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Evaluation System Design and Academic Performance Analysis Using Clustering and Simulation

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EVALUATION SYSTEM DESIGN AND ACADEMIC PERFORMANCE ANALYSIS USING CLUSTERING AND SIMULATION

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ABSTRACT

EVALUATION SYSTEM DESIGN AND ACADEMIC PERFORMANCE ANALYSIS USING CLUSTERING AND SIMULATION

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The starting point of this study was to understand the possible causes of evaluation system change in a military academic environment. With that motivation the objectives of this study were defined as examining student profiles in a military academy, establishing the nature of academic performance, comparing student groups that were identified by course scores, analyzing student performance changes over time and developing a manageable evaluation system and curriculum by comparing different scenarios.

An analysis was performed on the literature on academic performance prediction, cluster analysis methodologies and their development, and specifically summarized cluster analytic academic performance studies where these two fields intersected.

The study started with data collection, database creation and preparation for clustering and simulation studies. A two step clustering methodology was used for grouping courses and cadets. The validated cluster distributions were used as inputs into simulation study.

The simulation study started with modeling cadet movements among clusters over stages. The distribution of clusters was found for each course and the scores were transferred into grades using information gathered from historic data. A new evaluation system design procedure was summarized starting with benchmark examples. Then a simulation was used for the evaluation of new system design settings.

Assumptions of the simulation study were evaluated. Parameter settings and decision variables were defined and simulation experiments were conducted and results were interpreted by output analysis.

The study concludes with a summary of possible outcomes for alternative system designs. During this study it was observed that academic performance is affected by many cognitive noncognitive and demographic variables. Complex human behavior and its interactions with educational environment make it unpredictable. Though, any curriculum or evaluation system development study should focus on these differences and the difficulties due to variation among students.

To my beloved wife Sibel and my son Dorukhan.

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The only people I can imagine dedicating this book to be my wife Sibel and my son Dorukhan. My sweet wife was always understanding, supportive and helpful during my toughest times. My son was born in 2004 when I started my Ph.D. education and this dissertation and he are both the same age.

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LIST OF ABBREVIATIONS

TuAFA:	Turkish Air force Academy
TuAF:	Turkish Air Force
USAFA:	United States Air Force Academy
GPA:	Grade Point Average
UGPA:	Undergraduate Grade Point Average
TOEFL:	Test of English as a Foreign Language
EM:	Expectation Maximization

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

This chapter introduces the nature of the problem investigated in this research. It begins with a brief introduction of the academic performance and nature of military academic environment. The motivation and the research problem are explained, the purpose of the research is introduced, research questions and hypotheses are presented. The chapter concludes with the organization of this dissertation.

Problem Definition and the Planning of the Study

In May 2008 by the order of Commander of Turkish Air Force Academy (TuAFA), a study group was formed in order to model a new academic evaluation system. The purpose of this study group was to construct an academically and organizationally manageable system and more productive evaluation system. As being at the core of this study the purpose was to understand the possible causes of this change in a military academic environment. With that motivation the objectives of this study were defined as examining student profiles in a military academy, establishing the nature of academic performance, comparing student groups that were identified by course scores, analyzing student performance changes over time and developing a manageable evaluation system and curriculum by comparing different scenarios.

Academic Performance in Military Academies

Before giving research questions and associated hypotheses, information about the military academic environment and especially TuAFA's current system were presented in this part of the chapter.

Academic success in the college student population has been of interest to researchers, practitioners, educators, and policy makers for over 75 years. Spearman (1927) introduced general intelligence as a key factor. Later studies on academic performance can be categorized according to input types. First, category studies are based on traditional cognitive measures such as pre-undergraduate education grade point average (GPA) and test scores (SAT, ACT, SSE). Second, category studies are based on non-cognitive measures such as interests, personality changes (Poropat 2009), background experiences, motivational characteristics (trait-based personality assessments, college admissions tests) (Kuncel et al., 2004; Brown et al., 2008) and demographic measures (geographical region, sex). The last category includes studies using mixture of the both cognitive and non-cognitive measure (French et al., 2005; Oakes 2005; Taniguchi and Kaufman 2005; Shivpuri et al. 2006; Schmitt et al. 2007; Li et al. 2009).

Although studies that have examined academic performance of students in civilian undergraduate colleges, students were at large, and studies concerning academic performance in Military Academies are limited. Barnes (1983) tried to explain academic performance in terms of GPA using stress in relations with parents and faculty in U.S. Coast Guard Academy. Ercan et al. (2005) tried to explain graduation GPA using linear and nonlinear multiple regressions methods with both type of inputs in TuAFA. Evans (2003) explored relationships among approaches to learning (deep, surface), need for cognition, and three types of control of learning (adaptive, inflexible, irresolute) using factor analysis at Canadian Military College. In her doctoral thesis Ady (2009) argued for a relation of degree progression or academic performance among many variables such as rank, service time, etc.

Military Academy Case: Turkish Air Force Academy

As for the case of TuAFA, a brief introduction to the education system of the academy is presented in this part of the chapter.

TuAFA has two sources of cadets. First one is Military High School graduates and the other one is Public High School graduates. Public High School graduates are first evaluated based on points obtained in two categories (Math/Science-2) of the SSE examination which can be seen as an equivalent of SAT in the USA[1].

Every institution in Turkey has to design program curricula in order to meet accreditation of the Council of Higher Education as well as institutional goals. TuAFA's education program is formatted according to the goals of the Turkish Air Force (TuAF) while satisfying the standards and accreditation requirements of engineering by the Council of Higher Education. The curriculum is a collection of courses from applied sciences, engineering, foreign languages, social and military fields. A timetable and the curriculum are both oriented toward the development of cognitive, non-cognitive and psychomotor skills during the four years. There are also courses such as military training lessons, physical education lessons, leadership and commandership training and practices that are called coefficient lessons. These courses are non-credit courses but

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[1] Other selection stages are flight health examination, psychomotor and personality tests, student flight training selection, orientation training, sport tests, group interviews, individual interviews and Decision Committee interviews. Military High School graduates are subjected to only first four selection categories. For further information please refer to TuAFA's web site www.hho.edu.tr.

have an effect on the rankings of the cadets at graduation. Extracurricular activities that are organized to prepare each cadet to social life of an officer are also important in cadets' daily life.

Evaluation of student academic success is primarily based on one midterm and a final examination for each course. In the current system grades are over 100 for each course and these grades are converted in to credit letters. At the end of the year academic year academic year GPA is calculated based on these credit letters. A catalog of fixed based and fixed letter spaced marking system is being applied in order to evaluate end of semester grades as given in Table 1. There are different bases and limits for credit letters for three different categories of courses which are determined and announced by the Council of Academic Education of TuAFA at the beginning of each education year. These categories are technical (applied sciences courses and departmental courses), military and social (a base for DD – see Table 1 - was decided as 70 since 2009 but was 60 during the periods of analysis) and foreign language (only English for the time being).

Table 1. Catalog of letter and credit equivalent of grades

Technical	Military and Social Sciences	Foreign Language	Foreign Language (Freshman Year)	Letter	Credit
80-100	90-100	95-100	94-100	AA	4
75-79	85-89	90-94	90-93	BA	3.5
70-74	80-84	85-89	86-89	BB	3
65-69	75-79	80-84	82-85	CB	2.5
60-64	70-74	75-79	78-81	CC	2
55-59	65-69	70-74	74-77	DC	1.5
50-54	60-64	65-69	70-73	DD	1
0-49	0-59	0-64	0-69	F	0

There has been a four year (eight semesters) academic education system at TuAFA since 1974[2]. The curriculum is fixed for each department and students have no opportunity for course selecting. Overloading (taking courses from next year/semester's curriculum) or repeating only failed courses is not allowed. At the end of each year, a cadet has to pass all courses and get a 2.00 academic year GPA. Otherwise makeup or upgrade examinations are taken at the end of the spring semester. If conditions are still not satisfied a full retention rule is applied and the cadet is required repeat the whole year.

Military Academies differ from other academic environments especially in terms of student expectations. A cadet at TuAFA is already employed when he/she is enrolled to military academy although he/she is not paid a full salary. This leads to a different perception that will be examined in details in the clustering chapter of the dissertation. Because all he/she has to do is satisfying necessary conditions for graduation. An "AA" grade is not required for graduation all he/she has to do is passing all the courses in the curriculum.

Research Purpose and Implications about Current Evaluation System

The current system is blamed for not encouraging cadets to take responsibilities for their failures since decisions are already made on behalf of them by the Academy management. A new

[2] Bachelor degree education on Aeronautical and Space Engineering (Aviation until 1995, Aeronautical until 2010), Electronics, Computer and Industrial Engineering programs which began to be applied since 1991-1992 and legalized on 17th May 2000. As being an officer and a pilot-candidate, graduates of TuAFA receive diploma of an officer and also a diploma of BS in engineering.

evaluation system based on course passing, versus passing the academic year, was seen as an option to overcome that problem.

In the current system cadets need to pay equal attention to all courses in the curriculum, since when they fail a single course they fail the whole year. Cadets do not pay much attention to higher credit courses as expected from students of other undergraduate engineering courses.

There has been a very strong belief among instructors at TuAFA about student profile consistency over the years. Despite close watch of the academy management some cadets prefer taking make-up examinations which are conducted in a short period time instead of studying hard throughout the whole semester.

Increasing cadet's personal confidence by giving them right to select courses and also by opening flexible time slots in their daily life for more project-oriented studies were thought as some other benefits. By giving cadets a chance to repeat only the failed courses instead of the whole year, it was expected to develop a more productive system. Moreover, management wanted to see if academic education can be completed at the end of seven semesters by making overloading possible. It would be made possible by starting flight training in six months advance.

TuAFA is a member of European Air Force Academies (EUAFA) organization. The current system is not allowing visiting cadets from Europe to follow a parallel curriculum. It was planned to have a better coordination among the academies with the help of this system change.

Another benefit expected from the system change is the possibility of interdisciplinary studies among four major and possible minors (currently no minors are defined).

This study was not the first effort on the field system change at TuAFA. Two prior proposals were declined by the different levels of management due to less detailed analysis and risk of possible conflicts between upper and higher ranked cadets while taking the same course due to failures or overloads. Nevertheless the cadet profile was changed over time. Academy management believes that cadets are more open-minded and the environment toward cadets is friendlier when compared to previous years.

A combination of clustering and simulation methodologies is proposed because of the difficulties in making a point estimation of academic performance at a course using a prediction methodology (e.g. multiple linear regressions). The complex nature of the classroom environment and personal changes were also other important aspects of the problem.

In the literature it was shown that in order to understand academic motivational patterns clustering analysis has more potential than regression analyses Pintrich (2000) especially when interactions exist as shown by Meece and Holt (1993). They showed that cluster analysis compared to more traditional methods like multiple regressions analysis might show distinct patterns of motivation and help understanding individual differences.

Implementations of cluster analytic researches on academic performance are rather new. Alexander et al. (1995) searched for clusters of individuals on the bases the individual profiles using knowledge, interest, and recall performance on immunology and biology tests. Although their study was primarily oriented toward the analysis of interrelationship among knowledge, interest, and recall, in the study they showed clusters based on both cognitive and noncognitive factors on learning obtained from one academic area plays a significant role on another area too.

By the motivation of the commandment of TuAFA and the literature survey, the aim of this study was designed as developing a new evaluation system that is in accordance with international practice and based on the experience in the academy.

While designing new evaluation system, the systems of four major universities of Turkey (Bogazici University, Istanbul Technical University, Middle East Technical University and Istanbul University) and United States Air Force Academy (USAFA) were examined.

Research Questions

Specifically this study attempts to answer the following research questions:

1. What distinct student profiles emerge from measures of scores obtained from courses?
2. What changes are there in student performances during four years of engineering education?
3. How can success and failures rates at each course be modeled?
4. What would be the numbers of failures and discharged students in new academic evaluation system?
5. What would be the total number of graduated students?
6. What would be the total number graduated cadets at the seventh semester if overloading made possible?

This research seeks answer to the major question about numbers of failed, graduated and discharged/dropped students in a new academic evaluation system. Therefore predicting the "number students failed to graduate at the end of 10 semesters" and "number of students that can be academically graduated in seven semesters by overloading" were identified as primary research topics.

Having established the research questions, the following section introduces the hypotheses that were studied in this research.

Research Hypotheses

Proposition (1): *Some cadets show similar academic performances in courses that can be explained by cluster analysis.*

Hypothesis 1: Cadets are showing similar performances in groups of courses that can be explained by hierarchical cluster analysis in terms of both content and stage of the education.

Hypothesis 2: There is statistically significant difference between mean values of groups of cadets that can be obtained by cluster analysis using course scores on descriptive courses.

There was a very strong belief that there are groups of students showing similar academic performances in the courses with related context. This means that if a student is in the upper level in grades among his/her friends, he/she continues getting higher grades if courses are somewhat related. Because of profile and intellectual differences groups of students could be emerged through academic performance.

