

Modeling for Educational Enhancement and Assessment^{*}

Mary Besterfield-Sacre¹, Larry Shuman¹, Harvey Wolfe¹, Alejandro Scalise²,
Siripen Larpkittaworn¹, Obinna S Muogboh¹, Dan Budny¹, Ronald Miller³
and Barbara Olds³

¹University of Pittsburgh/²TransSolutions/³Colorado School of Mines

Abstract

Industrial engineering programs have typically adopted the new ABET accreditation criteria with more enthusiasm than other engineering programs, in part since the principles of continuous improvement and statistical measurement are commonly taught in most curriculums, and skills such as team work and data analysis are staples of modern IE curricula. However, such complementary skills should not limit the expertise that industrial engineers use to improve engineering programs. Mathematical models can be effective tools for both enhancing learning and assessment. This paper presents a number of modeling approaches that a team, consisting primarily of industrial engineers at the University of Pittsburgh has developed in conjunction with colleagues at the Colorado School of Mines over the course of several years to demonstrate the efficacy of this approach to ABET's requirement of continuous improvement. Using both logistic regression analysis and various neural network algorithms, we have employed empirical modeling to successfully improve retention in engineering, predict probation during the first year, and determine proper placement in math courses. We are also in the early stages of developing similar models to determine a student's intellectual development, determine student achievement based on students' attitudes towards engineering and themselves, as well as predict various EC 2000 outcomes based on students' attitudes. We describe each of these models separately in this paper to emphasize the need for modeling as a viable tool for evaluation in engineering education.

Introduction

The Accreditation Board for Engineering and Technology's (ABET) performance-based criteria, "EC 2000," require that each engineering program's faculty implement and maintain a closed-loop, continuous improvement system [1]. As part of that system, faculty must demonstrate that the program's graduates have, in fact, acquired certain knowledge and skills including a minimum set of eleven outcomes. In addition, the system must be flexible enough to allow for the continuous identification of areas for improvement and the ability to measure resultant improvements. Understanding the direct and indirect relationships among student attributes and outcomes is crucial because such knowledge can provide the foundation for continuous improvement in engineering education and a key to realizing the promise of the new ABET criteria. Industrial engineering departments possess and teach many of the skills necessary to be successful in the new ABET perspective, specifically statistics and quality management techniques. This paper focuses on another set of valuable skills – that of empirical modeling, which can be employed to achieve the objectives of the new accreditation criteria.

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One ultimate objective would be the ability to track students from the point that they enter engineering through graduation, measuring achievement of various outcomes at different points in their education. In doing this we may wish to address certain questions, including:

- To what extent can we predict retention of students?
- Which students will go on first-term probation?
- Can students be properly placed into critical courses such as Calculus to ensure success during the first year?
- Can we measure a student's intellectual development over the course of four years?
- Can we determine how GPA is influenced by the achievement of various educational outcomes? and
- Can we classify students' level of achievement based on their attitudes toward engineering?

These are all issues that can be addressed by modeling. This paper describes six such empirical models that have been developed to continuously improve engineering education. A team of faculty from the University of Pittsburgh and Colorado School of Mines has developed these models. In the following sections we will describe some of the models that we have developed that have enabled us to begin to address these and other questions. Though many of the models describe here have been implemented by the University of Pittsburgh School of Engineering, some of the models described are still under development. Outside industrial engineering, few engineering disciplines have taken full advantage of the usefulness of modeling to improve various aspects of engineering education. Through the following examples, this descriptive paper hopes to provide further insights to the usefulness of empirical modeling in engineering education.

Background on Modeling in Engineering Education

For the past ten years a team of industrial engineering faculty and students along with engineering education and evaluation specialists have been developing a series of predictive models to address critical aspects of the engineering education system at the University of Pittsburgh. Utilizing empirical data, our models have enabled us to improve engineering student retention during the freshman year from 72% in 1996 to 88% in 2001 and, we believe, enhance learning. Such models also enable faculty to better understand the educational system and hence better assess learning as students matriculate through the system. If properly developed and validated, such models could also identify those students who might be "outliers" (i.e., not achieving one or more outcomes; or have a high probability of leaving engineering even though they are academically successful). Second, by relating various educational outcomes to such measures as graduation rates or GPA (grade point average), engineering educators obtain a better understanding of the system within which they work. Hence, knowledge of these relationships would allow for more targeted interventions and improvements for both individual students and groups of students.

