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Development of an Early Alert System to Predict Students At Risk of Failing Based on Their Early Course Activities

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DEVELOPMENT OF AN EARLY ALERT SYSTEM TO PREDICT STUDENTS AT RISK OF FAILING BASED ON THEIR EARLY COURSE ACTIVITIES

Abstract

The emphasis on increasing student retention and graduation rates at institutions of higher education is driving the need for creation and implementation of early alert systems. Such early alert systems could be used in identifying students in academic trouble before failure. Early identification of students who are at a risk of dropping or failing a course will help instructors to adapt their course delivering techniques with student's learning styles and improve overall performance of a class. This paper discusses an early alert system to identify students who are at risk of failure based on their activity at the beginning of semester.

The proposed alert system considers various indicators, including the homework assignments and the mid-term exam corresponding to the first quarter, along with in-class participation as input parameters. Data collected in large sections of Mechanics of Materials course over four semesters were employed for development and validation of the early alert system. The data analysis showed that the proposed model is capable of predicting the final scores of the students with an acceptable accuracy (R^2=0.69). Feasibility of using the model was also validated using over 100 additional data points, which were randomly selected from the initial dataset. Good correlation was observed between the data and model predictions, with over 94% of the data points falling within the limits of a 90% confidence interval. The proposed model has possible implications in the similar

engineering courses provided that the required data are collected during early semester activities. This tool enables the instructor to detect and reach out to the at-risk student and provide proactive assistance, so that they are able to succeed in the course. Proactive assistance may include referrals to appropriate resources, providing tailored activities to improve the weakness of students and one-to-one academic skill building workshops.

Keywords: Academic assessment, Engineering course, Regression analysis, Prediction model, Early alert system

Introduction

Development of prediction tools to monitor the performance of students in fundamental courses has been a topic of interest in academic environments (Meier et al. 2016). Incorporation of such tools can help instructors to identify the students at the risk of failure at early stage of the semester. Knowing the students in risk of failing, enables the instructor to consider adaptive teaching techniques by means of taking proactive steps and concentrating on their progress, as well as considering necessary measures, including more office hours, one-to-one meetings and discussions, additional question and answer sessions, etc. Moreover, availability of such prediction tools makes it possible for the instructors to have a realistic understanding of the overall efficiency of learning process in class, which may eventually lead into updating the teaching strategies (Li et al. 2012).

Sophomore and junior students of engineering disciplines are usually needed to take various engineering core courses that may not be directly related to their major. Engineering core courses such as Statics, Dynamics, Mechanics of Materials, Thermodynamics, and Electrical Networks often provide the first real taste of engineering for students. Mechanics of Materials is one of the fundamental courses for various engineering disciplines that bridges the basic entry level college courses to the more advanced analysis and design ones. As an example, in the case of the civil and structural engineering students, the Mechanics of Materials is the pre-requisite for the structural analysis, and therefore the structural design courses, including the steel structures design, reinforced concrete structures design, etc. All students of civil, architectural, structural, aerospace, nuclear, petroleum, geological, and mechanical engineering, along with most of other engineering students need to take this course as a mandatory part of the undergraduate student's curriculum.

One of the most difficult tasks that an instructor can undertake is the engineering core courses, in which a large number of students are not majoring the subject, and are just trying to survive the course and move on. In some cases, students are not really interested in the course itself, and just feel the need to pass this course as part of mandatory curriculum of the university. This prevents students from working on the course enthusiastically and makes it difficult for them to put enough effort. Development of an early alert system provides instructors of such courses with an educational tool to predict students' performance, take a proactive role and eventually enhance class performance and student retention rates by the end of semester. A variety of analytical techniques, including neural networks, genetic algorithm, decision trees, and regression methods have been incorporated to develop tools for predicting the academic performance of students (Cohn et al. 2004). Given the simplicity and considering the natural correlations between the input factors and outputs, i.e. the final score, multivariate linear regression models are considered as one of the most reliable and widely used methods of analysis. Huang and Fang (2013) developed models based on multiple linear regression to predict the performance of students in Engineering Dynamics course. The authors considered the students' grade point average (GPA), grades earned in Engineering Statics, Calculus I and II, and Physics courses, as well as the scores earned in three Dynamics mid-term exams as input parameters to model the score in final exam of a total number of 239 students enrolled in three semesters. Green (2005) developed linear regression models to predict the final exam scores of the students enrolled in mechanical engineering courses based on their performance at mid-term quizzes.