Studies primarily using regression methods are unsuccessful in creating a high R_{adj}^2 values in the field of academic performance prediction. In one of them which were conducted in TuAFA (Ercan et al., 2005) R_{adj}^2 value of 0.56 is reached. Although numbers around 0.6 is found explanatory in social sciences it is not enough for a successful prediction.

Therefore courses were grouped by context as technical, social and military, computer science and English language courses by hierarchical clustering technique (by English language courses we mean English as a foreign language courses in this study). Next, courses were grouped by stages in parallel to the semesters they were taught. Finally, cadets were clustered by Expectation Maximization (EM) algorithm at each stage by the cadets' descriptive course scores in the clustering part of this study. The literature has supported the idea of domain knowledge Alexander et al. (1995), Meece and Holt (1993) and Braten and Olaussen (2005).

Proposition (2): *Distributions of the scores of clusters can be used in predicting performance measures of cadets at courses and these distributions can be used in Monte-Carlo simulation of the system design phase of the new evaluation system.*

Hypothesis 3: By a new curriculum and timetable design, graduation at seventh semester could be made possible.

Hypothesis 4: A modeling technique based on cluster analysis and Monte-Carlo simulation can be used in modeling "F" and "AA" rates within management's acceptance limits.

Hypothesis 5: A Monte-Carlo simulation model can be used in order to understand possible causes of decision variables on performance measures such as graduation time and number of graduated cadets in a newly designed evaluation system.

As mentioned above, this dissertation is oriented around five research questions. The first two questions are oriented toward clustering methodology study. The third question hypothesizes the possibility of a semester early graduation by curriculum development and timetabling. The last two questions are related to the simulation study and require good approximations of failures at each course. Also a good prediction "AA" score was required to model successful student graduation within accepted levels. A consensus was reached as a 0.02 difference between the predicted level and the historic data is acceptable during research team's meetings keeping in mind the complexity of the problem.

Plan of the Study and Organization of the Dissertation

The plan of the study is organized as given in the Figure 1. The background of the study, research question, and motivation is introduced in Chapter I. In Chapter II literature review is summarized and the driving force of cluster analysis in this study tried to be cleared. The chapter concludes with a summary of cluster analytic research in academic achievement areas. The research methodology is presented in Chapters III and IV. This area of the study is composed of two parts. In the first part, the methodology developed using cluster analysis is introduced. Detailed information about the research design, subjects, experiment procedures, data collection, and clustering methodology and the results of the clustering study are given in Chapter III.

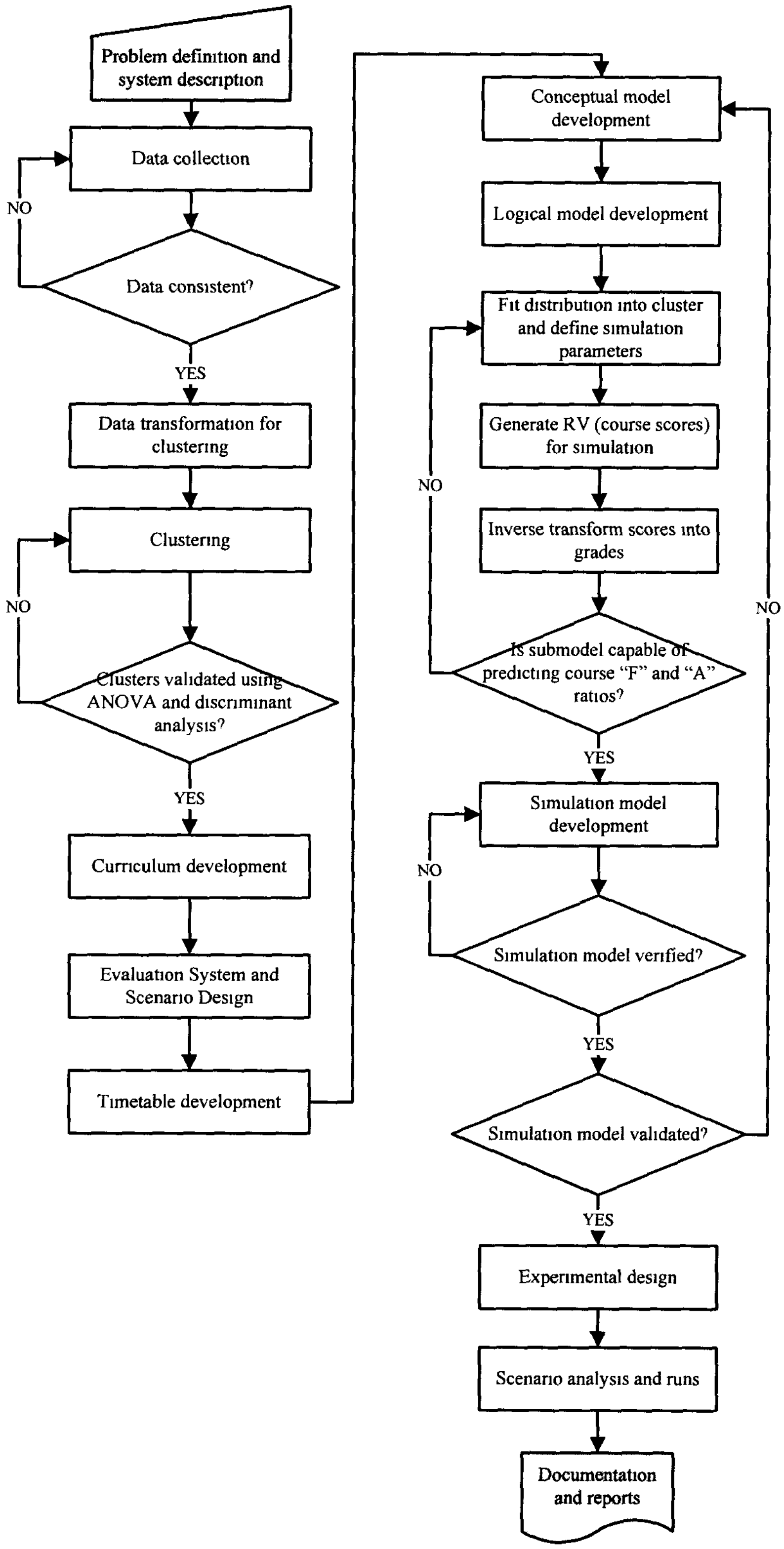


Figure 1. Plan of the dissertation study

A two step clustering procedure was conducted in this study which is validated by both discriminant analysis and Monte-Carlo simulation methods. In Chapter IV, the curriculum development phase is explained, two timetables are developed and a new evaluation system is proposed. Results obtained from clustering phase were integrated into a Monte-Carlo simulation model. A proposed new academic evaluation system is modeled in order to understand the effects of a system change. Chapter V presents the results of the experimental design and the output analyses. In the last chapter the findings, methodology, and practices are summarized, conclusions are made; limitations and future study recommendations are given. Finally, the dissertation finishes with references and appendices. The appendices contain the detailed data summary, statistical analysis and simulation output.

Significance of the Study and Summary

An attempt was made to extend prior longitudinal academic performance clustering work in three directions. One of the new aspects of this study to the literature is analyzing groups of students using cluster analysis based on student's scores on descriptive courses. Another new aspect is tracking four year movement of students among clusters as a result of the longitudinal study. A search was performed for clusters of lectures using hierarchical clustering methodology and developed a hierarchical structure between clusters of courses.

Furthermore a search was completed for clusters of students using a probabilistic clustering methodology and tracking movement among cluster throughout the stages of education. An integrated EM algorithm clustering methodology with Monte-Carlo simulation methodology in academic performance analysis field was used. No clustering-simulation integration study was found in the literature that modeled student success and used as a decision support system, at least to the author's knowledge.

As of the summary of proposed hypotheses, the research claim may be captured with the following statement:

"Cadets in TuAFA can be grouped based on their grades from selected representative courses and these grades can be used in the simulation and the design of a new academic evaluation system."

CHAPTER II

LITERATURE REVIEW

This chapter starts with a summary of the literature on academic performance prediction studies, then introduces cluster analysis methodologies and their development, and finally summarizes cluster analytic academic performance studies where these two fields intersects.

Academic Performance

Academic performance prediction is primary issue for managements of academic institutions because of the cost of retentions and drop-offs. Another problem is the gap between demand and supply of engineers. For example, as demand for engineering students is rising, applications to the engineering schools are declining in the US (National Science Board, 2004). Another critical point is issued in the research by French et al. (2005) as students who enrolled into an engineering education has completion rate around 0.5. Although these numbers are not relevant for military academic education, they point out the importance of the topic in psychology, engineering and education environment and can provide some insights related to this dissertation's case.

Many data analysis methods to understand and predict academic performance, enrollment and retention have continued to be implemented in the literature. Studies primarily concentrate on developing linear and nonlinear prediction methodologies. Although logistic regression, stepwise/hierarchical multiple regressions were the most frequent implemented methods; longitudinal data analysis, covariate analysis, factor analysis, cluster analysis, discriminant analysis were adopted depending on the nature of dependent variables (dichotomous: pass/fail, continuous: grade or GPA, discrete: credit letters) and the progressive nature of education.

In academic performance analysis, Spearman (1927) introduced general intelligence as a key factor in his book. Early works and studies based on Pearson product-moment correlations (r) were computed between each pair of variables and multiple correlations (R) and stepwise multiple regressions. Some important studies are summarized below.

Pierson and Jex (1951), discovered the basic relationships between the various sub-tests of the Pre-Engineering Inventory (undergraduate course scores) and the first year grade-point ratio in engineering at the University of Utah. Federici and Schuerger (1974) tried extending multiple regressions models which with including less traditional measures like interview ratings and biographical information. They tried to develop two models in order to predict not only the academic success but also their interpersonal skills as the examples are from master degree program at psychology. For academic competency they found GPA scores as the most significant factor.

In their meta-search, Covert and Chansky (1975) analyzed 306 masters of education students at a large urban university and used multiple correlation coefficients as a predictor. Their much debated study divided datasets into six subgroups according to sex and to each of the three levels of undergraduate grade point average. In the discussion part of their paper, they concluded two things; first, they suggested that elimination of candidates on the basis of one validity coefficient seems unjustified, since both sex and Undergraduate Grade Point Average (UGPA) had a moderator effect, and second, use of the three predictors (sex, UGPA and Graduate Record Examinations verbal score) as the only selection device for candidates would be questionable since, at best, these predictors were accounting for no more than 20% of the variance in the criterion measure of success.

As the literature moved toward analysis of academic achievement in engineering undergraduate education more emphasis on independent variables related to academic performance was observed. In their study French et al. (2005) proposed a hierarchical linear and logistic regression as a predictor of cumulative GPA and enrollment. They used both cognitive (high school rank, SAT scores, GPA) and noncognitive variables (academic motivation and institutional integration). They found motivational processes like institutional integration, seminar participation and noncognitive variables do not play significant role. They suggested management rather influence on academic achievement among engineering students and retention programs need to focus on cumulative GPA in addition to SAT_{Math} which was selected as indicator of academic achievement and enrollment in successive years at college. They concluded that a strong academic background, achievement of good grades, and academic motivation were needed for students to persist particularly in engineering major.

Li et al. (2009) examined the common characteristics of engineering students (science, technology and mathematics performance). They proposed three categories; external (peer influence, adult influence, curriculum requirements and cultural influence of institution), internal with two subcategories as cognitive characteristics (SAT scores, GPA, and learning style) and affective characteristics (motivation to success, impression of engineering and self-confidence in engineering knowledge) and demographic characteristics (age, gender, race, family socioeconomic status and school location) and their interactions as the predictors of academic performance.

When examining success in specific courses, one idea is to use information gathered from core courses. For example success in English language courses and its relation between semester grades and previously taken courses like a foreign language or demographic attributes (e.g. place of birth) was one idea. There are also studies showing correlation between English course and GPA or academic courses. For example, Ayers and Campana (1973) tried predicting success of college students on foreign language with information gathered from Modern Language Aptitude Test scores, the American College Test and UGPA and developed a regression equation. They found positive correlation between different lectures like mathematics and English language scores.

Human performance analysis is a very demanding and difficult research area. Dynamic environment of the classroom and the academy made the problem very complex. In his much debated study, Cziko (1989) argued that complex human behavior and its interactions with educational environment makes it an unpredictable and indeterminate field especially for experimental study generally because of models incapability and researchers subjectivity. Nevertheless many academicians especially Lehrer et al. (1990) objected to Cziko's controversial paper and his arguments about probabilistic models being incapable of dealing with unpredictability in educational research. There are also some papers that found Cziko's paper explanatory but harsh (Fabian 2000) and argued education at schools as being disconnected from reality and away from students' expectations. For example in one of the recent meta-studies Gasser et al. (2004) reported that in the literature there is an increasing consensus on the role of personality and interest plays around 40% to 50% role in academic performance.