Empirical modeling is commonly used to draw correlated inferences and define relationships among different factors (i.e., process elements and outcomes of a system). It can also be used for classification purposes (i.e. classify a set of students according to certain defined criteria). Empirically derived models may also be used to predict system outputs given information about

the inputs and processes (i.e. determining graduation GPA based on factors other than grades). While a diverse number of systems have been successfully modeled, it is only recently that attention has turned to the engineering education system. To date, many of the empirical modeling applications in engineering education have focused on retention or performance [2, 3, 4, 5, 6, 7, 8]. At the University of Pittsburgh, we have developed logistic regression models to predict attrition and performance in our freshman engineering program using quantified measures of student attitudes [9]. Further, we have developed and tested a model to predict those students who are at risk to go on first term probation [10]. Full implementation of these models will allow freshman advisors to better inform students of opportunities that engineering offers, devise programs of study that take advantage of students' varied interests, and set realistic retention goals. Our modeling of the engineering education system and its components has helped us quantify, define, and evaluate relationships among student attributes, their educational experiences and now the educational outcomes.

In addition to our previous work modeling critical aspects of the freshman year [11, 12], we have also developed and evaluated an empirical model of the engineering education system [13, 14]. This latter model is based on the assumption that the educational processes a student experiences (i.e., curriculum, in-class instruction, experience, etc.) are related to the graduate's engineering knowledge, skills, and attitudes. To model the results of an engineering education, we hypothesized a conceptual model of the system using the engineering education literature in conjunction with input from working engineers obtained through focus groups. Using this conceptual model, an alumni questionnaire was developed to measure various aspects of the model. Alumni responses from the questionnaire then were used to evaluate and verify the conceptual model.

Modeling Approach

The majority of the models described in this paper are classification problems. Depending on the model, we employed one of two different empirical modeling methods: logistic regression analysis or neural networks using a learning vector quantization (LVQ) algorithm. Logistic regression analysis was used for the first-term probation, retention and characteristics of graduation models, whereas the LVQ neural networks models was applied to the math placement, intellectual development, and level of achievement (based on one's attitudes) problems. Each modeling approach is described separately.

Logistic Regression

Regression analysis is one of the most widely applied empirical modeling techniques for determining relationships among variables, specifically between a dependent (or response) variable and one or more independent (or predictor) variables. The dependent variables used in our models are dichotomous (zero or one) variables. For example, the resulting dependent variable can take on the following values:

- 1 = if the student goes on first term probation, and
- 0 = if the student does not go on first term probation.

In general, a multiple linear regression model can be expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p + e$$

where

- y is the dependent (response) variable,
- x_i is the i^{th} independent variable,
- β_i is the i^{th} regression coefficient,
- β_0 is the intercept,
- p is the number of independent variables, and
- e is the error with mean zero.

To estimate the unknown parameters, the method of least squares is typically used. If the dependent variable is dichotomous (0 or 1), logistic regression is commonly used to estimate the model parameters. In a logistic regression the estimators no longer have the same statistical properties as with multiple linear regression such that the parameters of a model predict the proportion of a particular outcome, k_i/n_i (e.g., the proportion of freshman engineering students who go on first term probation). This can be described by the following logistic function:

$$E(k_i/n_i) = e^u / (1 + e^u)$$

where

$$E(k_i/n_i) \text{ is the predicted proportion, and}$$
$$u = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_p X_p.$$

Instead of using the least squares method, model parameters are estimated by the maximum likelihood method. The resulting estimated regression coefficients for the model can be interpreted in the same manner as ordinary least squares regression coefficients. To assess the adequacy of an estimated logistic regression model, we used the Hosmer-Lemeshow [15] goodness-of-fit test. This statistic tests the hypothesis of how well the derived model fits the data. The larger the p -value indicates that the predicted values fit the data in the model. SPSS version 10.0 and its Logistic Regression routine was used to develop the models described.

