±10%. The results show that the developed predictive models have the average prediction accuracy of 86.8%-90.7% and generate good predictions of 44.4%-65.6%. The implications of the research findings from the present study are also discussed.

Introduction

Almost every mechanical or civil engineering student is required to take the Engineering Dynamics course − a high-enrollment, high-impact, and core engineering course. This course is an essential basis and fundamental building block for advanced studies in many subsequent courses, such as vibration, structural mechanics, system dynamics and control, and machine and structural designs. However, many students fail this course because it covers a broad spectrum of foundational engineering concepts and principles, for example, motion, force and acceleration, work and energy, impulse and momentum, and vibrations of a particle and of a rigid body [1-3].

Prediction of student academic performance has long been regarded as an important research topic in many academic disciplines because it benefits both teaching and learning [4, 5]. Instructors can use the predicted results to identify the number of students who will perform well, averagely, or poorly in a class, so instructors can be proactive. For instance, if the predicted results show that some students in the class would be "academically at risk," instructors may consider taking certain proactive measures to help those students achieve better in the course. Representative examples of proactive measures include adding recitation sessions, adding more office hours, using computer simulations and animations to improve student problem solving, adopting a variety of active and cooperative learning strategies, to name a few.

A variety of mathematical techniques, such as multivariate linear regression [6], neural networks [7], Bayesian networks [8], decision trees [9], and genetic algorithm [10], have been employed to develop various models to predict student academic performance. Multivariate linear regression is among the most widely employed mathematical techniques. It is easy to understand and use because it does not require sophisticated mathematical skills for researchers to master. It also provides an explicit set of mathematical equations, allowing education researchers and practitioners to "see" how the predicted results are generated, and thus the predicted results can be interpreted in a reasonable and meaningful way [11]. For example, Green [12] developed a set of linear regression models for three mechanical engineering courses to predict a student's final exam score from the student's scores in mid-term quizzes. A modest correlation was found between a student's final exam score and mid-term exam scores. Yousuf [13] developed a multivariate linear regression model to predict student academic performance in Computer Science and Engineering Technology programs. The predictor/independent variables of Yousuf's model [13] included a student's career self-efficacy belief, math-SAT scores, high school GPA, and vocational interest. The results showed that self-efficacy contributed unique variance in prediction of student academic performance.

Objective, Scope, and Research Questions of the Present Study

The objective of the present study is to develop a validated set of multivariate linear regression models to predict student academic performance in an Engineering Dynamics course. The outcome/dependent variable (namely, the output Y) of the regression models is a student's score in the comprehensive final exam of the Dynamics course. The predictor/independent variables (namely, the inputs X_1, X_2, X_3, etc.) of the regression models include a student's

- X_1: Cumulative GPA
- X_2: Grade earned in Engineering Statics (a prerequisite course)
- X_3: Grade earned in Calculus I (a prerequisite course)
- X_4: Grade earned in Calculus II (a prerequisite course)
- X_5: Grade earned in Physics (a prerequisite course)
- X_6: Score earned in Dynamics mid-exam #1
- X_7: Score earned in Dynamics mid-exam #2
- X_8: Score earned in Dynamics mid-exam #3

where X_1, X_2, X_3, X_4, and X_5 represent a student's prior achievement before the student takes the Dynamics course, and X_6, X_7, and X_8 are a direct representation of a student's learning progression and achievement in the Dynamics course during the semester before the student takes the comprehensive final exam of the course.

The scope of the present study is limited in the investigation of the effects of cognitive factors (i.e., the above-stated eight predictor variables) on student academic performance in the Engineering Dynamics course. The effects of a student's non-cognitive factors (such as learning style, self-efficacy, motivation and interest, time devoted to learning, family background, race, and many others [14]), the instructor's teaching effectiveness and preparation [15], as well as teaching and learning environment [16] on student academic performance is beyond the scope of the present study and will be dealt with in the future study.

The research questions of the present study include:

1. What are the mathematical formulas of the predictive models?
2. How accurate are the predictive models? Or how well are the predictions if the models are used for students in different semesters?
3. How well are the predictions if using only part of the eight predictor variables to develop the models? For example, how well are the predictions if using only the first six predictor variables: student GPA, test scores in four pre-requisite courses, and the test score of the first Dynamics mid-term exam? If the predictions are available at the beginning of the course or after the first (or even second) Dynamics mid-term exam, instructors would have sufficient time to take proactive measures and do not need to wait until the semester is over.