Most of the previous studies have considered establishing correlations between the test scores and academic records of previous semesters and pre-requisite courses, and the end-of-semester scores of a certain course (Ashenafi et al. 2015). Obtaining such data will require permission to access the academic records of the students which may need a considerable load of paper work and time. However, the methodology investigated at this research is only based on the early semester activities of the students in the course without requiring any information about the past performance of students.

Objective and Scope of the Study

The present study aims at developing a prediction tool for identifying the students who are at risk of failure. In many fundamental courses like the Mechanics of Materials, the overall course attributes and goals, and the basic concepts of analysis are introduced at the first quarter of the semester. These concepts and back-bone theories will then be utilized throughout the semester to get into more advanced details of analysis, as well as more practical applications. As an example, and in the case of the Mechanics of Materials course, which is the test bed for the present study, basic concepts, including the definitions of stress and strain, mechanical properties of materials, design concepts of axial members, etc. are covered during the first quarter of the semester and form the basis of understanding the rest of analytical concepts of the course. The hypothesis of the present study is that the performance of students at the beginning of semester could provide a reliable tool for predicting the overall performance of the students throughout the semester as well as the final score by the end of the semester. Even though the model presented in this research is developed based on the data collected in Mechanics of Materials, the developed methodology can be extended to other courses with similar formative and summative assessments.

The present study incorporates various Student Performance Indexes (SPI) as input parameters of the prediction model: (1) scores earned through the first quarter of homework assignments; (2) student grades in the first mid-term exam, corresponding to the first quarter of the course materials; (3) the participation of the students in class activities, which were assessed by in-class practice problems. The output was the end-of-semester score of the students, estimated based on the early semester performances. Data obtained from performance of students enrolled in Mechanics of Materials course in a 4-year public university are incorporated as the test bed.

Research Method

Data collected during four semesters of spring 2015, fall 2015, spring 2016, and fall 2016 were considered in the study. Table 1 presents a breakdown of the demographic information of the students during the period of analysis. In total, over 500 data points were collected and analyzed.

Grades obtained for various homework assignments, mid-term exams, and percent accomplishment of the bonus questions were considered as the main input parameters for each student. The homework assignments covering the first quarter of the semester that were included in this study consisted of “HW1: mechanical properties of materials”, “HW2: design concepts and indeterminate axial members”, and “HW3: torsion- stress and twist”, and “HW4: torsion-power transmission and indeterminate torsion”. The homework assignments were all designed by the instructor, with no repeated question through the semesters. The first mid-term exam also covered the same topics. An online quiz system was incorporated as a formative assessment tool for monitoring the class activities. The in-class activities were covering a wide range of problems, from easy questions to promote engagement of all students, to more difficult ones to promote further thinking about the materials covered during the class.

Table 1- Demographic information of the students

	Distribution by major (%)				Final score distribution (%)				
Semester	CARE*	MAE**	NUC***	Other****	A	B	C	D	F
Fall 2015	8	47	8	37	27	20	30	13	10
Spring 2015	11	30	4	55	29	26	28	11	6
Fall 2016	8	56	6	30	33	25	25	11	6
Spring 2016	13	41	9	37	35	22	28	9	6

*Civil, architectural, and environmental engineering
**Mechanical and aerospace engineering
***Nuclear engineering
****Geological engineering, engineering management, petroleum engineering, economics, metallurgical engineering, ceramic engineering

The weight of each student performance index on the final course grade has changed slightly during the semesters. Therefore, the scores obtained for each of the introduced factors were normalized to a scale of 100. It is also worthy to mention that a total number of four mid-term exams and 12 homework assignments were considered for each of the aforementioned semesters. Homework grades accounted for 25% of the end-of-semester score, while the mid-term exam constituted about 46% of the end-of-semester score, and the remaining 29% was considered for the final exam. The bonus scores were added to the total 100% and capped at 7% of total possible score.

Figure 1 presents the histogram of the students' end-of-semester grades for the investigated semesters. The Anderson-Darling test was conducted to ensure the normal distribution of the final scores at 0.10 significance level. Statistical analysis relies on the fact that a calculated P-value less than the significance level means that the factor or the interaction between factors will be statistically significant while a P-value greater than α=0.10 threshold reveals the fact that such particular factor or interaction will not be statistically significant (Sadati et al. 2016). In other words, P-value less than 0.10 means that there is less than 10% chance that the observed behavior is due to noise, ensuring that the effect will be statistically significant. The P-values obtained for different semesters were <0.01 for the spring 2016, fall 2016, spring 2015 semesters and 0.008 for the fall 2015. The P-values of less than 0.10 support the fact that the investigated data followed a normal distribution.