Neural Networks Learning Vector Quantization (LVQ)

A neural network is an information processing system that uses highly interconnected groups of neurons that process information in parallel. Depending on the algorithm, weights are established between the neurons (denoted as input, hidden, and output layers) by learning through example and repetition. As a result, the network can receive input information (independent variables) and it will provide an answer at the output layer (dependent variable). Over the past ten years, a number of emerging algorithms have made neural networks a popular method for empirical modeling.

Learning vector quantization (LVQ) is a pattern classification method in which each dependent variable, Y_j , represents a particular class. The weight vector for an output unit is often referred to as a reference vector for the class that the unit represents. During training, the output units are positioned to approximate the decision surfaces of the theoretical Bayes classifier. After training, an LVQ network classifies an input vector by assigning it to the same class as the output unit that has its weight vector closest to the input vector. The architecture of an LVQ is given in Figure 1.

For our modeling applications, MatLab version R12 with its neural net toolbox and NeuralWorks version 5.3 were used to develop the majority of the networks used.

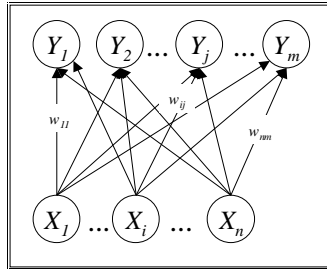


Figure 1. Architecture of a Simple LVQ model

Description of the Models Developed

The following sections describe several models used in engineering education. The first three sets of models focus on the quality of freshman engineering, the other three sets of models look at the development of engineering students as they matriculate through their undergraduate careers and focus more directly on the eleven enunciated outcomes.

Retention

One of the most productive avenues for modeling has been, and will continue to be retention. It is widely recognized that retention/attrition is one of the major challenges currently facing engineering educators. Almost 50% of the students entering an engineering program leave before graduation with a large part of this occurring during the first year [16, 17]. Some of the most influential work has been done by Seymour and Hewitt [18] and Tinto [19] who collectively have confirmed such causal factors as:

- Lose interest in engineering; find more interest in other majors.
- Poor teaching by engineering faculty.
- Overwhelming pace and load of engineering programs.
- Discouraging grading systems in engineering courses.

The developers of ABET's EC-2000 criteria recognized the importance of retention by specifically asking programs to measure and track it. Efforts to understand and reduce attrition [20, 21] have included predictive model development [22, 23] and the use of retention rates for benchmarking [24]. These applications helped identify and confirm the factors that affect retention allowing more appropriate, and effective interventions to be designed; e.g., the introduction of specific courses [25, 26]. A serious limitation of a number of the models to predict retention is the inclusion of independent variables whose values can only be obtained at the end of the freshman year. Consequently, such models are of little use when trying to identify those students who have a high probability of leaving engineering during the first year, when, as noted the substantial part of the attrition occurs. Besterfield-Sacre, et. al. have developed a model to predict students who leave in good standing based on variables obtained prior to students beginning their freshman year (e.g. attitudes about engineering and themselves, high school rank) [27].

First Term Probation

Both first term and second term probation are important contributors to overall attrition in engineering and, in general, graduation from college. First term performance is particularly crucial for the engineering student's future academic success. Budny, LeBold and Bjedov found a strong correlation between first-term GPA and retention; they also observed that good performance in basic mathematics and physics gave students the confidence to succeed [28]. We have verified this at the University of Pittsburgh, documenting that a substantial portion – approximately 50% - of students placed on first term probation drop or transfer out of engineering, many without getting off of probation. In contrast, no more than a fourth of those who are in good academic standing at the end of their freshman year leave without graduating [29].

Because of the importance of first-term probation as a precursor of attrition from engineering, we have developed a series of models to predict those students most likely to be placed on probation after one term. In doing this, we wanted to utilize those factors that could be measured before freshmen began their course work. This would enable us to then introduce targeted interventions for those students with the highest probability of being placed on probation after one term. If we could improve the first term performance of these at risk students, then the chance of their completing the engineering program would be substantially increased. In order to estimate the probability of being placed on first-term probation, we have utilized logistic regression [30].

Two logistic regression models were developed to identify students at risk of being placed on first term probation. Data from entering freshman classes for 1995-96 through 1999-00 were used in either fitting these models or served as an independent test set. Subjective and objective measures collected for each student included measures reflecting initial preparedness, ability, attitude and self assessed confidence, and first term performance (e.g. GPA).