Research Method of the Present Study

A total of 239 undergraduate students in three semesters were included in the present study to develop and validate the predictive, regression-based model. The following paragraphs describe the research method step by step.

Step 1: Collected data on student academic performance in Semesters A, B, and C. Descriptive analysis was performed to develop a fundamental understanding of the collected first-hand data.

Step 2: Randomly split the full dataset collected in Semester A into a training dataset and a testing dataset. First, the students' final exam scores (maximum: 100) were divided into different levels: 100-90, 89-80, 79-70, 69-60, and below 59. Then, the training dataset was randomly chosen from 50% of the data at each level to ensure the training dataset was a good representation of all students' performance in the class. The remaining 50% of the data at each level was used as the testing dataset. In this paper, the terms of "training" and "testing" are borrowed from the terms typically used in the neural network modeling technique. "Training" dataset is the samples employed to develop a regression model. "Testing" dataset is the samples employed to test the accuracy of the developed regression model.

Step 3: Used the training dataset to develop multivariate linear regression models, based on a different combination of predictor variables:

Model #1: predictor variables are X_1, X_2, X_3, X_4, and X_5
Model #2: predictor variables are X_1, X_2, X_3, X_4, X_5, and X_6
Model #3: predictor variables are X_1, X_2, X_3, X_4, X_5, X_6, and X_7
Model #4: predictor variables are X_1, X_2, X_3, X_4, X_5, X_6, X_7, and X_8

Model #1 only accounts for a student's prior achievement before taking the Dynamics course. Model #2 considers a student's prior achievement and his/her performance in the first Dynamics mid-term exam. Model #3 considers a student's prior achievement and his/her performance in the first and second Dynamics mid-term exams. Model #4 considers a student's prior achievement and his/her performance in all the three Dynamics mid-term exams.

Step 4: Test each regression model developed in Step 3 using the corresponding testing dataset. Multiple criteria including R-square, shrinkage, and prediction accuracy were employed to test each model. Because both training and testing datasets were from the same Semester A, Step 4 was also called the "*internal validation*" of the regression models.

Step 5: Applied the regression models developed in Semester A to the full datasets collected in Semesters B and C and determined the prediction accuracy of each model. Because the models were applied to students in a different semester, Step 5 was also called the "*external validation*" of the regression models.

Data Collection and Pre-Processing

Data on student academic performance was collected from a total of 239 undergraduate students in three semesters: 128 students in Semester A, 58 students in Semester B, and 53 students in Semester C. Table 1 shows student demographics. As seen from Table 1, the majority of the 239 students were either from the mechanical and aerospace engineering major (49.8%) or from the civil and environmental engineering major (31.0%). The vast majority of students were male (85.4%), and the female students accounted for 14.6%.

Table 1. Student demographics

	Major *			Sex	
	MAE	CEE	Other	Male	Female
Semester A (n = 128)	72 (56.3%)	34 (26.5%)	22 (17.2%)	108 (84.4%)	20 (15.6%)
Semester B (n = 58)	22 (37.9%)	20 (34.5%)	16 (27.6%)	51 (87.9%)	7 (12.1%)
Semester C (n = 53)	25 (47.2%)	20 (37.7%)	8 (15.1%)	45 (84.9%)	8 (15.1%)
Total (n = 239)	119 (49.8%)	74 (31.0%)	46 (19.2%)	204 (85.4%)	35 (14.6%)

* MAE: Mechanical and aerospace engineering
CEE: Civil and environmental engineering
Other: Biological engineering, general engineering, pre-engineering, undeclared majors, etc.

For each student, nine data points were collected including the final exam score (Y) of the Dynamics course and the values of eight predictor/independent variables (from X_1 to X_8). For a three-semester total of 239 students, $239 \times 9 = 2,151$ data points were collected. The collected data (Y, X_1, X_2, X_3, …, X_8) were initially in different scales of measurements: X_1 varied from 0.00 to 4.00; X_2, X_3, X_4, and X_5 varied from A to F (letter grades); and X_6, X_7, X_8, and Y varied from 0.00 to 100.00. Before using them to establish regression equations, the collected raw data must be pre-processed, which is described in the following paragraphs.