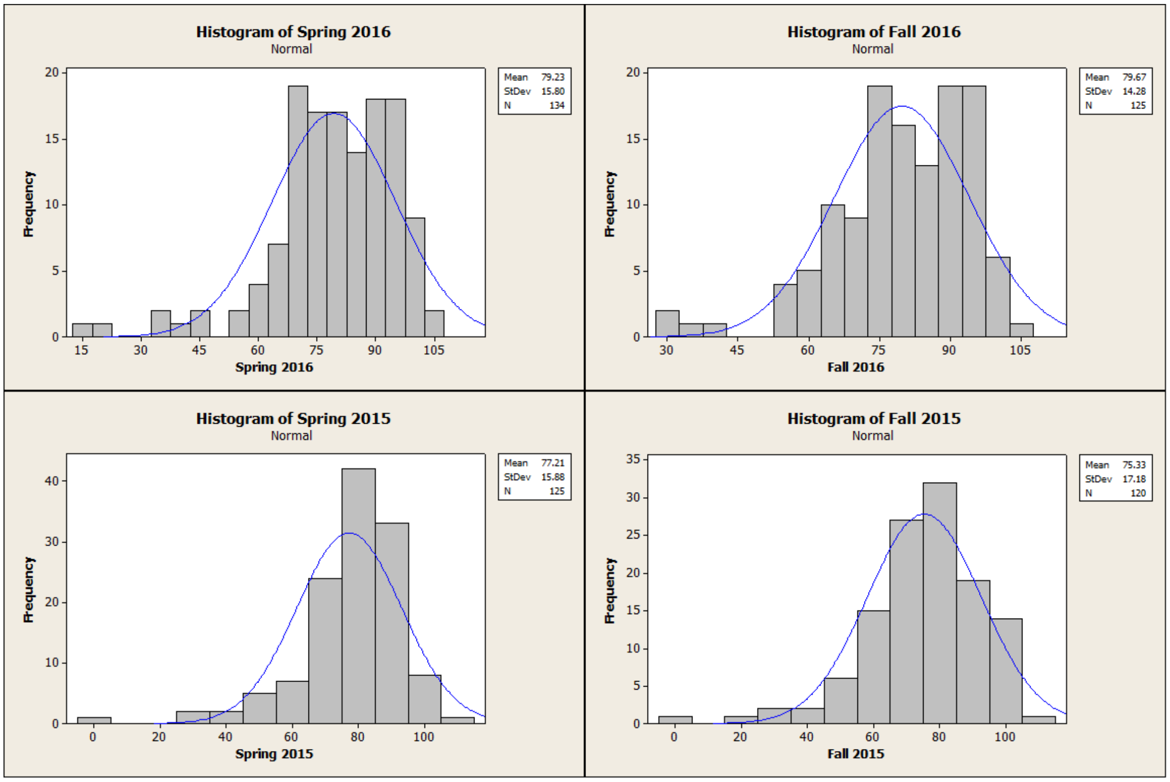

Figure 1- Histogram of students' final scores for the investigated semesters

In this study, a linear combination of input parameters was employed to form the end-of-semester score of the students. Assuming that the learning and performance of students follow a similar pattern during the four quarters of a semester, one can expect the use of a simple linear model for prediction of the performance based on the observations recording in the first quarter. It is suggested in present study to summarize the performance of students in first quarter of the semester with a Quarterly Performance Index (QPI). Three scenarios were investigated for developing the QPI as follows:

1. Developing a normalized QPI based on the homework assignments of the first quarter (QPI1) as presented in Equation 1:

$$QPI_1 = \alpha \sum_{i=1}^{4} HW_i \quad (1)$$

2. Developing the QPI based on the early semester homework assignments and the first midterm exam (QPI2) as presented in Equation 2:

$$QPI_1 = \alpha \times (\beta \sum_{i=1}^{4} HW_i + \gamma MT_1) \quad (2)$$

3. Developing the QPI based on the early semester homework assignments, the first midterm exam (MT1), and the average earned bonus scores (QPI3) as presented in Equation 3:

$$QPI_1 = \alpha \times \left(\beta \sum_{i=1}^{4} HW_i + \gamma MT_1 \right) + \delta BQ \quad (3)$$

where HW_i is the score for the i^{th} homework, MT_1 is the score earned for the first mid-term exam, BQ is the added points related to the bonus questions, and α, β, γ, and δ are the coefficients determined based on the weight of different elements of the final score.