The first model developed includes SAT, the square root of high school rank and a categorical variable that measures students' self-assessed confidence in their current study habits, as measured by the *Pittsburgh Freshman Engineering Attitudes Survey*® PFEAS [31]. After considerable analysis, a threshold limit 0.15 was chosen in order to classify the student as having a high probability of being placed on first-term probation. Hence, a student with a probability larger than or equal to 0.15 is predicted to be positive (i.e., proportion of a particular outcome, k_i/n_i , is likely to be placed on probation is ≥ 0.15). Otherwise, he /she is predicted to be in good academic standing.

Because the SAT score and/or the high school rank were not available for some students, a second model (Model 2) was developed which did not include these two variables. Again, a threshold limit of 0.15 was selected. In fitting Model 2, the following factors were found to be significant:

- Confidence in problem solving abilities (as measured by the PFEAS),
- Confidence in engineering abilities (as measured by the PFEAS),
- Confidence in study habits (as measured by the PFEAS), and
- High risk admission through a bridge program.

Surprisingly, a number of potential predictors were found not to affect the probability of being placed on first-term probation. These included gender, confidence in basic engineering knowledge, and such extrinsic factors like financial or family influences, to name a few.

In implementing these models, the first is used if SAT score and high school class rank are available, whereas the second model is used when the first is not applicable due to incomplete information. Table 1 summarizes the classifications results obtained from applying both models to the 1999-00 entering freshmen (this data were not used in the initial model development). The table shows that 54 out of 63 positives (students who were placed on first term probation) were identified (86%). In contrast, another 94 were incorrectly predicted to go on probation (false positives). That is, there is a “cost” of 1.74 false predictions for each correct prediction. The percentage of true positives could be increased to 100% by decreasing the threshold. However, the incremental cost in terms of increased false predictions would become unacceptable. Table 2 shows that the models performed equally well for special student populations (women, minorities and those in our pilot integrated curriculum), indicating the models’ robustness.

Table 1. Classification Results First Term Probation Model

Observed Probation	Predicted Probation	
	No	Yes
No	174	94
Yes	9	54

Table 2. Predictions for Special Populations - First Term Probation Model

Special Case	True Positives (Yes)	Cost
Male	86%	1.75
Female	83%	1.70
Integrated Curriculum	100%	1.86
Minority Program	85%	1.00

These models allow us to direct interventions to those freshmen that are at the highest risk of going on first term probation. Specifically, for the entering class of 1999-00, they allowed us to focus on slightly over a third of the class, and in that manner capture 86% of those who went on first term probation. This ability to hone in on those most in need reduces the cost of applying the interventions that included reducing the first term course load by not placing them in physics, and providing these students with special workshops and tutoring.

Freshman Math Placement

As noted, the first term is extremely important for engineering students; the first-term mathematics and physics courses have been found to be the incisive courses for overall success. All the freshman engineering students placed on probation after the Fall 2000 semester had done poorly in their mathematics course. Like most engineering programs, University of Pittsburgh students are given mathematics placement tests. Here students whose Math SAT scores are below 650 must first take an algebra and trigonometry achievement test to determine if they are ready to start in Calculus. Students whose Math SAT is 650 or above and who have taken calculus in high school, may take a calculus placement test to determine if they are qualified to take Calculus 2 or Honors Calculus. We observed that a substantial number of students who were

placed into Calculus 1 ended up with a grade below C. An examination of their math placement tests and their Math SAT scores indicated no apparent pattern. In order to improve the placement of these students we adapted a “Mathematics Inventory” test that had been used successfully by Budny at Purdue to place students [32]. The inventory consists of the concepts covered in the first two semesters of a college calculus sequence. For each concept, students rate their degree of familiarity from “never heard of it” to “understand it and know how to apply it.” To improve placement, we decided to model this process using a neural network approach. Data were available from 284 freshmen engineering students and included the Algebra-Trigonometry Placement Examination (individual scores from six sections[†]), Calculus Placement Examination (total score) the Math Inventory (scores from nine sections), the PFEAS, the Force Concept Inventory (for placement in honors physics), Math SAT and high school class rank. The first semester math grade was used as the dependent variable. In total, 38 factors, which possibly affect the math performance, were considered. After conducting preliminary statistical analysis, we found that most of the students who took the calculus placement exam did well in their math course – whether it was Calculus 1, 2 or Honors Calculus. In contrast, poor math performance tended to be confined to those students who took the Algebra-Trigonometry Placement exam. Hence model development was focused on this reduced dataset of 110 students.