First, all letter grades in X_2, X_3, X_4, and X_5 were converted into the corresponding numerical values, so linear regression models (other than logistic regression models) could be developed.

The conversion was based on the following scales: A = 4.00; A- = 3.67; B+ = 3.33; B = 3.00; B- = 2.67; C+ = 2.33; C = 2.00; C- = 1.67; D+ = 1.33; D = 1.00; F = 0.00.

Then, the numerical values of all data were normalized, so each data varied within the same range from 0 to 1, as shown in Table 2. The purpose of data normalization was to avoid the cases in which one variable received a high or low weight in its regression coefficient due to its initial low or large scale of measurements. The normalized value of data was calculated through dividing the initial value of the data by its maximum possible value in its same category. For instance, the maximum GPA that a student could receive is 4.00. Supposing one student earned a GPA of 3.55, the normalized GPA of that student would be 3.55 ÷ 4.00 = 0.89.

Table 2. Normalization of the collected raw data

Variables	Meaning	Initial value of data	Normalized value of data
X_1	Cumulative GPA	0.00 - 4.00 (numerical value)	0.00 - 1.00
X_2	Grade earned in Engineering Statics	Letter grade A, A-, B+, B, etc.	0.00 - 1.00
X_3	Grade earned in Calculus I	Letter grade A, A-, B+, B, etc.	0.00 - 1.00
X_4	Grade earned in Calculus II	Letter grade A, A-, B+, B, etc.	0.00 - 1.00
X_5	Grade earned in Physics	Letter grade A, A-, B+, B, etc.	0.00 - 1.00
X_6	Score earned in Dynamics mid-exam #1	0.00 - 100.00 (numerical value)	0.00 - 1.00
X_7	Score earned in Dynamics mid-exam #2	0.00 - 100.00 (numerical value)	0.00 - 1.00
X_8	Score earned in Dynamics mid-exam #3	0.00 - 100.00 (numerical value)	0.00 - 1.00
Y	Score earned in Dynamics final exam	0.00 - 100.00 (numerical value)	0.00 - 1.00

Descriptive Analysis

There exists a variety in semester to semester student body and the classroom composition. The reliability of the predictive models should be tested in different semesters. Tables 3-5 show the results of descriptive statistics of the normalized data collected in three semesters. Compared to students in Semester A, students in Semesters B and C had a lower mean and a higher standard deviation in most variables. For example, compared to students in Semester A as a whole, students in Semesters B and C had a lower cumulative GPA, a lower Statics score, a lower mid-exam #3 score, and a higher standard deviation in GPA, Statics, and mid-exam #3 score.

The above finding implies that students in Semesters B and C (as a whole) did not perform as well as students in Semester A, and that students in Semesters B and C were more diverse in their academic performance. To more clearly show the difference of student performance, Figs. 1-3 show the histograms of students' normalized final exam scores in the Dynamics course in the three semesters. In short, Semesters B and C provided two excellent “external” cases to validate the reliability of the regression models.

Table 3. Descriptive statistics of the normalized data for Semester A (n = 128)

Variable	Minimum	Maximum	Mean	Standard deviation
Cumulative GPA	0.62	1.00	0.8586	0.09569
Engineering Statics	0.40	1.00	0.8076	0.18898
Calculus I	0.40	1.00	0.7580	0.18555
Calculus II	0.40	1.00	0.7813	0.18336
Physics	0.40	1.00	0.7925	0.15960
Mid-exam #1	0.27	1.00	0.7870	0.15764
Mid-exam #2	0.44	1.00	0.7778	0.13716
Mid-exam #3	0.47	1.00	0.8477	0.12407
Final exam	0.32	1.00	0.7175	0.16683

Table 4. Descriptive statistics of the normalized data for Semester B (n=58)

Variable	Minimum	Maximum	Mean	Standard deviation
Cumulative GPA	0.51	0.99	0.8110	0.11207
Engineering Statics	0.33	1.00	0.6725	0.20628
Calculus I	0.42	1.00	0.7642	0.19330
Calculus II	0.42	1.00	0.7284	0.20030
Physics	0.19	1.00	0.7356	0.18682
Mid-exam #1	0.33	1.00	0.7109	0.18474
Mid-exam #2	0.38	1.00	0.7813	0.14446
Mid-exam #3	0.40	1.00	0.8080	0.14989
Final exam	0.33	1.00	0.6916	0.15754