Cluster Analysis

Grouping students in terms of their similarities was found as one of the solutions. A categorization or classification system represents a pragmatic way to organize data so that they can be interpreted efficiently and effectively (Everitt et al., 2004). As being one of the grouping approaches, cluster analysis is a statistical classification methodology of creating classes/subsets in data. If classes of a dataset n are not explicitly defined or well-known, clustering methods can be used in divide instances into natural groups of k. Elements of the same cluster share a high degree of association/similarity. The methodology was proposed in 1930s (Tryon 1939, Zubin 1938) however this method did not become prevalent until the discovery of advanced computer technology. After publication of Sokal and Sneath's (1963) biology book on numerical taxonomy, cluster analysis began attracting academicians in almost every field. Clustering methodologies are used especially in the marketing sector where researcher's main purpose is to find associated products in a very large set of data.

In clustering methodologies, instances may be a member of exclusive groups, may fall into several groups, may be assigned to each cluster with a certain probability, or may be a member of a hierarchical tree type clusters based on the problem and the algorithm issued.

In many publications these clustering analysis methodologies are reviewed and introduced to researchers that might use these techniques to reduce data into manageable or interpretable units (Everitt et al., 2004; Blashfield, 1976). Hierarchical clustering techniques with within average linkages and probabilistic EM algorithm clustering were used in this study and only brief information about the literature of these techniques was introduced here. Interested readers may refer to the many books in this field.

In hierarchical clustering methodology all instances are members of the single cluster. It defines a main cluster where all data and clusters belong to that cluster. The main purpose in this methodology is to reduce variance.

Hierarchical cluster analysis results are generally summarized with the aid of graphic techniques called dendrograms, icicle plots, or tree diagrams. Dendrograms represent similarity levels and grouping patterns that helps analyzer to understand the families of partitions

Two general approaches exist in the literature: agglomerative and divisive. Agglomerative clustering approach forms main cluster at the end while starting with putting every observation into a single cluster. Divisive clustering is approach forms groups from the main cluster to the single clusters.

Some of the hierarchical methods used in the literature are average linkage method, centroid method and Ward's method.

In this study, while creating clusters of cadets in courses an EM algorithm, which comes with Weka software, is used. The EM algorithm is a stable (Watanabe and Yamaguchi, 2004) probabilistic clustering method assumes that data come from a mixture of several populations. The basis for this technique is a body of statistical theory called finite mixtures. A finite-mixture is a set of probability distributions, representing *k* clusters, which govern the attribute values of that cluster. In the EM algorithm the purpose is to find the most likely set of clusters for the observations (Mclachlan and Krishnan, 2008; Witten and Frank, 2005; Nisbet et al., 2009).

The overall likelihood across all observations is the "goodness" of the clustering solution, and it increases at the each iteration throughout the process. This likelihood may be only "local". The user generally defines parameter settings and accuracy: In Weka V-fold cross-validation method is used. In Weka EM clustering, a measure is the average negative log-likelihood computed for the observations in the testing samples (Weka 3.6.2 Manual, 2010).

Cluster Analytic Studies on Academic Performance

In the literature survey a study of clustering based on course grades/scores could not be found. However many important studies and constructs that were trying to model academic performance in varying fields and stages of educational life primarily on psychological variables were found. Although these variables are beyond the scope of this study they brought important insights to this research.

There are numbers of studies using either hierarchical, non-hierarchical, or some combination of the two cluster analytic methods in the motivation and achievement goal orientation literature do exist. These studies were primarily in the field of educational psychology as mentioned above. Along with the developments of clustering methods it was observed that many academicians used clustering methodologies in profiling differences in academic environment among students, classrooms, schools and instructors. Implementations of cluster analytic researches on academic performance started a decade after cluster analysis gained its popularity at the end of 70s. In his paper Blashfield (1976) named Sokal and Sneath's book (1963) as revolutionary. In this paper performances of some hierarchical clustering methodologies into psychological studies were discussed. Blashfield concluded that the performance of Ward's minimum variance hierarchical clustering methodology as being the methodology with the most accurate solution. After this publication many researcher started using this methodology in their studies if academic performance and profiling students using clustering analysis needed. Some of these papers and their importance to the literature are summarized in the following paragraphs. However, according to Alexander and Murphy (2004) little is still known about the nature of academic development, and more longitudinal explorations of student profiles are certainly needed.

With the advances in computer sciences, new methodologies found applications in academic performance studies. There are ample documents in education and psychology literature where cluster analysis was used. Some examples of these methodology implementations are: item response theory (Ayers and Junker, 2008) cluster analysis (Meece and Holt, 1993; Alexander et al., 1995, 2004; Alexander and Murphy, 1998, 2004; Braten and Olaussen, 2005).

In one of the early implementations of clustering Moos (1978) used hierarchical cluster analysis developed by Carlson (1972) while creating a typology of classrooms among American high schools. Correlation matrix based on series of answers given to a test called Classroom Environment Scale Test. Ninety questions were used and clusters of control oriented, innovation oriented, affiliation oriented, task oriented and competition oriented students were identified in this study.

Cairns et al. (1989) used Ward's minimum variance hierarchical clustering technique in their observational study about early school dropouts. They conducted interviews with the children and their families and put the outcomes of these surveys in to clustering analysis. They reached results such as socioeconomic status; race and early parenthood were associated with dropouts.

Alexander (Alexander et al. 1995, Alexander and Murphy, 1998; Alexander and Murphy, 2004; Alexander et al., 2004) used knowledge, personal interest and strategic processing as clustering variables and developed theory named as Model of Domain Learning (MDL). In MDL knowledge, interest and strategic processing (used "recall" instead of "strategic processing" in Alexander et al., 1995) were named as critical in professional expertise. Alexander et al. (1995) searched for clusters of individuals on the bases of individual profiles using performances on seven variables in these three categories. They evaluated performance of the clusters' obtained from the first domain (biology) on another domain (physics) in their experimental study. They used hierarchical clustering methodology and identified three clusters of students. Although the main purpose of the study was summarized as an analysis of interrelationship among knowledge, interest, and recall; in the study they showed premedical students and graduate students who were among the most knowledgeable and most interested in one domain (human immunology), were more interested, recalled their knowledge and continued similar performances in another related domain (physics). In their second experiment which was conducted with undergraduate students taking an introductory educational psychology course, they validated the theory and they reached the parallel results to the first experiment. As a conclusion, clusters showed distinct performances in their text processing test and three critical issue and their interactions were playing important role in the student's (professional) success. In 1998, Alexander and Murphy conducted the first longitudinal study on academic performance. They applied pre-semester and post-semester tests to educational psychology students. In this study they wanted to inspect changes that occurred in students over a semester. They questioned if a participating student was really positively affected over a semester from the instructor. Using the same clustering methodology, three clusters were identified at pretest and four identified at posttest. They also analyzed shifts in profiles by tracking student's cluster memberships in pretest and posttest clusters. In a follow-up study by Alexander et al. (2004) the MDL theory was evaluated in profiling in the field of special education students. They proposed cluster-analytic with a longitudinal examination of students would model academic profiles.

Bembenutty (1999) examined student's academic delay of gratification and used hierarchical clustering methodology. Motivational variables were used as clustering measures. Three clusters were found in this study on college students' psychological test answers who enrolled in undergraduate math course. Students in Cluster 1, which was named as "high task-goal oriented learners", found to be high in delay of gratification and motivation. Students in Cluster 3 were found low in all stages and Cluster 2 students were found to be the intermediate; which concluded that there were significant differences among clusters in academic delay of gratification and its motivational determinants were a function of goal orientation.

Another longitudinal cluster analytic academic performance analyses was conducted by Braten and Olaussen (2005). They employed agglomerative hierarchical technique using motivational variables in samples of Norwegian student nurses and business administration students. They extended Alexander's work by targeting two different academic contexts (groups of participants), and tracked students movement among clusters in terms of their cluster membership changes through one year.

There are also numerous studies where performance of students in a specific course is examined using clustering methodologies instead of overall performance. For example Ahmadi and Raiszadeh (1990) used nominal performance measure (pass/fail) in discriminant analysis and Schultz et al. (1998) used a two step cluster analysis where they both showed that pre-statistics knowledge and core mathematics skills play significant role in getting high grades in statistics course. Boiche et al. (2008) examined how different types of motivation proposed by self-determination theory combined onto distinct profiles as identified by cluster analysis. They also examined the performances of these profiles during 10-week gymnastics teaching. They revealed three motivational profiles and found self determined cluster performing better.

Academic Evaluation Systems

Academic evaluation systems are classified into three categories. In the first category, there are implementation of pass/fail systems which are generally accepted in medical education programs and postgraduate education programs (Provan and Cuttress, 1995; Gonnella et al., 2004). The main difficulties and side effects of this system were summarized as: no need to repeat already passed courses and masking of performance measures of who passed only narrowly from others. In order to overcome this masking and increase defensibility of pass/fail systems academicians especially in the medical education area are trying to develop new methods for estimating cut score in high stake examinations evaluated in letters or pass/fail systems and transform these into letter grades (Burch and Norman, 2009). In the second category, there is a credit/letter based evaluation system. The main side effect of that system can be continuation of students who just learned enough to pass. The last category is combination of two systems, like at TuAFA and other military academies in Turkey. In this type generally there is a make-up examination that is planned to be at the end of academic year. In this type of evaluation system, students again take advantage of the evaluation system by just studying enough to pass at the make-up examinations. Since the curriculum is fixed students are told to take which courses to take each semester. One side effect of such a system is decreasing diversity among students based on their personal interests because of the lack of elective courses. Students' underdeveloped self esteem is another side effect.

Clustering studies in curriculum development are rare. In his research, Brennan (2004) tried clustering courses which satisfy industry's demands in a study on curriculum reform. He did not implement a clustering methodology explicitly but rather looked for the course coverage and clusters of courses were identified based on educational objectives. Institutions need to meet the needs of industries in engineering education while satisfying accreditation boards' demands according to Brennan. Core competencies of the graduates should be achieved by necessary curriculum changes. In their study, Calida et al. (2010) approached academic departments as critical infrastructures and combined clustering and complexity induced vulnerability methodologies. They approached curriculum development problem in competitiveness perspective. According to them, the fast changing environment and context are main threats to the resiliency of academia.

Summary

In this chapter, the concept of academic performance was summarized. Academic performance was related with instructional environments such as: psychological variables classified as cognitive and non-cognitive and also environmental variables such as classroom environment, teacher performance, and classroom atmosphere. Increased uncertainty with these variables and their interactions make the topic still attractive in the literature. Also a lack of longitudinal research in academic performance topics was identified.

Clustering analysis was found to be one of the possible solutions when dealing with increasing number of variables. Performance of clustering analysis on determining groups of students was found to be promising in academic research.

Curriculum development and studies on evaluation systems was the last literature survey topic. Pass/fail system is currently used in medical education and some of the law schools and the military academies as in our case. However there is an increasing debate arguing the performances of narrowly passed students that are undistinguishable in that system. And as a final remark of this chapter it can be said that curricula should be developed in order to meet instructional goals and accreditation requirements in engineering education programs.

CHAPTER III

THE CLUSTERING METHODOLOGY

In this chapter, data collection, data structure and data preparation for the study are explained. Two step clustering methodology used for grouping courses and cadets are also presented. The chapter concludes with an output analysis and validity of the clusters produced.

Pre-Processing

Data Structure

In this part of the chapter, the structure of the data was examined. Information about the collection and the pre-processing of the data is given. A database developed for clustering procedure included records of a total of 276 industrial engineering undergraduate cadets enrolled between the years of 2003-2006 to the Academy. The data structure is given in Table 2. Cadets enrolled during 2002 and prior were not selected in this longitudinal study because of a very detailed curriculum change that was carried out in 2003. (In this study *Academy* is used for TuAFA and *Squadron* is used for group of students who enrolled at the same year).

Table 2. Cadets examined.

Enrollment year	Squadron Name	Number of Students examined
2003	Squadron 2	72
2004	Squadron 1	54
2005	Squadron 4	59
2006	Squadron 3	91
	Total:	276 cadets

The database consisted of grades from 69 courses which represent 94.5% of the industrial engineering curriculum at the Academy. Course classification is given in Table 3. "English" was used while referring to the "English as a Foreign Language" course. Also *technical course* refers to both "applied sciences courses" and "industrial engineering departmental courses". Although computer sciences courses were placed under the departmental courses they were accepted as a different category in the clustering study as will be explained later in this chapter.

Table 3. Course numbers analyzed in the study

Technical			**Computer Sciences**	**Social & Military**	**English**
Applied Sciences	**Department**				
	Core	**Elective**			
7	21	7	3	23	8

Courses that were not examined in the curriculum were courses planned to be removed from the curriculum when the ongoing project with the new evaluation system is adopted. A detailed flowchart of data collection and data preparation methodology is given in Figure 2.