Using both neural networks and regression analysis, several models were produced. A Learning Vector Quantization neural network model yielded the best results, and was selected as the standard model. The resultant network was composed of four input nodes. Each node represented one of the following independent variables: gender, score for the fifth section (most difficult) of the Algebra-Trigonometry Placement exam, student attitude towards math, and background in differential calculus[‡] as reflected from that section of the Math Inventory. Two output nodes or classes - good (C or better) and poor (C- or lower) performance in Calculus 1 were used. Three different patterns of nodes (8, 12 and 14) were used in the network competitive layer – resulting in three different networks. The dataset was randomly divided into 72 observations for the training set and 38 observations in test set data. Networks were trained first by LVQ1 and then followed by LVQ2. Predicted math performance was based on a “majority vote” (at least two out of the three results) from the three different competitive networks. The predicted results of test set observations compared to the actual results are shown in Table 3. Although the test set was relatively small – 38 observations – the model correctly predicted 33 of the 38 results. It identified 12 out of 15 poor performers and 21 out of 23 good performers. Only 2 of the 14 predicted poor performers actually did C or better work in their first semester calculus course. Results for the other model formats, while good, were not as accurate as the LVQ models.

Table 3: Math Placement - Predicted vs. Actual Performance for Neural Network Test Set

	Predicted Results	
Actual Results	Good	Poor
Good (C or better)	21	2
Poor (C- or lower)	3	12

[†] The Algebra-Trigonometry Placement Examination was divided into five algebra sections of increasing difficulty and one trigonometry section.

[‡] Differential Calculus was the only section of the Math Inventory that appeared to yield significant results.

Given these results, it was decided to implement the model as part of the advising/testing process for the 2001-02 entering Freshman Class. Advisers used the LVQ model predictions in combination with the first term probation predictions and an independent review of the math placement results. If all three indicators suggested that the student should be placed in Pre-calculus rather than Calculus, then the student was so advised. In cases where the predictive models indicated conflicting results; e.g., “Pre-Calculus,” but not “first-term probation,” then placement was at the adviser’s discretion, using all six Algebra-Trigonometry sections as a final determinant. As a result, the number of freshmen placed into Pre-Calculus doubled from the past year, going from approximately 25 to 48, even though the quality of the incoming class was comparable or slightly higher to the previous years as measured by SAT scores (no difference), high school class rank (slightly better), and percent of students in top 10% of high school graduating class (51% vs. 46%). First semester grades have only been available for two weeks; preliminary results are shown in Table 4.

Table 4. Math Placement Results Fall 2001-02

Calculus 1 Performance			
Prediction	Resigned	Poor	Good
Go into Calculus	5	12	210
Go into Pre-Calculus	1	3	17
Pre-Calculus Performance			
Prediction	Resigned	Poor	Good
Go into Calculus	0	0	2
Go into Pre-Calculus	0	13	10
Other (N/A)	1	1	4

On the surface the model appears to have improved first semester math performance. The number of poor (C- or below) Calculus 1 grades has dropped from approximately 50 the previous year to 15. In contrast, performance in Pre-calculus was not good, suggesting that these students may not have been ready for engineering and, hence, the placement was correct. Even though 17 students took Calculus 1 and did “good,” in spite of the model’s prediction, their grade distribution tended to be less than the students who were predicted to do well. Given what we consider are very good results for the first year of using both models for placement, we will be refitting both the first-term probation and the math placement models for use with the 2002-03 entering freshman class.