Table 5. Descriptive statistics of the normalized data for Semester C (n=53)

Variable	Minimum	Maximum	Mean	Standard deviation
Cumulative GPA	0.58	1.00	0.8379	0.10613
Engineering Statics	0.00	1.00	0.7738	0.24276
Calculus I	0.42	1.00	0.7223	0.19369
Calculus II	0.00	1.00	0.7145	0.20884
Physics	0.42	1.00	0.7479	0.16748
Mid-exam #1	0.27	1.00	0.7255	0.15164
Mid-exam #2	0.31	1.00	0.7276	0.15226
Mid-exam #3	0.47	1.00	0.7709	0.15200
Final exam	0.38	1.00	0.6647	0.17726

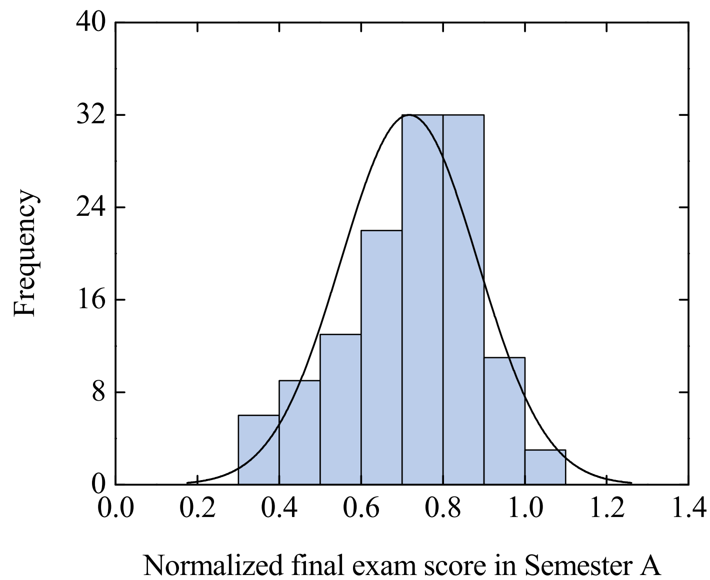


Figure 1. Histogram of students' normalized final exam scores in Semester A (n = 128)

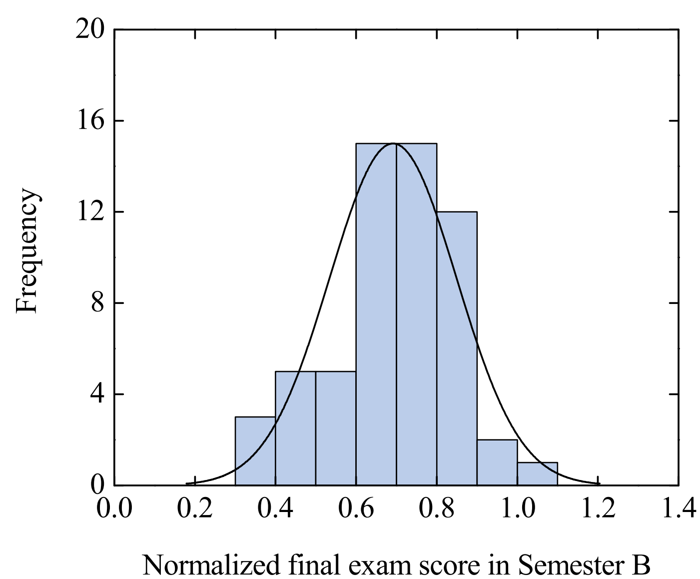


Figure 2. Histogram of students' normalized final exam scores in Semester B (n = 58)