Data Preparation and Analysis

Data containing students grades and other information related to courses and students before 2006 were stored in a computer which was a Linux based server in Computer Center of TuAFA. Data were delivered as a raw text file. After 2006, student data were stored in the Intranet of TuAF. Data were delivered as an MS Excel sheet from the system by the help of Planning Department of Dean's Office. Two sources kept records with different student IDs and different logics, though they should be matched in order to create a consistent dataset. Two records of data combined into a single database in MS Excel at the starting phase of the study. In the data analysis part of this chapter, *sample* or *instance* was used for a grade/score of a cadet taken from a course.

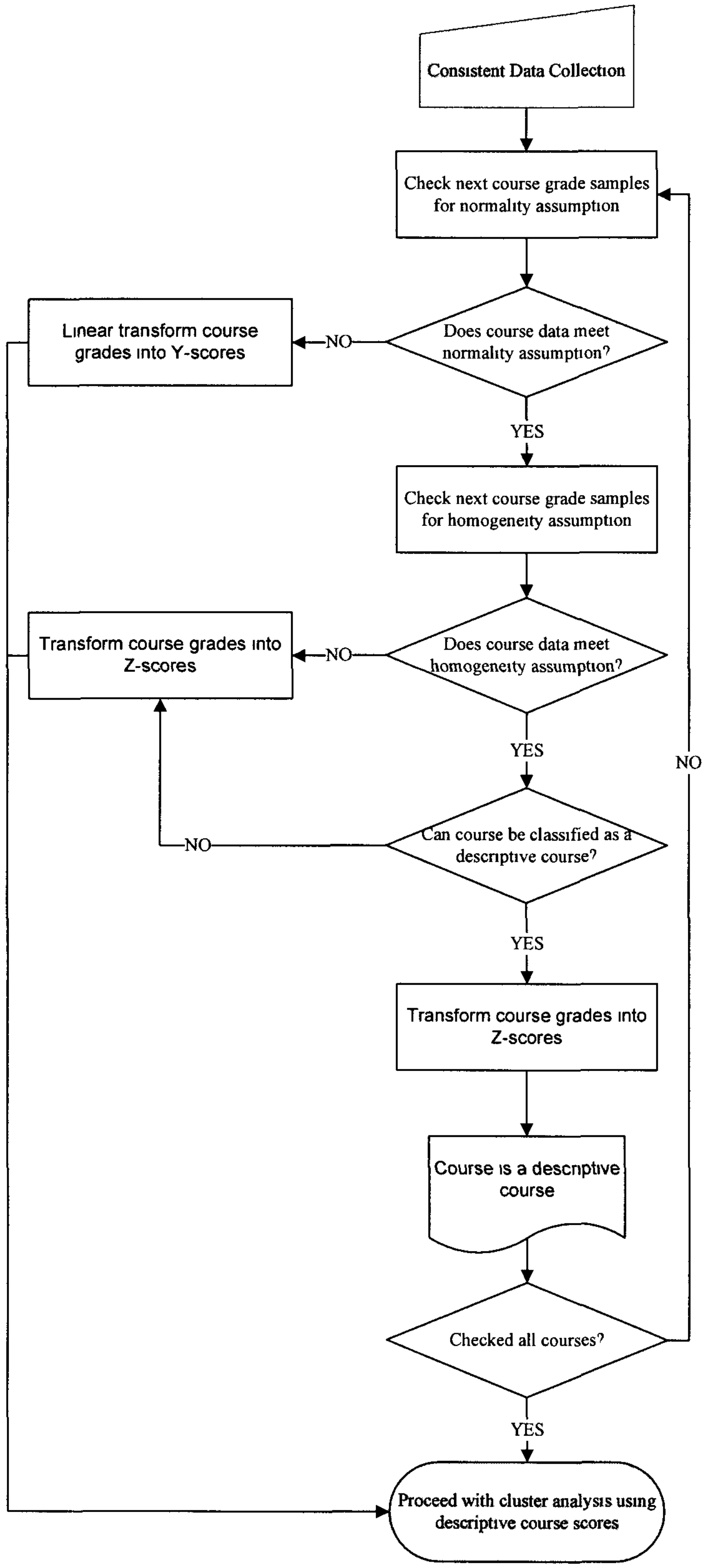


Figure 2. Data collection and preparation methodology

After creating the dataset, consistency of samples were checked. First, the means of each year's grades were examined using. Second, samples were verified if they came from the same population. A mean difference analysis was conducted with one-way analysis of variance (ANOVA) and population assumptions were controlled with Levene's test of equal variances.

ANOVA Test

A one-way ANOVA test is a technique used to compare means of two or more samples. An ANOVA test has assumptions. They are equality of the variances of the samples and the normality of the samples. In this study, error bar charts were considered as a descriptive graphical tool before implementing the ANOVA test. As an example of graphical mean test, error bar charts for three applied sciences course grades (Calculus-I (MAT101), Physics-I (FIZ101), and Chemistry (KIM100)) were presented in Figure 3. (Course codes and representing courses can be checked by the proposed curriculum given in Appendix A.)

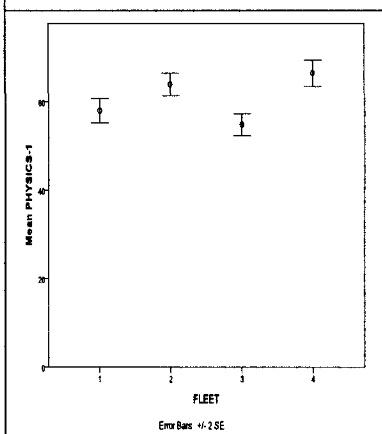
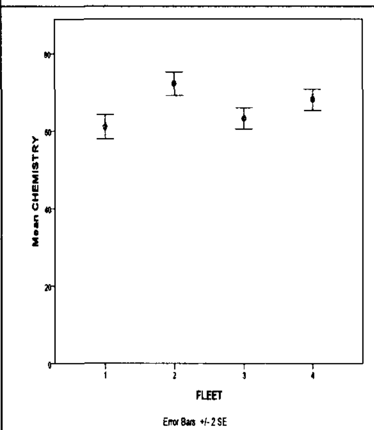
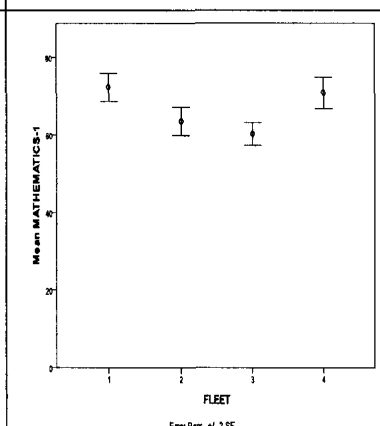
FIZ101	KIM100	MAT101
		

Figure 3. Sample error bar of the three core applied sciences courses

When error bar charts examined, one can describe graphical change in the mean values of grades year by year. Assumption of equal variances seems to hold for all three example course roughly looking at figures. For further analysis Levene's test of homogeneity was conducted with a null hypotheses (indicating equal variances between squadrons/years for each course) given below.

H_0: The variances of groups are homogenous

H_a: The variances of groups are inconsistency

The level of significance is accepted as 0.05 in statistical tests of this study.

The SPSS output of Levene's test of homogeneity for three applied courses of the first semester is given in Table 4. Since significance values exceeded 0.05 for all three example courses, it was concluded that the Levene statistic failed to reject the null hypothesis and the assumption about group variances was justified.

Table 4. Test of homogeneity of variances for three core applied sciences courses

	Levene Statistic	df1	df2	Sig.
FIZ101	.995	3	272	.396
KIM100	1.464	3	272	.225
MAT101	1.698	3	272	.168

The second assumption, about normality or approximately normally distributed samples, was checked both graphically and statistically. When Q-Q plots showed no substantial deviation from normal distribution and goodness-of-fit tests results did not reject the normality hypothesis it was concluded that there was not enough evidence for rejection of the normality assumption. Plots and goodness-of-fit test results of MAT101 course obtained by StatFit 2.0 and SPSS software are given in Figure 4 and Table 5. After conducting these tests for each course and each squadron ANOVA tests were performed.

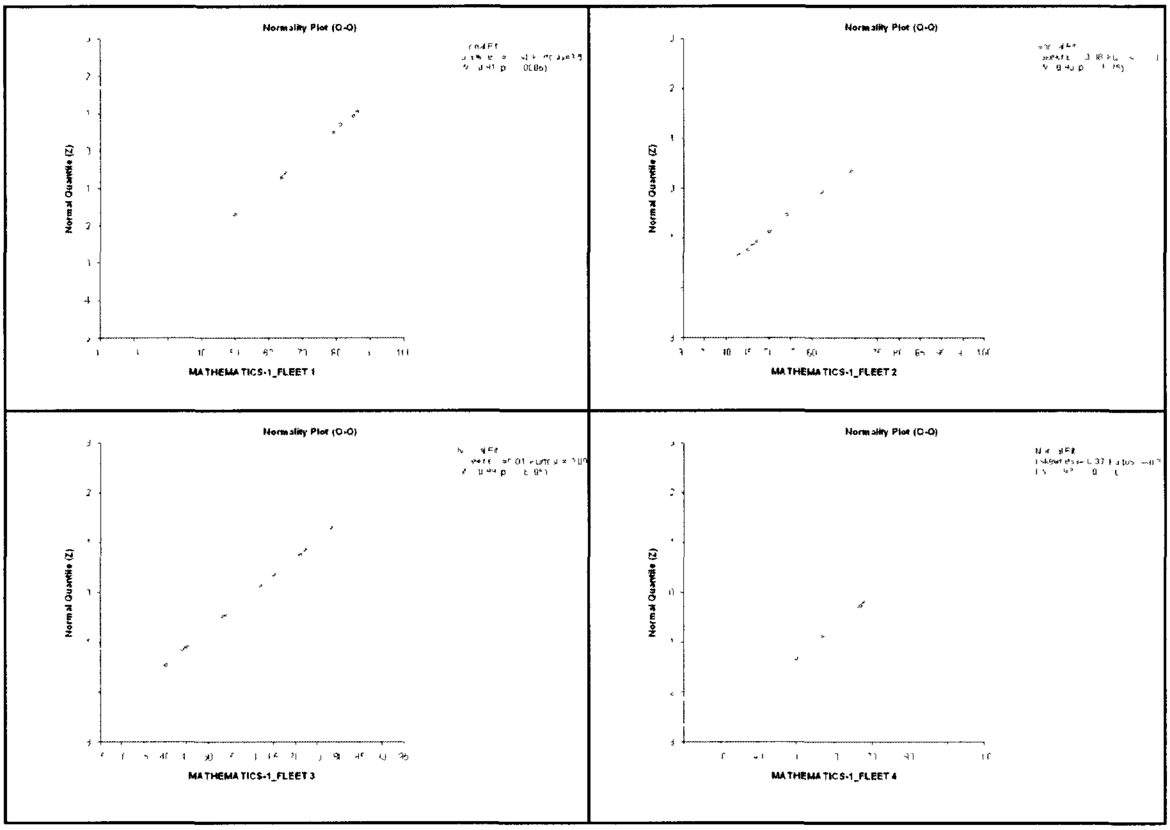


Figure 4. Q-Q plots of MAT101

The null hypotheses of ANOVA test is given below indicating the mean difference is insignificant in the samples where j is the courses and the indices 1 to 4 is squadrons/years.

$$H_0 : \mu_{j,1} = \mu_{j,2} = \mu_{j,3} = \mu_{j,4} \quad \forall j$$

$$H_a : \text{any one of the sample means is different}$$

The ANOVA table result for three applied sciences courses is given in Table 6 as an example. Since significance values were lower than 0.05, it was concluded that the hypothesis of equal means did not hold. A complete list of Levene test statistics results, normality check results and ANOVA results of the above hypothesis for all courses were given in Table 42 through Table 45 in Appendix B. These results were later taken into consideration while choosing courses to use in clustering procedure.