Models to Predict Intellectual Development

Cogito[®] is a software package under development at the Colorado School of Mines to measure intellectual development in college students. It was designed to replace an hour-long interview process followed by expert evaluation of a subject’s intellectual development level on the Perry and Reflective Judgment (RJ) scales [33, 34]. Both intellectual development models measure students’ position along a hierarchical construct of stages representing increasingly more sophisticated ways of understanding and solving complex problems. These range from an immature “right/wrong” view focused on letting authority (e.g., teacher, textbook) decide how to solve a problem through a relativistic view that all answers are equally valid to a more mature view of problem solving in context while addressing a variety of constraints. To emulate this process, Cogito[®] uses open-ended scenarios based on controversial topics as the mechanism for

collecting student responses. Four scenarios have been written and tested; each focuses on a dilemma or controversy with posed questions for which test subjects provide responses during an interactive session. As with the traditional interview method, the interest is on how the subject has developed a solution to the dilemma and the supporting evidence (if any) rather than the actual solution. Response fields in the computerized scenarios have been carefully written to differentiate this type of information.

We have been using a series of LVQ network models with the Cogito[®] data set, currently consisting of approximately 100 students who have undergone both an extensive RJ interview and then utilized Cogito[®] to evaluate three scenarios. Using the RJ score as a dependent or outcome variable, we are attempting to fit the responses to the various scenarios in order to be able to predict a student's RJ score based on his/her response to the scenarios. Analysis using neural networks and statistical methods continues with the overall goal of having Cogito[®] predict a subject's intellectual development level within approximately 0.5 of the levels obtained by interview measurements [35, 36].

Classification of Level of Achievement

We have also explored using an LVQ neural network to predict a student's class status (freshman, sophomore or junior) based upon his/her self-assessed confidence in several engineering areas. To do this, the *Sophomore Engineering Learning and Curriculum Evaluation Instrument* © (SELCEI) and the *Junior Engineering Learning and Curriculum Evaluation Instrument* © (JELCEI) were used with data from the PFEAS. Like the PFEAS, both the SELCEI and the JELCEI solicit the students' opinions about engineering. The Sophomore and Junior Instruments cluster specific questions into seven categories:

- Engineering as a career,
- Engineering ability,
- Enjoyment of math,
- Engineering as an exact science,
- Perception of the work engineers do,
- Compatibility with engineering and
- Ability to work in groups.

These seven measures were used as the input variable for the LVQ model. The output variables, class status, were represented as a "1" for freshman, "2" for sophomore and "3" for junior. The size of the training set was determined by the amount of data available for each class and the desire to provide an equal number of data points for each target response group. 150 observations were used to train the network, with 45 observations (15 observations for each class) used to test the network. The network correctly classified 87% of the freshmen, 67% of the sophomores and 87% of the juniors in the test set. The accuracy of the network to classify sophomores correctly was consistently lower than that for freshman and juniors. It may be that sophomore-engineering students exhibit a reduced confidence after their first year of engineering, which limits the network's ability to accurately classify them.

Characteristics at Graduation

The following section describes several models to predict the characteristics of graduating seniors. To do this, both linear and logistic regression were used with data from our attitudinal surveys, including data from the *Senior Exit Survey*[®], completed by all seniors when they apply for graduation.

Graduating GPA

Several models have been developed in an effort to relate graduating GPA to a number of factors including EC-2000 outcomes. Independent variables included outcome measures obtained from the *Senior Exit Survey*[®], SAT scores and high school class rank, and variables representing educational enhancements while an undergraduate including internship, co-op, undergraduate research assistantship, study abroad, and plans to attend graduate school. For example, using data from 121 graduating seniors (who entered engineering as non-transfers and graduated in 2001), a model with an $R = 0.758$, $R^2 = 0.574$ and adjusted $R^2 = 0.544$ was obtained (i.e., over 50% of the variation in GPA was explained by this model. Significant variables included in order: Math SAT, High School Class Rank, Ability to Analyze Data, Knowledge of Contemporary Issues, Ability for Life Long Learning, Plan to Attend Graduate School, Co-op Experience, Ability to Use Modern Engineering Tools, Knowledge of Mathematics, Study Abroad Experience, and Ability to Communicate Effectively. A model for graduating seniors from the previous year (2000) was comparable with a slightly smaller R -value (0.661) and also smaller R^2 and adjusted R^2 . However, the sample size for this model was also smaller. Though very much in their infancy, these models suggest that it is possible to identify those outcomes that contribute the most to the students' academic achievement. Clearly, the student's academic ability and achievement upon entering as measured by high school class rank and Math SAT score are the two most important predictors of graduating GPA.