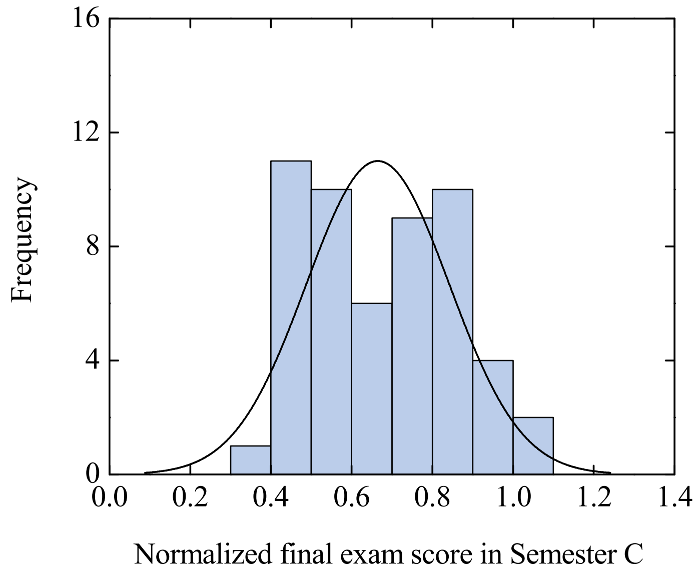


Figure 3. Histogram of students' normalized final exam scores in Semester C (n = 53)

Regression Models for Predicting Student Academic Performance

The multivariate linear regression technique was employed to develop four predictive models based on the training dataset collected in Semester A. The mathematical formula of each predictive model is expressed as:

Model #1:

$$Y_1 = 0.131 + 0.756X_1 - 0.100X_2 - 0.128X_3 - 0.011X_4 + 0.152X_5 \tag{1}$$

Model #2:

$$Y_2 = 0.031 + 0.621X_1 - 0.147X_2 - 0.093X_3 - 0.041X_4 + 0.148X_5 + 0.323X_6 \tag{2}$$

Model #3:

$$Y_3 = -0.002 + 0.607X_1 - 0.153X_2 - 0.091X_3 - 0.041X_4 + 0.148X_5 + 0.307X_6 + 0.078X_7 \tag{3}$$

Model #4:

$$\begin{aligned} Y_4 = &-0.309 + 0.556X_1 - 0.194X_2 + 0.002X_3 - 0.028X_4 + 0.102X_5 \\ &+ 0.251X_6 - 0.070X_7 + 0.591X_8 \end{aligned} \tag{4}$$

The values of the regression coefficients of predictor variables X_i were determined using the method of least squares commonly used in the multivariate linear regression technique. These values represent the expected change in Y for one unit change in X_i.

Each predictive model was evaluated using the following four criteria that involved the use of either training or testing datasets:

1) R-square value that represents the percentage that a model can explain its output based on a training dataset. The higher the R-square value, the better the model.

2) Shrinkage value that indicates the loss of predictive ability when a model is applied to other samples (i.e., testing datasets in this case). Shrinkage is calculated as

$$\text{Shrinkage} = R^2 - \left[1 - \frac{n-1}{n-k-1} \cdot \frac{n-2}{n-k-2} \cdot \frac{n+1}{n}(1-R^2)\right] \tag{5}$$

where n is the number of students, and k is the number of predictor variables in the model. The lower the shrinkage value, the better the model.

3) Average prediction accuracy for final exam scores, which indicates on average, how well a model predicts final exam scores of all students in the Dynamics course. The average prediction accuracy for final exam scores is calculated as

$$\text{Average prediction accuracy for final exam scores} = \frac{1}{n} \cdot \sum_{i=1}^{n} \left| \frac{P_i - A_i}{A_i} \right| \times 100\% \tag{6}$$

where n is the total number of predictions; P_i is the predicted final exam score of the i^{th} student in the class (i = 1 to n); and A_i is the actual final exam score of the i^{th} student. The higher the average prediction accuracy, the better the model.

4) Percentage of good predictions among all predictions. This percentage is calculated as the number of good predictions divided by the total number of predictions. In the present study, a good prediction is defined as the one with the prediction error of ±10%, that is, the predicted value is within 90-110% of the actual value. The higher the percentage of good predictions, the better the model.

Table 6 summarizes the comparison of the four models. The full dataset (n = 128) collected in Semester A was evenly split into the training dataset (n = 64) to develop the predictive model and the testing dataset (n = 64) to "internally" validate the predictive model. As seen from Table 6, the average prediction accuracy varies within only 2% (minimum: 88.7% for Model #1; maximum: 90.7% for Model #4) among the four predictive models. However, the percentage of good predictions varies within 9.3% from 56.3% (for Models #2 and #3) to 65.6% (for Model #4). In terms of both the average prediction accuracy and the percentage of good predictions, Model #4 − which includes all the eight predictor variables − is apparently the mathematically best model among the four models.