Moreover, the potential correlations between different scenarios of QPI and the second and the third mid-term exams (MT2 and MT3), the correlations between the mid-term exams, the correlations between QPIs and the final exam (FE), the correlation between the in-class practice performance and the mid-term and final scores, and the correlations between the QPIs and the final (end-of-semester) score were investigated. Table 2 offers a summary of the regression results.

Several uncertainties are affecting the correlations between each of the constituents of the end-of-semester score. This may result in relatively weak correlations between such factors. For instance, the correlation between the MT1 and MT2 exhibited a R^2 of 0.25. Moreover, the correlation between the bonus activities and the mid-term exams revealed R^2 squares of less than 0.1. However, satisfactory correlations were observed in the case of the defined QPIs and the final scores, with R^2 values of 0.40, 0.63, and 0.67 in the case of the scenarios of QPI1, QPI2, and QPI3, respectively. Figures 2-4 present the correlations between different QPIs with end-of-semester scores of the students.

Table 2- Values of R^2 for the linear correlations between various investigated factors

	Mid-term 1	Mid-term 2	Mid-term 3	Mid-term 4	Final Exam	Final Score
QPI1	0.09	0.15	0.12	0.10	0.15	0.40
QPI2	NA	0.31	0.31	0.31	0.38	0.63
QPI3	NA	0.32	0.31	0.32	0.40	0.67
Mid-term 1	NA	0.25	0.27	0.28	0.33	0.43
Mid-term 2	NA	NA	0.34	0.40	0.38	0.55
Mid-term 3	NA	NA	NA	0.47	0.54	0.63
Mid-term 4	NA	NA	NA	NA	0.1	0.68
Bonus	0.03	0.08	0.04	0.14	0.13	0.24