Estimating Outcomes

Efforts were made to estimate the achievement of the 11 EC-2000 outcomes as a function of students' attitudes as obtained from the *Senior Exit Survey*[®]. At best, these models only explained between 9 and 36 percent of the variation in the data. Table 5 provides for outcome "k" – an ability to use the techniques, skills, and modern engineering tools necessary for engineering practice.

Table 5. Estimation of Outcomes Using Seniors' Attitudes

Outcome	R	R ²	Adjusted R ²	Predictor Variables
Modern tools and techniques	0.602	0.363	0.322	<ul style="list-style-type: none">• Engineering as a career• Perception of work engineers do• Engineering compatibility

In order to explain a greater amount of the variation, additional items from the Senior Exit Survey that related to the students' classroom experiences were introduced as dichotomous variables. Quadratic models were fit in order to adjust for some of the non-linearities. The result was a set of models with more explanatory power as shown in Table 6. These results suggest that acceptable models can be built that will enable faculty to relate attitudes and processes to outcome. This is an important step in better understanding what factors influence engineering outcomes, and offers the potential of developing additional outcome measures.

Table 6. Estimation of Outcomes – Quadratic Model and Additional Factors

Outcome	R	R ²	Adjusted R ²	Predictor Variables
Design a system or component	0.540	0.291	0.277	<ul style="list-style-type: none"> • Preparedness for engineering work • Solid background for an engineering career • Research experience
Function on multi-disciplinary teams	0.589	0.347	0.311	<ul style="list-style-type: none"> • Preparedness for engineering work • Conducted undergraduate research • Solid background for an engineering career • Participated in study abroad • Importance of taking courses outside major • The importance of global perspective in courses • Life long learning emphasized
Life long learning	0.633	0.401	0.380	<ul style="list-style-type: none"> • Life long learning emphasized • Preparedness for graduate work • Plans for graduate school • Participated in an internship, • Importance of taking courses outside major

Besterfield-Sacre, et. al have described how regression modeling can be used to predict how well students might achieve specific outcomes [37]. They also show how individual models can be combined to produce an index that measures overall student achievement of the outcomes. Such an index might serve as a measure of overall quality of education with respect to the EC 2000 outcomes.

Conclusion

This paper has briefly described six areas in which empirical modeling may be used to improve engineering education. Though many of the models described are still too immature for use, others have been used extensively for their proposed purpose and have resulted in improved student success. The contributions that industrial engineers can make to evaluation and assessment of engineering education should not be limited to statistical analysis and implementation of quality management techniques. An overlooked area that IEs have a great impact to the mantra put forth EC 2000 is to provide usable empirical models to measure monitor and continuously improve educational systems.

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Biographical Information

MARY BESTERFIELD-SACRE is an Assistant Professor in the Industrial Engineering Department at the University of Pittsburgh. Her principal research interests are in empirical and cost modeling applications for quality improvement in manufacturing and service organizations, and in engineering education evaluation methodologies. She received her B.S. in Engineering Management from the University of Missouri - Rolla, her M.S. in Industrial Engineering from Purdue University, and a Ph.D. in Industrial Engineering at the University of Pittsburgh. Prior to joining the faculty at the University of Pittsburgh, Mary was an assistant professor at the University of Texas - El Paso, and has worked as an Industrial Engineer with ALCOA and with the U.S. Army Human Engineering Laboratory.

LARRY J. SHUMAN is Associate Dean for Academic Affairs, School of Engineering, University of Pittsburgh and Professor of Industrial Engineering. His areas of interest are improving the engineering educational experience and the study of the ethical behavior of engineers. Together with Dr. Atman, Dr. Shuman co-chaired the 1997 Frontiers in Education Conference held in Pittsburgh. He is a co-author of *Engineering Ethics: Balancing Cost Schedule and Risk - Lessons Learned from the Space Shuttle* (Cambridge University Press, 1997). Dr. Shuman has been principle or co-principle investigator on over twenty sponsored research projects funded from such government agencies and foundations as the National Science Foundation, US Departments of Health and Human Services and the Department of Transportation, the Robert Wood Johnson Foundation, and Engineering Information Foundation. He holds the Ph.D. in Operations Research from the Johns Hopkins University and the B.S.E.E. from the University of Cincinnati. He is a member of the FIE Steering Committee, and is the Academic Dean for the "Semester at Sea" for the Spring 2002 semester.