Table 6. Predictive models developed based on the dataset collected in Semester A

Predictive model	Using the training dataset (n = 64)	Internal validation using the testing dataset (n= 64)		
	R-square	Shrinkage	Average prediction accuracy (%)	Percentage (%) of good predictions among all predictions
#1	0.175	0.165	88.7	57.8
#2	0.256	0.181	89.4	56.3
#3	0.258	0.214	89.7	56.3
#4	0.403	0.200	90.7	65.6

External Validation of the Developed Regression Models

The external validation of the above-developed predictive models was conducted based on the data collected in Semesters B and C. The results are summarized in Table 7. To make comparisons clearer, part of the internal validation results that have been provided in Table 6 is also included in Table 7.

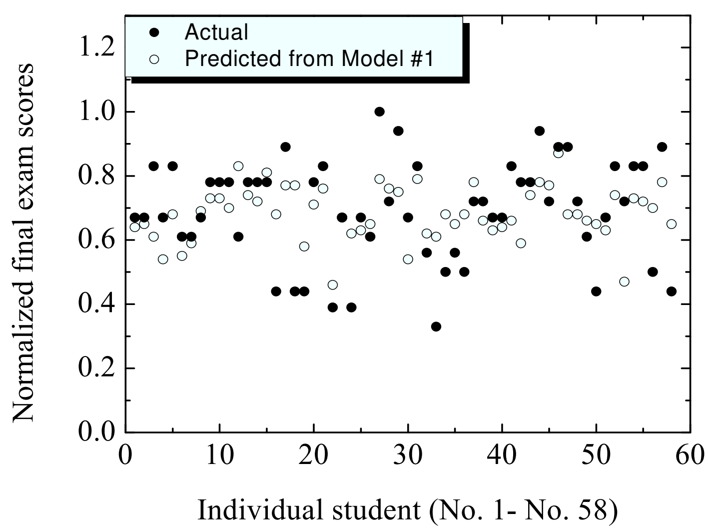
Table 7. Validation of the developed predictive models

Predictive model	Average prediction accuracy (%)			Percentage (%) of good predictions		
	Internal validation (Semester A, testing dataset n = 64)	External validation (Semester B, full dataset n = 58)	External validation (Semester C, full dataset n = 53)	Internal validation (Semester A, testing dataset n = 64)	External validation (Semester B, full dataset n = 58)	External validation (Semester C, full dataset n = 53)
#1	88.7	89.1	86.8	57.8	55.2	44.4
#2	89.4	89.3	88.0	56.3	53.5	46.3
#3	89.7	89.8	88.0	56.3	56.9	50.0
#4	90.7	89.8	88.6	65.6	56.9	56.6

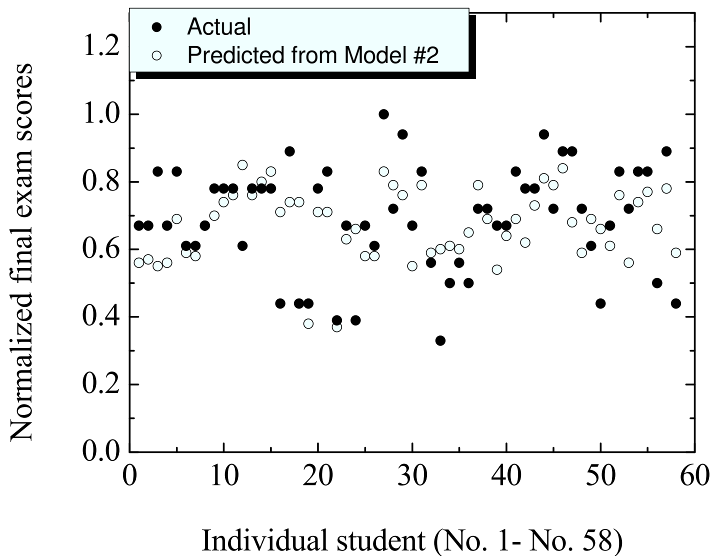
As seen from Table 7, the prediction accuracy of the developed regression models slightly varied when they were applied to different semesters for external validation. The average prediction accuracy slightly varied within a range from -2.1% (Model #4 applied to Semester C) to 0.4% (Model #1 applied to Semester B). However, in the majority of cases, the percentage of good prediction was reduced by a relatively wide range from -2.6% (Model #1 applied to Semester B) to -13.4% (Model #1 applied to Semester C). The only case that the prediction accuracy increased was the one in which Model #3 was applied to Semester B.