Table 5. Goodness of fit of Calculus-1 course for four squadrons

Squadron-1

data points	54
estimates	maximum likelihood estimates
accuracy of fit	3 e-004
level of significance	5 e-002

summary

distribution	Chi Squared	Kolmogorov Smirnov	Anderson Darling
Normal(72 3, 13 1)	4 7 (4)	0 156	0 888

detail

Normal		
mean =	72 2778	
sigma =	13 1451	
Chi Squared		
total classes		5
interval type		equal probable
net bins		5
chi**2		4 7
degrees of freedom		4
alpha		5 e-002
chi**2(4,5 e-002)		9 49
p-value		0 319
result		DO NOT REJECT
Kolmogorov-Smirnov		
data points		54
ks stat		0 156
alpha		5 e 002
ks stat(54,5 e 002)		0 181
p-value		0 129
result		DO NOT REJECT
Anderson-Darling		
data points		54
ad stat		0 888
alpha		5 e-002
ad stat(5 e-002)		2 49
p-value		0 421
result		DO NOT REJECT

Squadron -2

data points	72
estimates	maximum likelihood estimates
accuracy of fit	3 e 004
level of significance	5 e-002

summary

distribution	Chi Squared	Kolmogorov Smirnov	Anderson Darling
Normal(63 5 15 4)	3 33 (5)	8 46e-002	0 588

detail

Normal		
mean =	63 5139	
sigma =	15 3686	
Chi Squared		
total classes		6
interval type		equal probable
net bins		6
chi**2		3 33
degrees of freedom		5
alpha		5 e-002
chi**2(5,5 e-002)		11 1
p-value		0 649
result		DO NOT REJECT
Kolmogorov-Smirnov		
data points		72
ks stat		8 46e-002
alpha		5 e-002
ks stat(72,5 e-002)		0 158
p-value		0 65
result		DO NOT REJECT
Anderson-Darling		
data points		72
ad stat		0 588
alpha		5 e-002
ad stat(5 e-002)		2 49
p-value		0 659
result		DO NOT REJECT

Squadron -3

data points	91
estimates	maximum likelihood estimates
accuracy of fit	3 e-004
level of significance	5 e-002

summary

distribution	Chi Squared	Kolmogorov Smirnov	Anderson Darling
Normal(60 3 13 9)	0 978 (5)	5 49e 002	0 236

detail

Normal		
mean -	60 2637	
sigma -	13 9156	
Chi Squared		
total classes		6
interval type		equal probable
net bins		6
chi**2		0 978
degrees of freedom		5
alpha		5 e-002
chi**2(5,5 e-002)		11 1
p-value		0 964
result		DO NOT REJECT
Kolmogorov-Smirnov		
data points		91
ks stat		5 49e-002
alpha		5 e-002
ks stat(91,5 e-002)		0 14
p-value		0 933
result		DO NOT REJECT
Anderson-Darling		
data points		91
ad stat		0 236
alpha		5 e-002
ad stat(5 e-002)		2 49
p-value		0 977
result		DO NOT REJECT

Squadron 4

data points	59
estimates	maximum likelihood estimates
accuracy of fit	3 e 004
level of significance	5 e 002

summary

distribution	Chi Squared	Kolmogorov Smirnov	Anderson Darling
Normal(70 9, 15 4)	1 59 (4)	9 74e-002	0 561

detail

Normal		
mean =	70 8644	
sigma =	15 4376	
Chi Squared		
total classes		5
interval type		equal probable
net bins		5
chi**2		1 59
degrees of freedom		4
alpha		5 e-002
chi**2(4,5 e-002)		9 49
p-value		0 81
result		DO NOT REJECT
Kolmogorov-Smirnov		
data points		59
ks stat		9 74e-002
alpha		5 e-002
ks stat(59 5 e-002)		0 174
p-value		0 596
result		DO NOT REJECT
Anderson-Darling		
data points		59
ad stat		0 561
alpha		5 e-002
ad stat(5 e-002)		2 49
p-value		0 686
result		DO NOT REJECT

Table 6. ANOVA table of course grades with grouping variable squadron

		Sum of Squares	df	Mean Square	F	Sig.
FIZ101	Between Groups	6206.290	3	2068.763	16.328	.000
	Within Groups	34462.144	272	126.699		
	Total	40668.435	275			
KIM100	Between Groups	5020.708	3	1673.569	11.166	.000
	Within Groups	40769.103	272	149.886		
	Total	45789.812	275			
MAT101	Between Groups	6943.215	3	2314.405	10.850	.000
	Within Groups	58019.405	272	213.307		
	Total	64962.620	275			

Standardizing Course Grades

Clustering was used as an appropriate tool for identifying groups of students. The database consisted grades taken 69 courses that were given by six different departments. For that reason data integration should be done before implementing clustering methodology in order to avoid inconsistency and to speed up the mining process. In the literature pre-processing using data transformation such as normalization was given as an appropriate way to improve the accuracy and efficiency of clustering algorithms (Han and Kamber, 2001; Shalabi et al., 2006). Because of that, at the clustering cadets stage, standardized semester scores rather than grades were chosen as the clustering variables.

There are many methods for data transformation such as linear normalization, normalization with respect to mean or median, and normalization by decimal scaling. Statistical normalization was preferred for this study, as given in Equation (1), while using clustering algorithms if enough evidence for rejection of normality assumption could not be found.

$$Z_{ijk} = \frac{X_{ijk} - \bar{x}_{jk}}{s_{jk}} \qquad (1)$$

In above statistical normalization equation "$\bar{x}$" is the average value of the sample where "s" is the standard deviation of the sample.

Since not all course grades fit into normal distribution, as shown in Appendix B, a linear (min-max) transformation formula was used for linear normalization where grades were transformed into scale values between 0 and 1 as given in (2).

$$Y_{ijk} = \frac{X_{ijk} - Min_{jk}}{Max_{jk} - Min_{jk}} \qquad (2)$$

In the standardization equations "*i*" stands for case (cadet), "*j*" stands for course and "*k*" for semester/squadron. When a Z-score is used it is abbreviated as "*Z*" next to course code (e.g. *MAT101Z* indicating Z-score at Calculus-I for cadets). When a linear transformed core is used it is abbreviated as "*Y*" next to course code (e.g. *MAT101Y* indicating linearly standardized score at Calculus-I for cadets).

2-Step Clustering

In the project which is the driving force and the motivation of this study, the duty was modeling the new passing system based on the historic data of the student performance. In order to develop a simulation model, a methodology was developed that can model student performance throughout their undergraduate education. Monte-Carlo simulation models were built with uncorrelated grades assumption. However this was a very naïve and incorrect approach since course grades were correlated. The methodology developed by integrating clustering analysis and simulation was accepted as a solution to that problem.

Two-step clustering flowchart that was followed in the clustering part of the overall methodology is presented in Figure 5. The first step of the clustering algorithm was identification of stages and course groups. Courses grouped based on stages and course performance similarities using the information gathered from hierarchical clustering figures and correlation matrices. At the second step cadets were grouped using scores obtained from descriptive courses. With this 2-step clustering the aim was to capture the changes in student profiles by means of academic performance by tracking cluster membership changes over the stages.

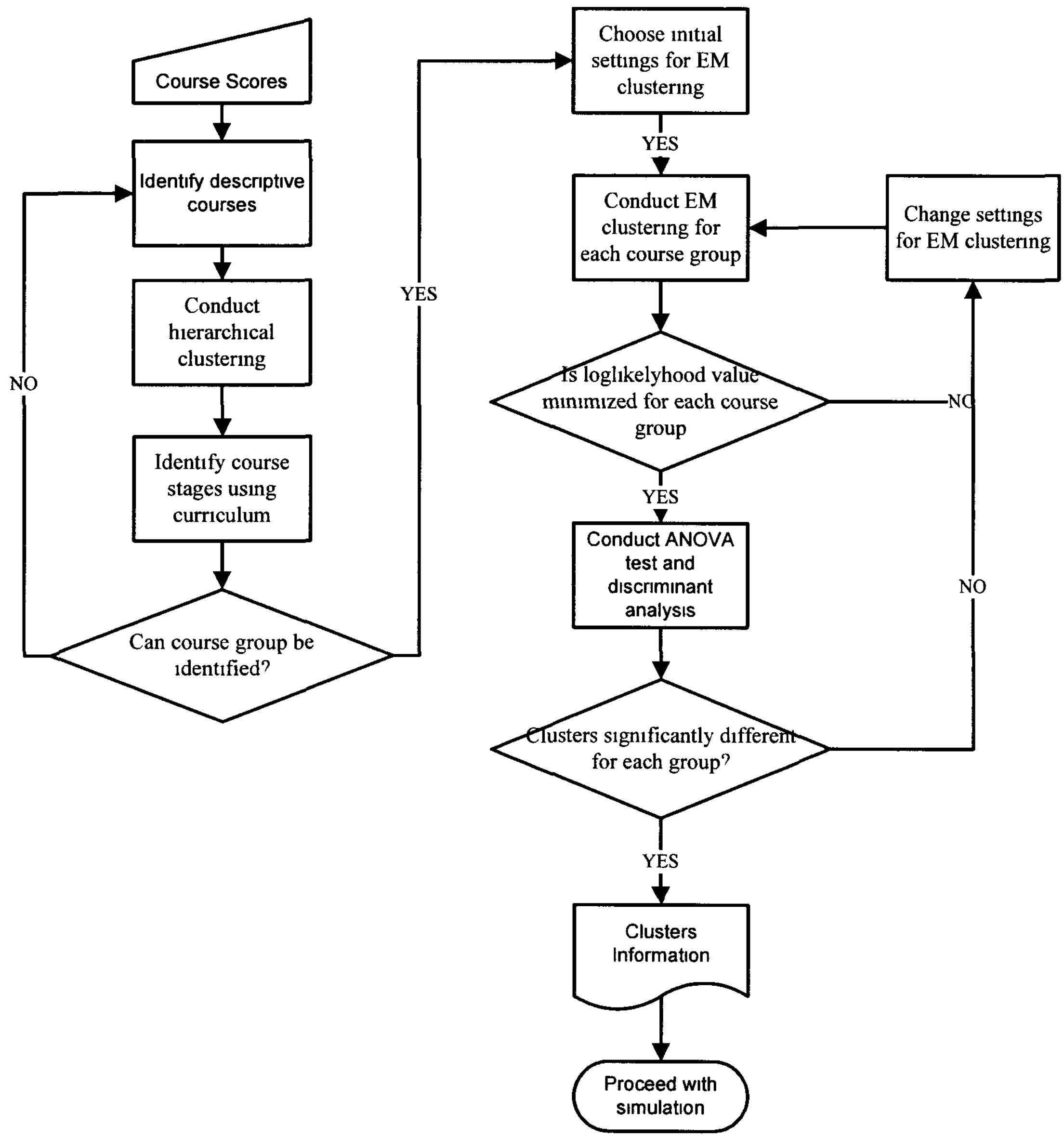


Figure 5. Clustering methodology

Definition of the Stages

Four-year industrial engineering education was separated into stages. For the technical courses three stages were defined. For foreign language courses two stages were defined and for the computer science courses a single stage were used, as explained in details at the next section of this chapter.

The first stage courses were taken at the freshman year in which cadets generally learn calculus, physics and chemistry and other introductory courses. The performance of cadets in these core courses plays major role in student success at the later stages. Second stage courses were mostly sophomore year courses where introductory information to the Industrial Engineering is provided (e.g. Probability, Statistics, Linear Algebra, and Introduction to Industrial Engineering). These courses are generally the prerequisites of the next stages. Third stage courses were selected as the rest of other courses taken at junior and senior years.

Step 1: Clustering Courses

While creating clusters of courses interviews were conducted with colleagues at the Industrial Engineering Department and other departments of TuAFA. With the information gathered from statistical analysis and experts opinions while selecting courses for clustering the following remarks were taken into consideration.

- *Remark 1:* In this study 69 course grades/scores were the variables. Not all courses are homogenous in years/squadrons. Those courses that Levene's homogeneity of variances hypotheses rejected (Appendix B) were statistically inconsistent and not used in clustering. Courses used in clustering as descriptive courses were generally given by the same instructor over four years. This would be one of the reasons for homogenous grade distribution among squadrons. These reasons are not explicitly pointed out in this study.

- *Remark 2:* Courses used in clustering should be representative of cadet success. These courses were core courses and prerequisite for other courses in the curriculum. As indicated by Giudici and Figini (2009) using variables of little importance will inevitably worsen the results. This was a crucial problem since it would strongly condition the final result.

Correlation of the first semester course scores is given in the Table 7 as an example. Correlation coefficients were found significant for all courses in the example.

Table 7. Correlations of first semester courses

		KIM100Y	MAT101Y	BLG100Y	HRT100Y	HVG101Y	ING101Y
FIZ101Y	Pearson Corr.	.548(**)	.585(**)	.251(**)	.498(**)	.365(**)	.241(**)
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000
	N	276	276	274	276	276	275
KIM100Y	Pearson Corr.	1	.375(**)	.112	.407(**)	.331(**)	.167(**)
	Sig. (2-tailed)		.000	.065	.000	.000	.006
	N		276	274	276	276	275
MAT101Y	Pearson Corr.		1	.264(**)	.282(**)	.324(**)	.131(*)
	Sig. (2-tailed)			.000	.000	.000	.030
	N			274	276	276	275
BLG100Y	Pearson Corr.			1	.369(**)	.351(**)	.258(**)
	Sig. (2-tailed)				.000	.000	.000
	N				274	274	273
HRT100Y	Pearson Corr.				1	.386(**)	.341(**)
	Sig. (2-tailed)					.000	.000
	N					276	275
HVG101Y	Pearson Corr.					1	.237(**)
	Sig. (2-tailed)						.000
	N						275

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Since not all courses were similar in context, performance requirements, class atmosphere and many other factors identifying only stages was not as explanatory as required for the simulation model implementation. An attempt was made to group courses according to student performances and to use hierarchical clustering with scores obtained from Equation (2). An example of the resulting dendrograms is given in Figure 6. A dendrogram, a type of visual aid, was used to help in determining the appropriate number of meaningful clusters of courses represented in the data.