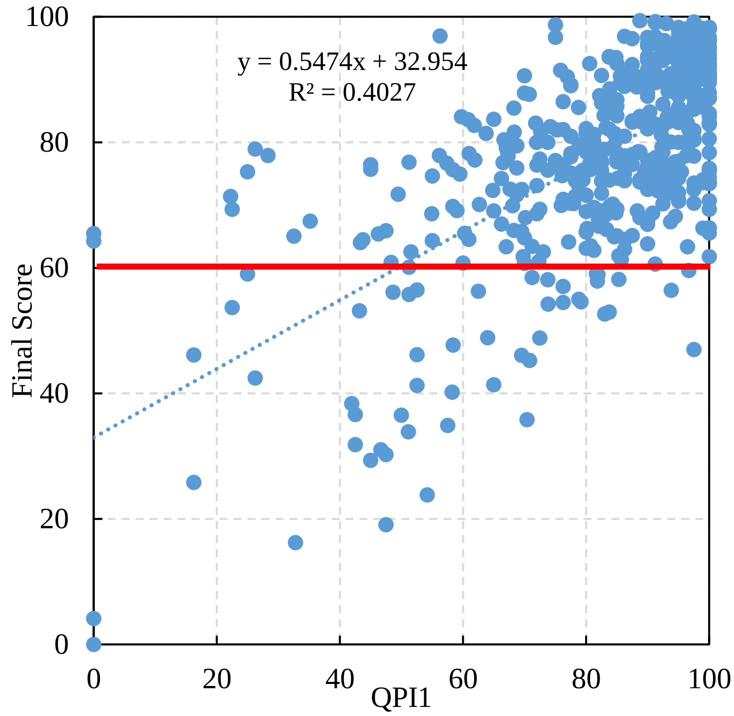

Figure 2- Correlation between QPI1 and final scores of the students

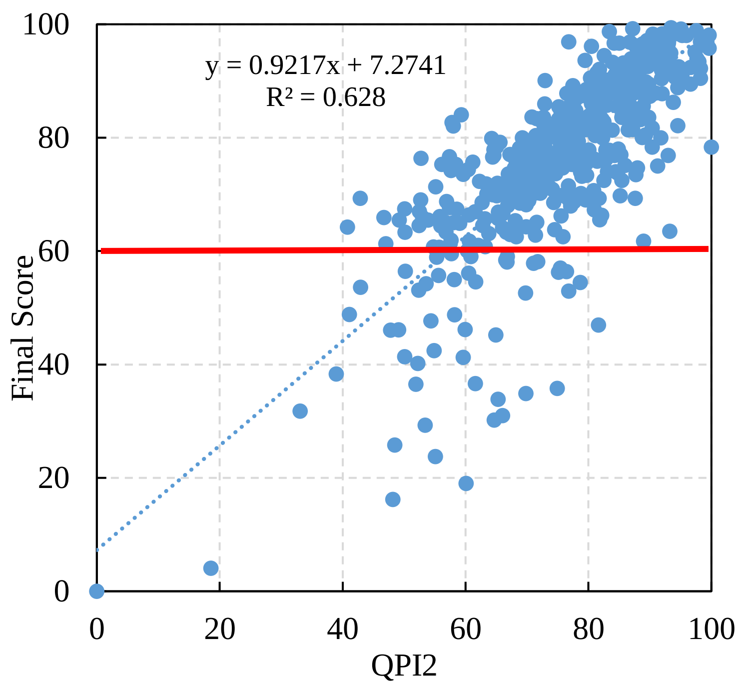

Figure 3- Correlation between QPI2 and final scores of the students

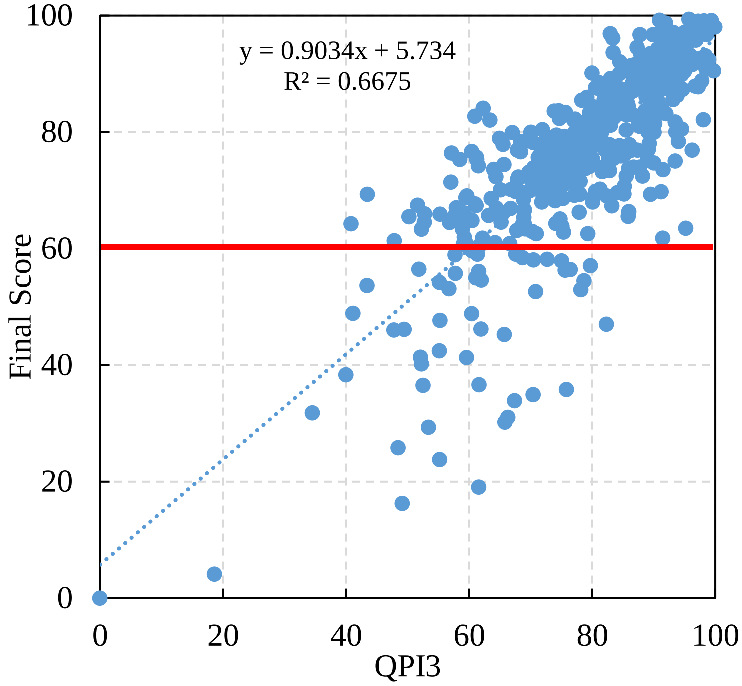

Figure 4- Correlation between QPI3 and final scores of the students

The strong correlation between the QPIs and the final score is in agreement with the hypothesis of assuming a correlation between the early semester performances of students, with their end-of-semester score. Such a correlation demonstrates the importance of monitoring the initial performance of students and emphasizes the effect of understanding the basic concepts and background theories on overall understanding of the more advanced topics of such fundamental courses.

Table 3 summarizes the correlations between various QPIs within different ranges (with 20 scores steps) and the probability of failing the course. More than 63% of the students who failed the course exhibited QPI1value of less than 60. In addition, 61% of the students who failed the course had QPI2 and QPI3 values of less than 60. Moreover, it was observed that over 92% of the students failing the course exhibited QPI values of less than 80, while in 99% of failure cases QPI2 and QPI3 of less than 80 was observed.