Based on the results of both internal and external validation in the three semesters, it can be found that the developed predictive models have the average prediction accuracy of 86.8%-90.7%, and generate good predictions of 44.4%-65.6% (again, a good prediction is defined as the one with the prediction error of ±10%). In addition, Model #4 − which includes all the eight predictor variables − is apparently the mathematically best model among the four models.

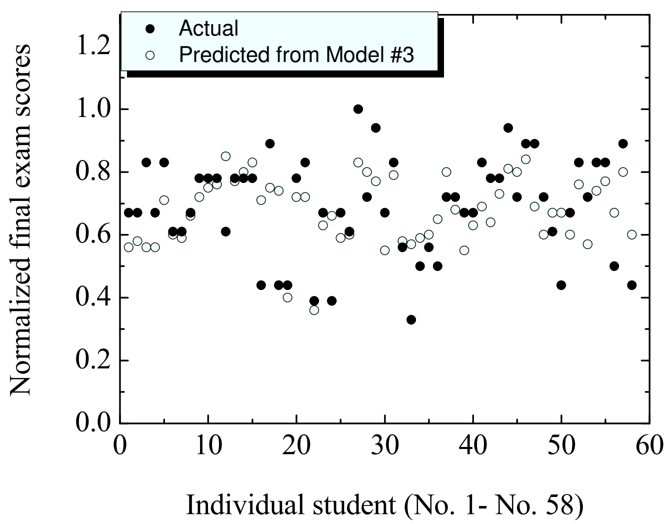
As four representative examples, Figs. 4a) – 4d) show the predicted and actual normalized final exam scores for each of the 58 students in Semester B, based on Models #1, #2, #3, and #4, respectively. In Fig. 4, each student was associated with two data points: a solid symbol for the actual final exam score and an open symbol (above or below the solid symbol in the same vertical line) for the predicted final exam score.



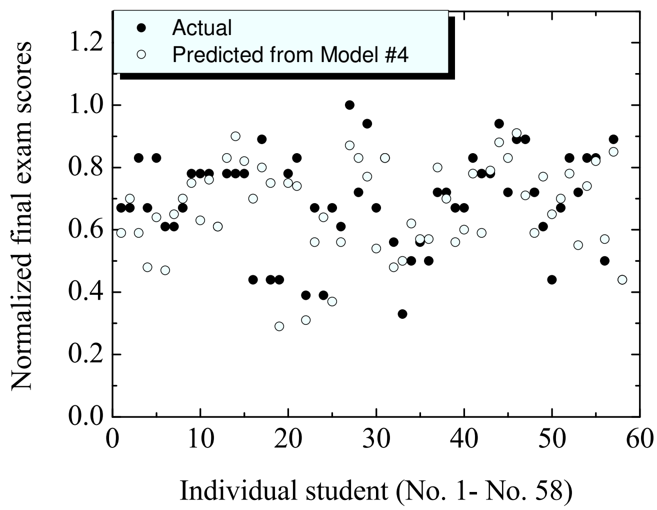
a) Model #1



b) Model #2



c) Model #3



d) Model #4

Figure 4. Comparison of the predicted and actual normalized final exam scores for the 58 students in Semester B.

Implications of the Research Findings

The research findings from the present study imply that if an instructor would like to predict the "average" academic performance of all students in his/her Dynamics class, the instructor can choose any one of the four predictive models (#1, #2, #3, or #4) to use. The average prediction accuracy of these models only slightly varies. For this application, Model #1 − which only takes into account a student's prior achievement before the student takes the Dynamics course − is the most useful model because it can be used even before a semester begins and thus the instructor has sufficient time to consider what proactive measures s/he will use in the new semester.