HARVEY WOLFE has been a Professor in the Department of Industrial Engineering at the University of Pittsburgh since 1972 and served as Department Chair from 1985 through 2000. He received his Ph.D. in Operations Research from the Johns Hopkins University in 1964. He is a Fellow of the Institute of Industrial Engineers and serves as Member at Large of the Professional Enhancement Board of the Institute of Industrial Engineers. He served as President of the Council of Industrial Engineering Academic Department Heads in 1999-2000. He is serving his second six year term as an ABET evaluator. After many years working in the area of applying operations research methods to the health field, he is now active in the development of models for assessing engineering education. He is a co-author of *Engineering Ethics: Balancing Cost Schedule and Risk - Lessons Learned from the Space Shuttle* (Cambridge University Press, 1997).

ALEJANDRO E. SCALISE, PH.D. is originally from Mendoza, Argentina. He obtained his Ph.D. in Industrial Engineering from the University of Pittsburgh. Dr. Scalise has held academic positions in the department of Computer Science at the Universidad de Mendoza and in the department of Industrial Engineering at the Universidad Nacional de Cuyo, in Argentina. He has also worked, as project engineer, at Nuclear Mendoza and since August 2001 is associate consultant at TransSolutions. His main interests include applications of modeling, simulation, neural networks, and heuristic methods.

SIRIPEN LARPKIATTAWORN received a chemical engineering bachelor degree from Chulalongkorn University, Thailand, in 1994. She has a master degree in industrial engineering from University of Pittsburgh. She is currently a Ph.D. candidate in industrial engineering department, University of Pittsburgh. Her areas of interest are quality management, statistics and neural networks. She has four-years of industry experience with Exxon (Thailand) and two-years experience in education research.

OBINNA S. MUOGBOH is a Ph.D. candidate at the University of Pittsburgh. He received his B.Eng. in Electronic Engineering in 1996 from University of Nigeria, Nsukka, Nigeria, and his M.Sc. in Industrial Engineering in 2000 from University of Pittsburgh. He has been working as a research assistant in Industrial Engineering Department, University of Pittsburgh since 1997. His research interests include information technology, modeling, and computer-aided product design and realization.

DAN BUDNY is Academic Director of Freshman Programs and Associate Professor in Civil Engineering at the University of Pittsburgh. He received the B.S. and M.S. degrees from Michigan Technological University and the M.S. and Ph.D. degrees from Michigan State University. His research has focused on the development of programs that assist entering freshman engineering students. Of particular note are the highly successful counseling and cooperative learning programs for first year students. Dr. Budny has numerous publications and presentations on engineering education. He is also widely recognized for outstanding teaching, receiving numerous university and national awards. Dr. Budny is very active in ASEE within the Freshman Programs and the Educational Research and Methods Divisions, and he is on the ASEE Board of Directors.

RONALD L. MILLER is Professor of Chemical Engineering and Petroleum Refining at the Colorado School of Mines where he has taught chemical engineering and interdisciplinary courses and conducted research in educational methods and multiphase fluid flow for fifteen years. He has received three university-wide teaching awards and the Helen Plants Award for Best Workshop at the 1992 Frontiers in Education national conference and currently holds a Jenni teaching fellowship at CSM. He has also received grant awards for educational research from the National Science Foundation, the U.S. Department of Education, the National Endowment for the Humanities, and the Colorado Commission on Higher Education. Dr. Miller is chair of the chemical engineering department assessment committee and acting chair of the CSM Assessment committee.

BARBARA M. OLDS is Associate Vice President for Academic Affairs and Professor of Liberal Arts and International Studies at the Colorado School of Mines where she has taught for the past fifteen years. She is also Principal Tutor of the McBride Honors Program in Public Affairs for Engineers and chair of CSM's assessment committee. She has given numerous workshops and presentations on assessment in engineering education. Dr. Olds has received the Brown Innovative Teaching Grant and Amoco Outstanding Teaching Award at CSM and was the CSM Faculty Senate Distinguished Lecturer for 1993-94. She also received the Helen Plants Award for Best Workshop at the 1992 Frontiers in Education national conference and was awarded a Fulbright fellowship to teach and conduct research in Sweden during the 1998-99 academic year.