Table 3- Distribution and probability of failing the course based on each category of QPIs

	0 - 20	20 - 40	40 -60	60 - 80	80 - 100
QPI1	2 (5%)	4 (11%)	17 (47%)	10 (28%)	3 (8%)
QPI2	2 (5%)	2 (6%)	18 (50%)	13 (36%)	1 (3%)
QPI3	2 (5%)	2 (6%)	18 (50%)	13 (36%)	1 (3%)

Development of Prediction Tool

Given the satisfactory correlation between the investigated QPIs and the end-of-semester scores, the hypothesis of considering linear correlation between the performance of students in the first quarter and the rest of semester was incorporated for development of a prediction tool. Linear regression analysis was incorporated to establish correlations between the early semester performance and the end-of-semester score as suggested in Equation 4.

$$Final\ Score = \alpha_0 + \sum_{i=1}^{n} \alpha_i HW_i + \beta MT_1 + \gamma BQ \tag{4}$$

Where α_i, β and γ are the regression coefficients, HW_is are the scores corresponding to each of the homework assignments, MT_1 is the score obtained from the first mid-term exam, and BQ is the score obtained from in-class performance, i.e. bonus questions.

Initially, 80% of the available data points were randomly selected and used for the linear regression analysis and development of the prediction model. Rest of the data were then utilized to validate the observations. A statistical analysis tool (Minitab 16) was used for performing the regression analysis. In addition, analysis of variance (ANOVA) was conducted at 0.10 significance level to examine the incorporated input and output values. Table 4 offers a summary of the regression and the ANOVA results.

Table 4- Summary of the regression coefficients and ANOVA results

Term	Regression	Lower 90% CI	Upper 90% CI	P-value	F-value	VIF
Intercept	13.4569	9.12893	17.7848	0.000	145.151	-
HW1	-0.0020	-0.04536	0.0415	0.941	0.006	1.49585
HW2	0.1117	0.07838	0.1451	0.000	30.491	1.52507
HW3	0.0628	0.02680	0.0989	0.004	8.266	1.50078
HW4	0.0776	0.04701	0.1083	0.000	17.470	1.42658
MT1	0.5211	0.47551	0.5668	0.000	354.500	1.08044
BQ	2.1138	1.68266	2.5450	0.000	65.336	1.23224

The P-value of all considered input parameters were lower than 0.10, indicating significant effects on the observed end-of-semester scores. The only exception was the HW1, with P-value of 0.941 which is higher than the 0.10 significance. Statistically, it means that the final score is less impacted by the student performance in their very first homework. This is justified by the fact that the first homework assignment in the studied course consist of introductory questions that are used as warm-up homework to present students with the online homework system.

Given the natural variations of students performance as well as the limitations on the studied semester, obtained coefficients of determination of R^2=0.69 and Adjusted-R^2= 0.68 indicate that the model has satisfactory accuracy for predicting the performances. It should be noted that the limited variation between the values obtained for R^2 and Adjusted-R^2 reveals the fact that proper number of variables are included in the developed model.

Considering the probability of correlations between the input parameters, i.e. the performance of students at different assessments, possibility of multi co-linearity was investigated in developing the model. Variable inflation factor (VIF) with values limited to 1.5 (as presented in Table 4) suggest negligible co-linearity between the input parameters, therefore approving the reliability of the observations (Montgomery 2008). The low value of regression coefficient obtained for the first homework assignment, indicates that the effect of this input parameter on the final score is negligible, which is in agreement with previous findings. On the other hand, the relatively higher regression coefficients obtained for the first mid-term exam and the in-class participation, along with very low P-value obtained for these parameters highlight the importance of these factors on predicting the final performance of the students. An important observation is a high regression coefficient value obtained for in-class practice problems; it shows that students who were more involved in in-class practice problems become more successful on the final exam. Even though the bonus point assigned for in-class practice problems is very low compared to the total course score, such a high regression coefficient shows the importance of student participation in class activities on their learning throughout the semester. Equation 5 summarizes the regression results.

$$\begin{aligned} Final\ Score = {} & 13.4569 + 0.1117\times HW_2 + 0.0628\times HW_3 + 0.0776\times HW_4 \\ & + 0.5211\times MT_1 + 2.1138\times BQ \end{aligned} \tag{5}$$

Model validation

As stated earlier, 20% of the data points were considered for the model validation. Figure 5 compare the students' end-of-semester scores with the values predicted using Equation 5, along with the 90% confidence intervals. Good correlation was observed between the measured data and the predicted values. More than 94% of the verification data points were within the limits of the 90% confidence interval, indicating the acceptable predictions by the developed model.