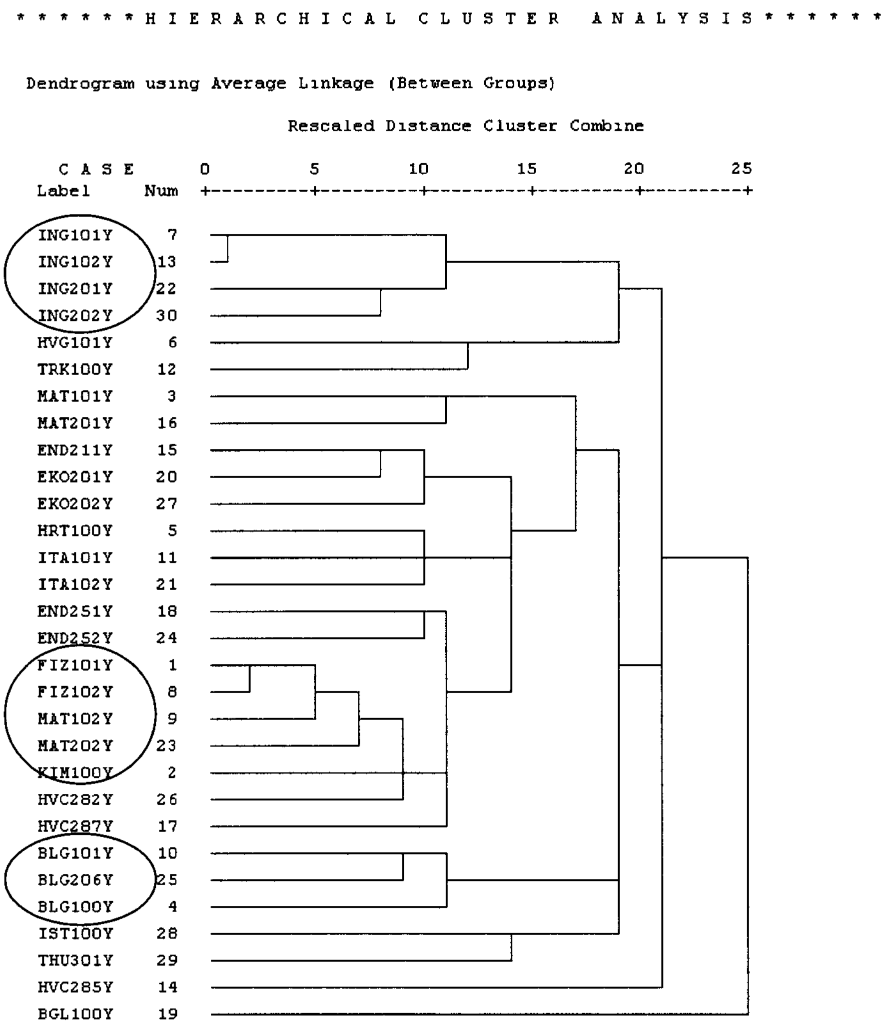


Figure 6. Clusters of courses identified in the Dendrogram

Results obtained from correlation tables were made visual by hierarchical clustering dendrograms. The same procedure was conducted for three stages versus over semesters. With the information obtained from dendrograms, three distinct course clusters were identified:

- courses which require extensive computer ability,
- English as a foreign language courses and
- The rest of the courses that can be explained by descriptive courses of the stages.

Groups of courses with their codes are given in Table 8.

Table 8. Groups of courses identified in the first step of the clustering

	Stage-1	Stage-2	Stage-3
Technical	FIZ101Z FIZ102Y HRT100Z HVG101Y ITA101Z KIM100Z MAT101Z MAT102Z TRK100Y	BGL100Y EKO201Z EKO202Y END211Z END251Z END252Z HVC282Z HVC285Z HVC287Z IST100Z ITA102Z MAT201Z MAT202Z THU301Z	AYZ400Y BGL200Z END303Z END304Y END322Z END332Z END341Z END342Z END361Z END382Y END402Z END422Z END423Z END429Z END452Z END472Z END492Y HRK401Z HSA300Z HTR400Z HUK301Z HUK302Z HVC381Z HVC382Z HVC391Z ISL402Z LID402Y LOJ201Z PSK301Z SYT400Z YON304Y END413Z END414Z END424Z END425Z
English	ING101Z, ING102Z ING201Z ING202Y		ING301Z, ING302Z ING401Y ING402Y
Computer	BLG100Y BLG101Z BLG206Z		

At this phase; by using correlation tables and dendrograms an idea about the course groups in terms of student performance could be visualized. Foreign language courses and computer sciences course were grouped together. Another reason for identifying English and computer sciences courses as different groups from technical courses was their follow-up structure and context continuity. No other distinct cluster information was observable from the dendrograms and correlation tables.

Although the group is named as technical, group does not contain only technical courses. It was the idea to create clusters of students for social and military courses. However no representative homogenous courses were found at the dataset for that course group. In Cakir and Gheorghe (2010), it was shown that clusters of cadets exist who were identified using EM algorithm methodology on applied sciences courses of the first semester at TuAFA. Clusters were also found showing distinct academic performances throughout the undergraduate education with some minor exception courses. Technical cluster membership values were used for all the social and military science courses of the same stage.

Step 2: Clustering Cadets Using EM algorithm

There is no explicit way of determining which variables to use in clustering analysis (Guidici & Figini, 2009,). However the analyst is expected to select the relevant variables which represent data. In 1998, Alexander and Murphy conducted first cluster analytic longitudinal study on academic performance studied student profiles and profile changes over a semester. In 2005, Braten and Olaussen (2005) extended this study into one academic year. In both studies clusters were based on self-reported measures of interest, mastery goals, task value and self-efficacy. A similar methodology can be performed to previous studies but the aim of this research is to find clusters that can be created using student performances on descriptive courses as explained in the first proposition. Previous studies can also be extended by not focusing on solely on overall performance but also on individual course performance.

Taking two remarks into consideration and using the information gained from correlation tables, results of hierarchical clustering and expert opinions courses selected as descriptive for each stage are presented in Table 9. Like all other engineering curricula, the first year curriculum consists of applied science lectures. There are four calculus/mathematics, two physics and a chemistry course in the first three semester of the undergraduate curriculum. These courses keep 18, 8 and 3 course-hours respectively and have 28.5 credits in total. For the first stage, three applied science courses; (Calculus-I (MAT101), Physics-I (FIZ101), and Chemistry (KIM100)) were selected as clustering courses based on their weights and importance for further courses using expert judgments. For the second stage, two applied sciences courses (Linear Algebra (MAT201) and Differential Equations (MAT202)) and two introductory departmental courses (Probability (END251) and Statistics (END252)) were selected as clustering courses. These courses are the basis for future departmental courses. For the third stage, five departmental courses (Operation Research-I (END303), Engineering Economy (END341), Planning for Engineers (END342), Systems Simulation (END361) and Manufacturing Processes (HVC391)) were identified as courses that can be used in clustering process. The last course is an interdepartmental course that is taught by Aeronautical and Space Engineering Department.

Table 9. Courses used in clustering cadets

Group	Stage-1	Stage-2	Stage-3
Technical	FIZ101Z KIM100Z MAT101Z	END251Z END252Z MAT201Z MAT202Z	END303Z END341Z END342Z END361Z HVC391Z
English	ING101Z, ING102Z		ING301Z, ING302Z
Computer	BLG101Z BLG206Z		

Clustering Cadets at Technical Group Courses

The first year is common to all programs and can be thought as a foundation year that is used to help students develop the core competencies required for success in further engineering studies. Courses from applied sciences at this stage were the general characteristic of the freshman year of the proposed curriculum.

Even though Weka produced clusters in different order, they were renamed for simplicity and easy understanding. The following terms were used while naming clusters.

- Clusters with high score average named as cluster-1 and high profile.
- Clusters with medium score average named as cluster-2 and medium profile.
- Clusters with low score average named as cluster-2 and low profile.

Before clustering using Z-scores in selected descriptive courses, sample scores were pooled. Next, as proposed by the literature several runs were made in Weka with different seed values and standard deviation settings. Since a global optimum was not guaranteed in the EM algorithm, models with highest log likelihood values were chosen and are explained in the following paragraphs while presenting six Weka output tables.

Clustering output using EM Algorithm in Weka was given in Table 10 for technical group stage-1 (CT_1) courses. Three clusters were found with the minimum likelihood value of -3.78319. As given in the table, 18% of the samples were assigned to cluster-1, 28% of the samples were assigned to cluster-2 and the 54% of the samples were assigned to cluster-3.

Table 10. Result of clustering technical group stage-1 course scores.

Number of clusters selected by cross validation: 3			
	Cluster		
Attribute	1	2	3
	(0.18)	(0.54)	(0.28)
==================================			
FIZ101Z			
mean	1.2953	0.1159	-1.0629
std.dev.	0.4776	0.6178	0.6293
KIM100Z			
mean	1.0425	0.0901	-0.8494
std.dev.	0.5821	0.7774	0.8348
MAT101Z			
mean	1.0353	0.2032	-1.0624
std.dev.	0.5908	0.6835	0.7023
Log likelihood: -3.78319			

The second year is common to all Industrial Engineering programs and also shares many courses with the other engineering disciplines. This year can also be thought of as a foundation year that focuses heavily on the engineering science required to support later discipline-specific courses in junior and senior years. Clustering using the EM Algorithm obtained from Weka output is given in Table 11 for technical group stage-2 (CT_2) courses. The minimum likelihood value model gave four clusters. As seen from results, 13% of the samples were assigned to cluster-1, 37% of the samples were assigned to cluster-2, 35% of the samples were assigned to cluster-3 and 15% of the samples were assigned to cluster-3.

Table 11. Result of clustering technical group stage-2 course scores.

Number of clusters selected by cross validation: 4				
	Cluster			
Attribute	1	2	3	4
	(0.13)	(0.37)	(0.35)	(0.15)
================================				
MAT201Z				
mean	1.0768	0.3122	-0.1143	-1.3076
std.dev.	0.4097	0.6654	0.727	0.9139
END251Z				
mean	0.9878	0.5406	-0.5699	-0.8507
std.dev.	0.6216	0.6185	0.7081	0.9727
MAT202Z				
mean	1.3694	0.3358	-0.3193	-1.1906
std.dev.	0.3183	0.5639	0.7328	0.7872
END252Z				
mean	1.1533	0.4777	-0.5199	-0.9407
std.dev.	0.6352	0.6238	0.5341	1.0363
Log likelihood: -4.91635				

Clustering using the EM Algorithm obtained from Weka output is given in Table 12 for technical group stage-3 (CT_3) courses. The minimum likelihood value model gives three clusters. As seen from results, 16% of the samples were assigned to cluster-1, 60% of the samples were assigned to cluster-2, and 24% of the samples were assigned to cluster-3.

Clustering Cadets at Computer Sciences Group Courses

Clustering using EM Algorithm obtained from Weka output is given in Table 13 for computer sciences courses group (CC). The minimum likelihood value model gives three clusters. As seen from results, 14% of the samples were assigned to cluster-1, 64% of the samples were assigned to cluster-2, and 22% of the samples were assigned to cluster-3.

Table 12. Result of clustering technical group stage-3 course scores.

Number of clusters selected by cross validation: 3

Attribute	Cluster 1 (0.16)	2 (0.60)	3 (0.24)
END341Z			
mean	1.1307	0.1014	-0.9269
std.dev.	0.6724	0.7178	0.8124
END361Z			
mean	1.3557	0.0304	-0.912
std.dev.	0.719	0.6214	0.7751
END303Z			
mean	1.0594	0.1095	-0.9001
std.dev.	0.576	0.7753	0.8306
HVC391Z			
mean	1.0004	-0.02	-0.5603
std.dev.	0.9477	0.7607	0.9208
END342Z			
mean	0.824	0.0336	-0.5874
std.dev.	0.8813	0.7735	1.0292

Log likelihood: -6.44679

Table 13. Result of clustering computer sciences group course scores.