However, if an instructor wants to generate a large number of good predictions, so s/he can focus on individual students, particularly those "academically at risk" students, Model #1 should not be used because of its lowest percentage of good predictions. Either Model #2 or Model #3 can be used after the first or second mid-term exams because both models have moderate predictability to generate good predictions. For example, if Model #2 or Model #3 predicts that a student will receive a final exam score below 50 (out of 100), the student will be identified as a potential "academically at-risk" student. The student will be first interviewed and their classroom performance will be observed, so the instructor can develop a clear understanding of the student's learning abilities and difficulties. Based on the instructor's judgment, additional instructional interventions may be implemented on that student. The examples of additional instructional interventions may include one-on-one tutoring and review on the most important concepts and principles after the class, assigning more representative technical problems for the student to practice, providing remedy lessons to improve the student's mathematical level, and asking the student to re-study the old topics that the student learned in the previous relevant courses. Computer simulations and visualization of Dynamics problems will also help the student learn better. A detailed discussion on these instructional interventions is beyond the scope of this paper.

Although Model #4 is the mathematically best among the four models, it can be used only after the third exam when the semester is almost over and intervention for the at-risk students is difficult. In this sense, the primary application of Model #4 might be "interpretation" rather than "prediction," which means Model #4 can be used to "explain" how each of the eight predictor variables affects a student's final exam score.

To increase the percentage of good predictions, a student's non-cognitive factors (such as learning style, self-efficacy, motivation and interest, and many others [14]), the instructor's teaching effectiveness and preparation [15], as well as teaching and learning environment [16] on student academic performance will be included in the future modeling work. In addition, the models developed in the present study are based on the data collected in the Dynamics course that was taught in a consistent manner by the same instructor (the second author of this paper) with the same exam grading criteria. Therefore, the effect of teacher variability is not taken into consideration in the models. It can be expected that a significant amount of future work is required to take all the stated non-cognitive factors and teacher variability into considerations due to the extreme complexity of student learning.

Finally, it must be pointed out that the predictive models developed in this paper were based on the data collected at our public university. The developed models can be employed as a general tool to predict student academic performance in the Dynamics course, so they can benefit both teaching and learning. When extending the regression technique to another institution of higher learning, it is suggested to collect the data on student academic performance at that particular institution to develop a corresponding regression model. This will ensure that the regression model best represents teaching and learning at that particular institution.

Conclusions

Prediction of student academic performance helps instructors develop a good understanding of how well or how poorly the students in their classes will perform, so instructors can take proactive measures to improve student learning. The present study has addressed three research questions through quantitative modeling and analysis. The answers to the three questions are summarized in the following paragraphs.

Based on a total of 2,151 data points collected from 239 students in three semesters, four multivariate linear regression models (Eqs. 1-4) have been developed in the present study to predict student academic performance in an Engineering Dynamics course. The inputs (predictor/independent variables) of the models include a student's cumulative GPA; grades earned in Engineering Statics, Calculus I, Calculus II, and Physics; as well as scores earned in three Dynamics mid-exams. The output (outcome/dependent variable) of the models is a student's final exam score in the Dynamics course.

Multiple criteria have been employed to evaluate and validate the developed predictive models, including R-square, shrinkage, the average prediction accuracy, and the percentage of good predictions. Descriptive analysis shows that students in Semesters B and C (as a whole) did not perform as well as students in Semester A, and shows that students in Semesters B and C were more diverse in their academic performance. Thus, Semesters B and C provided two excellent "external" cases to validate the reliability of the predictive models developed from the data collected in Semester A. In terms of both the average prediction accuracy and the percentage of good predictions, Model #4 − which includes all the eight predictor variables − is apparently the mathematically best model among the four models.

The results of both internal and external validation show that the developed predictive models have the average prediction accuracy of 86.8%-90.7% and generate good predictions of 44.4%-65.6%. If an instructor would like to predict the "average" academic performance of all students in his/her Dynamics class, the instructor can choose Model #1 (based only on previous coursework) because it can be used even before a semester begins and thus the instructor has sufficient time to consider what proactive measures s/he will use in the new semester. If an instructor wants to generate a large number of good predictions, so the instructor can focus on individual students, particularly those "academically at risk" students, Model #2 or Model #3 − which has moderate predictability to generate good predictions − can be used after the first or second mid-term exams.

Finally, while the present study focuses on the engineering dynamics course, the methodology developed in this paper is applicable throughout the typical mechanics course sequence (statics, dynamics, mechanics of materials, and vibrations).

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