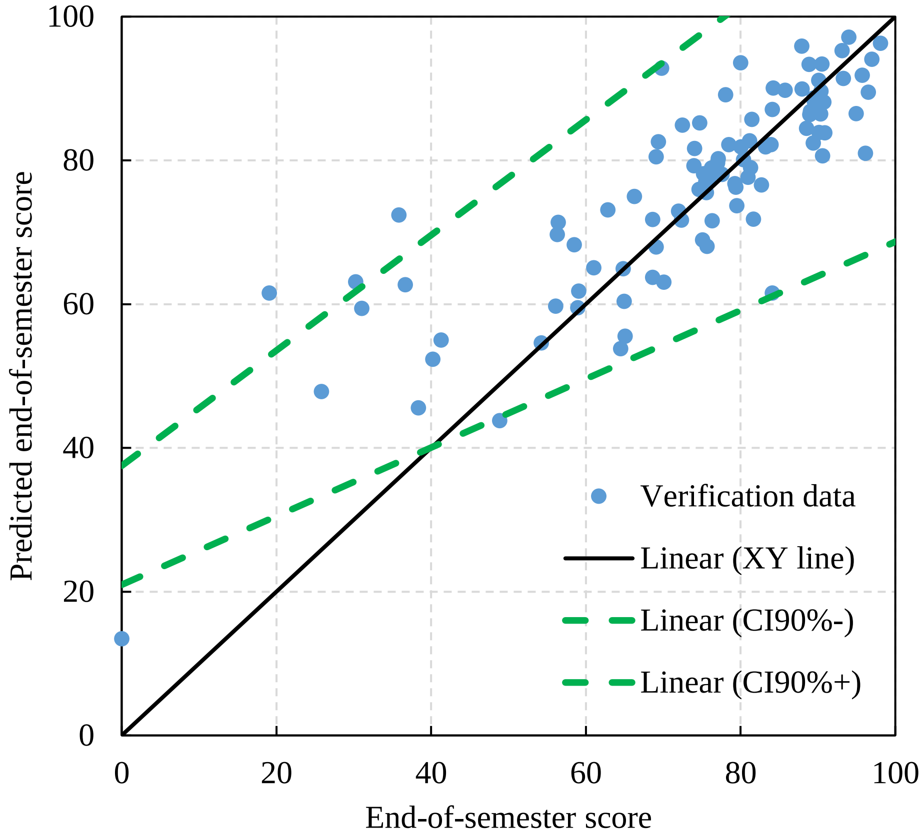

Figure 6- Predicted scores compared to the students' end-of-semester scores

Conclusions

The present research addresses the issue of predicting performance of students at risk of failure in engineering courses, within a test bed of Mechanics of Materials course. The goal was to develop an early alert system, to predict the end-of-semester score of students based on their early semester activities. The developed model enables instructors to detect students who are in risk of failing and help them plan proactive approaches to be successful in the course. Data obtained within a period of four semesters were incorporated for development and validation of the model. Based on the obtained data, the following conclusions are warranted:

- Student's performance at the beginning of semester is highly correlated to their performance throughout the semester. This enables developing an early alert system by monitoring students at the beginning of semester.
- Early semester homework assignments, mid-term exams, and in-class practice problems can be employed as Students Performance Indicators (SPI) for developing the prediction model.
- Among the considered SPIs, the in-class practice problem indicator that reflects the active involvement of students in class exercises showed the highest regression coefficient. This emphasizes the importance of student's participation in class activities on their learning throughout the semester.
- The developed model was capable of predicting the performance of the students with acceptable accuracy (R^2=0.69). The model validation analysis revealed that the developed model has successfully predicted the end-of-semester score of students. More than 94% of

the verification data points were within the limits of the 90% confidence interval, indicating satisfactory predictions by the developed model.

- Overall, this research has developed a reliable prediction model as an early alert system for Mechanics of Materials course. While the prediction model and studies described in this research is implemented and validated for a specific course, it can be extended to other engineering core courses. This educational tool is specifically important in courses offered in large sections in which instructors deal with a large group of students.

Future work

The results obtained through this investigation were incorporated to monitor the performance of over 370 students enrolled in the mechanics of materials course at Missouri University of Science and Technology, during spring 2017 semester. Students at risk of failing the course were identified and more time and focus was devoted to enhance their performances. Data obtained from performance of these students (over 370 students) will be added to the current database by the end of spring semester, 2017. Result will be updated and the proposed model will be verified with new data. In addition, performance of students on different types of in-class practice questions, effect of virtual lectures, and class attendance will be included in future models.

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