Number of clusters selected by cross validation: 3

Attribute	Cluster 1 (0.14)	2 (0.64)	3 (0.22)
BLG101Z			
mean	1.111	0.1761	-1.3002
std.dev.	0.7801	0.6914	0.453
BLG206Z			
mean	1.5303	-0.085	-0.7666
std.dev.	0.5012	0.6912	0.7338

Log likelihood: -2.62251

Clustering Cadets at English Languages Courses

English is accepted as the prime communication language in aviation. This is why a high proficiency level in English speaking and writing is approved as a very important aspect of graduates in TuAFA as pilot candidates. English courses are credit courses in order to motivate cadets. Since fall semester 2008, students have taken four of the technical courses in the academic curriculum in English.

English courses have 4 proficiency levels (beginner, intermediate, advanced, super) based on a cadet's TOEFL (Test of English as a Foreign Language) exam score. The examination is held at the beginning of each year. Unfortunately only the last two squadrons that were examined were subjected to the described proficiency structure. Previously, in the old leveling systems, there were three-to-nine levels and no super level was defined. In the new level system "super level" cadets are granted by Management with a straight grade of “AA”. There is also another exemption for these super level cadets that they do not take regular exams like their other level cadets. Courses are generally focused on speaking/presentation and composition type studies with an English native language speaker. Examination questions are generally paragraph/composition writing type.

Since the first two squadrons were subjected to a different scaling and no super level was defined the last two squadron’s grades were used in the analysis. At each semester, there is an English as a foreign language course. While clustering, both courses in freshman year were found ineligible based on the first remark. Both courses of sophomore year failed in homogeneity of variances test. That is two stages were used, as given in Table 9. In Table 14 and Table 15 clustering results are shown using freshman year courses (ING101, ING102) and junior year courses (ING301, ING302) while clustering with the EM algorithm. Three clusters were identified at both stages.

Table 14. Results of clustering English stage-1 course scores

Number of clusters selected by cross validation: 3			
	Cluster		
Attribute	1	2	3
	(0.21)	(0.61)	(0.18)
ING101Z			
mean	1.1218	0.1029	-1.627
std.dev.	0.3349	0.5648	0.5206
ING102Z			
mean	1.2395	-0.0688	-1.151
std.dev.	0.2795	0.624	0.958
Log likelihood: -2.37194			

Table 15. Results of clustering English stage-2 course scores

Number of clusters selected by cross validation: 3			
	Cluster		
Attribute	1	2	3
	(0.35)	(0.42)	(0.23)
ING301Z			
mean	0.7356	-0.3965	0.0106
std.dev.	0.2981	1.017	0.047
ING302Z			
mean	0.8943	-0.4781	0
std.dev.	0.2108	0.8876	0.8974
Log likelihood: -2.15199			

Validation of Clusters

At the validation step, cluster membership was used as categorical variables. The same approach is followed in the longitudinal studies of Alexander and Murphy (1998) and Braten and Olaussen (2005) where clustering was selected as an appropriate tool for defining clusters among students. However since both studies are from educational psychological area, independent variables were selected among the questions of the analyst's surveys on students psychological situation. In this case, cadet's scores in representative courses were used as variables.

For the validation of the clusters a three step procedure was followed. First ANOVA was used to test the significance of the cluster. Second a non-parametric Kruskal-Wallis rank test was used. Third a discriminant function analysis was used to finalize the validation procedure.

Validation of Clusters by ANOVA

The hypotheses used in validation steps are given below. The null hypothesis indicating mean difference is insignificant in the clusters where "*j*" was the courses and the "*k*" was clusters.

$$H_0 : \mu_{j,k=1} = \mu_{j,k=2} = \mu_{j,k=3} = \mu_{j,k=4} \quad \forall j$$

$$H_a : \text{ any one of the cluster means is different}$$

ANOVA tables of the clusters are given in the tables in Appendix C. Since significance values are all less than 0.05 level, it was concluded that clusters means were significantly different. These results validated the clustering procedure and clusters created by the EM algorithm using Z-scores.

Projections of Clusters on Other Courses and Validation by Kruskal-Wallis Test

The performances on the other courses which can be thought as projections (using the same cluster membership) were also checked. A Kruskal-Wallis nonparametric mean rank test was conducted when testing cluster group differences. This test was used because of the underlying assumptions of ANOVA. A Kruskal-Wallis nonparametric test is a one-way analysis of variance by rank. It tests whether or not the values of a particular variable differ between two or more groups. Unlike standard ANOVA, it does not assume normality (SPSS, 2007).

Constructed null and the alternative hypotheses were written as,

H_0: Clusters created by representative course performances were valid for other courses at the same stage

H_a: Clusters created by representative course performances were not valid for other courses at the same stage.

Courses with small number of data

Four courses were left out of cluster projections because of the small amount number of data availability on these courses. All of these courses are complementary technical elective courses and opened only a single semester during research time span. These lectures are listed at Table 16.

Table 16. Courses that were not clustered due to lack of data

Course Name	Course Code
Systems Analyses and Evaluation	END 413
Supply Chain Management	END 414
Group Technology and Flexible Manufacturing Systems	END 424
Computer Integrated Manufacturing Systems-I (CIM-I)	END 425

A Kruskal-Wallis nonparametric analysis of ranks results for all courses were given in Table 49 through Table 53 in the Appendix D. When the significance level found to be below 0.05, it was concluded that cluster locations were different and valid. This was true for all courses in the curriculum with three exception courses.

Mean ranks of clusters were presented in Table 54 through Table 57 in Appendix E. High profile cadets continued getting high scores in other projected courses. The same conclusion was reached for medium and low profile cadets.

The difference in mean ranks was found to be statistically insignificant in three courses. More information about these courses and grading methods may be required. Graduation Project (END492) is a credit course where cadets submit their projects in teams of two. These teams are not created according to academic performance. Generally, friendship among cadets plays major role in formation of the teams. Leadership (LID402) is a course that distinguishes itself from other courses in terms of team projects and presentation assignments weight in grading where non-cognitive inputs may play a significant role. Also this course is given by different instructors. The last course is Production Systems Analysis (END425) and this course is a technical elective course that was open for only one semester. This course was also lacking enough number of data so it was left that course out of cluster assignments and used as a single cluster. These three courses constitute only 3% of the total examined courses.

In summary, it was shown that clusters of students that were observed with the EM algorithm can be used in defining cadet's performances on overall performance. This might be the result of many underlying cognitive and non-cognitive input variables effecting academic performance which was out of the scope of this study. These clusters of cadets were showing distinct performances all throughout undergraduate education.

Validation of Clusters by Discriminant Analysis

Finally as a last tool, a discriminant function analysis was used in order to validate the clusters (Braten and Olaussen, 2005) that were created by descriptive courses. Discriminant function analysis is one of the methodologies used for modeling a dependent categorical variable's value based on its relationship to one or more independent predictors. The procedure starts with choosing the first function that separates the sample as much as possible. Then it chooses a second function that is uncorrelated with the first one and provides a new separation. The procedure continues until the number of categories defined by dependant categorical variable is reached.

The procedures described below were conducted for all six course groups and results were given in Table 59 through Table 64 in Appendix F. The discriminant function analysis results for CT_1 courses were given Table 17 as an example. In the example table, the result indicated that 94.9% of the cadets were clustered correctly in the clustering procedure. Next Box's M statistic was examined in order to test the equality of covariance matrices. In this test when significance level found less than 0.05, it was concluded that equal covariance matrices hypothesis was rejected. In the example result given in Table 18 and other test the null hypothesis was rejected. If it had been found that value larger than a predefined significance value the assumption of multivariate normality would have been rejected. Next another test of separate matrixes was performed to see if it gave radically different classification results. The result for the example group CT_1 is given in Table 18. When the results were not changed in the next test with separate-groups covariance matrix post hoc multiple comparisons were performed with Wilks' lambda. This statistic is the ratio of the within-groups sum of squares to the total sum of squares. Wilk's lambda takes values between 0 and 1. Small values indicate strong group differences. The F statistic value and degree of freedom values in the same table were used to obtain significance values given in the last column as shown in Table 19 as an example. If the significance value was small, this indicated that difference between groups were significant. For all courses (without the two courses described above) results showed that all cluster groups were significantly different from one another.

Table 17. Classification results obtained by discriminant functions analysis of CT_1

Classification Results(b,c)

		tech.cluster.1	Predicted Group Membership 1	2	3	Total 1
Original	Count	1	51	0	0	51
		2	9	135	5	149
		3	0	0	76	76
	%	1	100.0	.0	.0	100.0
		2	6.0	90.6	3.4	100.0
		3	.0	.0	100.0	100.0
Cross-validated(a)	Count	1	51	0	0	51
		2	9	135	5	149
		3	0	0	76	76
	%	1	100.0	.0	.0	100.0
		2	6.0	90.6	3.4	100.0
		3	.0	.0	100.0	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b 94.9% of original grouped cases correctly classified.

c 94.9% of cross-validated grouped cases correctly classified.

Table 18. Box's Test of Equality of Covariance Matrices.

Test Results

Box's M		35.232
F	Approx.	2.878
	df1	12
	df2	117628.046
	Sig.	.001

Tests null hypothesis of equal population covariance matrices.

Table 19. Test of equality of group means for validation.

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
FIZ101Z	.314	297.671	2	273	.000
KIM100Z	.545	113.998	2	273	.000
MAT101Z	.433	179.001	2	273	.000

At the end of the described discriminant function analysis testing procedure it was concluded that that group membership values were accurately predicted. This accuracy reached 94.9% for the CT_1 as shown in Table 17. The prediction accuracy for the CT_2 clustering process was 89.2% and the prediction accuracy for the CC was 88.4. High values of CT_1 compared especially to computer courses clusters indicating that courses used in clustering process were better descriptive. Results validated significantly different groups were obtained by the EM algorithm. The obtained results are summarized in Table 20.

Table 20. Validation by Discriminant Analysis Results

<table>
<tr><th>Group</th><th>Stage-1</th><th>Stage-2</th><th>Stage-3</th></tr>
<tr><td>Technical</td><td>94.9</td><td>89.2</td><td>94.1</td></tr>
<tr><td>English</td><td colspan="2">93</td><td>94.3</td></tr>
<tr><td>Computer</td><td colspan="3">88.4</td></tr>
</table>

Summary

In this chapter, hierarchical clustering methodology and correlation tables were used to cluster and group courses both in context and stage. Next EM clustering methodology was performed on course scores in order to cluster cadets in these course groups. Clustering procedures were validated using ANOVA tables, Kruskal-Wallis non-parametric test, and a discriminant function analysis procedure. Four courses were removed from the clustering procedure because of the small number of data. In two courses, clusters were not statistically different. Two of the research hypotheses were validated at this stage. The hypotheses that were tested in this chapter and the results obtained are summarized in Table 21.

Table 21: Summary of the results of hypothesis-1 and hypothesis-2

Hypothesis 1: Cadets are showing similar performances in groups of courses that can be explained by hierarchical cluster analysis in terms of both content and stage of the education.	Decision: Based on the hierarchical clustering results and corresponding ANOVA tables conducted at different stages of education this hypothesis was validated.
Hypothesis 2: There is statistically significant difference between mean values of groups of cadets that can be obtained by cluster analysis using course scores on descriptive courses.	Decision: This hypothesis is validated the EM clustering methodology and Kruskal-Wallis test results. It was concluded that, clusters created by descriptive courses were significantly different on not only on courses used for clustering but also on the projected courses.

CHAPTER IV

THE SIMULATION MODEL

Simulation has many advantages over traditional analytical approaches. It mimics what happens in the real system or possible outcomes of a design as in this case. By changing input parameters and model characteristics alternative scenarios can be created and evaluated (Banks et al., 2005). .In this chapter, a system design procedure is summarized for the new evaluation system. Next simulation for the validation of cluster results is used in order to perform the simulation. Then a simulation was used for the evaluation of the new system designs. The first simulation model used for the validation purposes is used as a submodel in the evaluation system simulation model.

System Design and Scenario Definitions

In this study, developing a new curriculum was required in addition to a new passing system proposal. The main reason for that curriculum change proposal was the need for a decrease in course hours in the junior and senior years. In the current curriculum a cadet spends around 31 course hours per week while taking academic courses. When it is compared to average of 16-21 hours of academic courses per week on the average in engineering education curricula in Turkey, problem becomes much clearer.

While designing new curriculum and evaluation system the academic evaluation systems of four major universities of Turkey and USAFA were examined. By doing that the aim was to compare education processes and performance metrics used in these best practices.

Benchmark Examples

In this part of the chapter some examples of evaluation systems were examined as benchmarks. Examples were selected from Turkey and USA. In all examined schools flexible course schedules are offered to students and credit letter grading system is implemented. Universities defined similar rules when dealing with course failures and academic performance improvement[3].

Current Evaluation System and Curriculum

Before moving further into system design brief information about the education processes and grading system of TuAFA should be given. The current evaluation system in TuAFA is a combination of pass/fail system and letter grading system. In the literature survey and benchmark example research it was found that the pass/fail system is currently implemented in medical schools, dental schools, and law schools in addition to military academies of Turkey, and other countries. We also found a few colleges employing this system for only freshman year in engineering undergraduate education programs in Turkey. Except military academies no university follow such an evaluation system for the eight semester engineering education.

There is a make-up and upgrade examination period at the end of the each academic year, starting two weeks after the last day of final examinations of the spring semester. In order to enter make-up examinations a cadet is required to get at least 1.2 academic year GPA. Cadets who failed courses in the semester must take make-up examinations. If a 2.00 semester GPA (sGPA) limit is not reached but all courses are passed, the cadet takes upgrade examinations. There is also an additional make-up examination which is called single course make-up exam period after the regular make-up and upgrade examination period. This opportunity is given to cadets who passed

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[3] Bogazici University, Middle East Technical University, Istanbul Technical University, Istanbul University and United States Air Force Academy were selected as benchmarks. For further reading about their evaluation systems refer to each university's regulations that were given in Appendix G.

all courses but failed a single one course and satisfied the 2.00 academic year GPA requirement. Senior cadets are given one additional chance to take a second additional make-up examination with the approval of Academic Council of TuAFA.

A cadet is required to get at least 2.00 academic year GPA at the end of all available make-up and upgrade examinations and pass all courses of the curriculum for the current year. Otherwise the cadet is required to follow retention rules. That means losing a year in the academy. Cadets were given only a single retention opportunity. If second retention is required, the cadet is discharged from the academy and required to pay all expenses.

The retention rule is simple process with disadvantages and advantages. The major disadvantage is when cadet fails cadet needs to take all courses even if a course is passed in the previous year. Another disadvantage is when a course is removed from curriculum by the department, cadets who failed that course repeat the year in vain. The major advantage of this system is in the planning phase of the courses and controlling cadet's daily life. Every cadet follows a predetermined timetable and commanders always know where cadets are (for more detailed information please refer to Military Academies Regulation in Turkey at http://www.mevzuat.adalet.gov.tr/html/20849.html).

In order to overcome disadvantages of the pass/fail system, cadets are very closely monitored by the Academy Management. The Commander and Dean follow every cadet's performance and every course success and fail ratio throughout the year. Every classroom of cadets is assigned an advisor by the Dean's Office of TuAFA. An advisor is not necessarily from the cadet's department.

New Evaluation System and Curriculum Design for TuAFA

Being a very important benchmark to TuAFA while developing a new evaluation system this study benefited from USAFA's experience as well as the experiences of major universities of

Turkey. Two different settings were proposed for lower limit values. Probation list rules were proposed in the new system. While designing the curriculum for first four semesters, more course hours than any of the other benchmarks was placed. The main reason for this was the limitation on the course hour timetable. Courses must be given between 8:00 AM and 16:30 PM. Eight course-hours slots instead of the current seven course-hours slots were proposed.

A comparison table among benchmark universities in means of weekly total course hours for a normal course load progression for graduation is presented in Table 22. As can be seen from the comparison table, the course hours total at TuAFA is at least 30 hours more than the other universities. Their normal graduation curriculums have 16-21 hours on the average.

Table 22. Total course hours comparison for eight semesters

Semester	ITU	METU	BU	USAFA	TuAFA (current)	TuAFA (proposed)
1	23	25	27	16.5	25	27
2	23	26	26	18.5	25	27
3	21	18	21	19	26	25
4	20	21	20	18.5	26	25
5	19	17	18	19	28	21
6	18	20	19	18.5	27	21
7	18	18	18	18.5	28	19
8	22	22	20	18.5	26	18
Total	**164**	**167**	**169**	**147**	**211**	**183**

The proposed curriculum given in Appendix A for TuAFA has 27-27-25-25 course hours for the first four semesters. Course hours could not be decreased further because of the additional military and social science courses required for graduation.

At USAFA, 32 majors and two minors are offered to cadets. This provides cadets an option to select a variety of courses that fits their timetable. Currently TuAFA only offers four majors and no minors were defined in industrial engineering education. In the proposed curriculum two minors are proposed for Industrial Engineering Education.

In order to create spare time for cadets and empty course hour slots for overloaded/failed/retaken courses a new timetable was needed. By doing that the aim is to show availability of course-hours and applicability of curricula. Example timetables that were developed for this dissertation study are given in Appendix H. These tables were designed in accordance with primary goals of the curriculum design that can be summarized in two sentences.

- The designed curriculum and the timetables need to allow a semester to graduate early by overloading courses from next semester's curriculum.
- The designed curriculum and the timetables need to provide course hour slots for course repetitions.

The proposed curriculum satisfies the accreditation of the Council of Higher Education of Turkey and the mission of TuAF defined by-laws. The curriculum was also approved by the Planning Department of the Dean's Office according to the classroom, personnel and other resource constraints which were left out of the scope of this study.

A Semester Early Academic Graduation and Probation Rules

In the proposed system a Dean's list (a version of Honor List) called ERDEM is proposed. ERDEM is an acronym for the Turkish version of "a semester early flexible graduation". It also has the meaning of "wisdom" in Turkish. When a cadet is at the beginning of fourth semester, if he/she has minimum 2.70 cumulative GPA and English level is at least intermediate level he/she is proposed to be put on the ERDEM list. If a cadet is tagged as ERDEM and eligible to overload he/she is allowed to take maximum of 10 additional hours of courses (maximum of three technical courses).

A probation rule was proposed in the new system, since retention rule is revoked. A cadet was required to satisfy cumulative GPA and sGPA limits, otherwise he/she is placed on the probation list. Also if a cadet is placed in the probation list, the cadet is removed from ERDEM list.

Course Taking Rules

In the current system since a year of passing grades is followed with a fixed curriculum and timetable, there is no need for definition of rules for course eligibility. However in the proposed system these rules need to be developed.

Many courses in the curriculum have follow-up structure. For example a student has to be successful in "Linear Algebra" to continue successfully to the follow-up course "Operation Research-1". This structure was not clearly understood at the academy when this research began. In the current system, all prerequisites were automatically satisfied when cadet passes the year since leveling courses taken previously were passed. Most of the instructors mixed prerequisite courses through related courses. Necessary prerequisites were defined for each course at the beginning. After some education and explaining the new passing system a better structure of prerequisites diagram is constructed and presented in Figure 7.

In the designed industrial engineering curriculum two major flows of courses exists. The first flow is the flow of *linear algebra* which starts with MAT201 and MAT101 and continues with operations research courses. The second major flow is *stochastic courses* which starts with MAT102 and continues with probability and statistics courses.

The proposed rules for course taking are

- all prerequisite courses have to be passed in previous semesters,
- overloading is only possible for listed cadets for a maximum of 10 course hours.
- while repeating failed courses maximum of 6 course can be added,
- if a cadet is on the probation list for the first time the cadet should repeat courses with FF
- if cadet is on the probation list for more than one time the cadet should repeat courses with DD and DC,

- if cadet fails a course at the end of make-up exams, the course should be repeated.

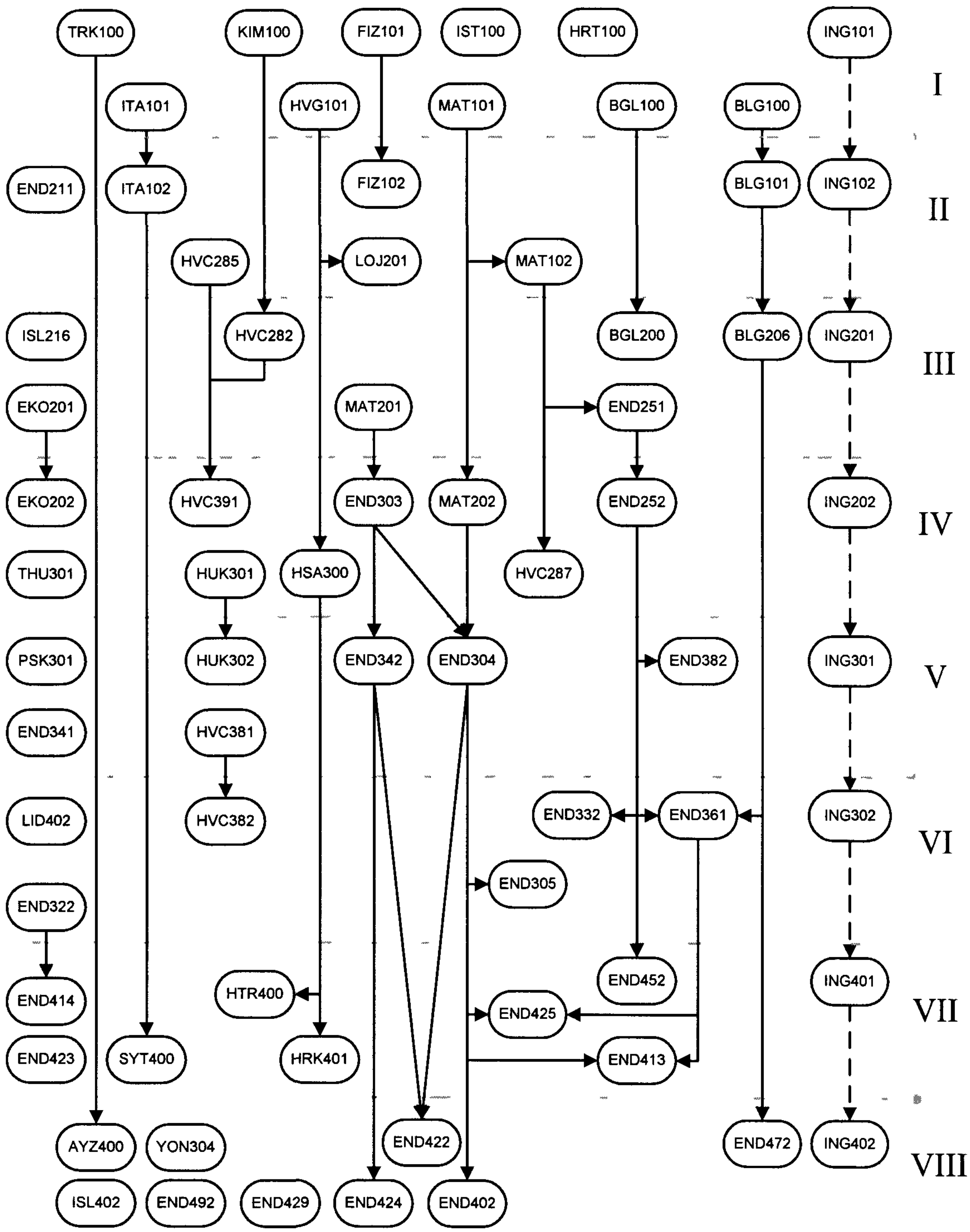

Figure 7. Prerequisite courses in the proposed curriculum

Technical complimentary courses were defined as a new concept to the academy. These courses were separated into two groups, each having four courses.

- In the first group were courses which were coded as END4X1 and END4X3. These courses were "Systems Analyses and Evaluation (END413)", "Statistical Decision Making (END452)", "Systems Decision Theory (END402)" and "Scheduling (END422)" and named as a "Systems Engineering" minor.

- In the second group were courses with END4X2 and END4X4. These courses were "Supply Chain Management (END414)", "Computer Integrated Manufacturing Systems-I (CIM-I) (END425)", "Group Technology and Flexible Manufacturing Systems (END424)" and "Just in Time (JIT) Manufacturing (END429)" and named as a "Production Management" minor.

Courses in the same group were proposed to be replicable for one another. Which means that, if a cadet failed from one of the END4X1 courses in the seventh semester, the cadet can replace the grades and credits of this course by taking one of the END4X3 courses as a replacement and the other one as the technical selective in the eighth semester. For the cadets who were taking a ninth semester and did not take a required complimentary courses because of the course hours constraints in the eight semesters it was made possible to replace complimentary courses using any available complimentary course in order to replace the next semester's complimentary courses.

Another new concept to the academy is the social complimentary courses. Two social complimentary courses were created to be opened in both semesters and to be replicable to one another.

All complimentary courses need not to be the courses selected for this simulation and designing study. These courses were chosen because the data on these courses were available and the courses were accepted as possible candidates by the department.

Make-Up and Upgrade Examinations

A single make-up and upgrade examination was proposed in the new system. A semester grade for the cadet was replaced with the examination grade when passed. Since 2003 although make-up and upgrade examination grades were entered into the transcript, credits did not necessarily have to have a letter equivalent. Credits shown in Table 1 were given only if it was required to pass 2.00 sGPA limit. Otherwise only 1 credit was given to cadet whatever the grade was. The same procedure is proposed in the new model with a minor difference. In the new system, increments were made just enough to pass cumulative GPA and sGPA lower limit values not up to the currently followed 2.00 sGPA limit. If a cadet did not satisfy these limits he/she was to be placed on the probation list. In order to take an upgrade examinations course should be taken at the same semester and credit letter should be DD or DC.

Rules defined in order to be eligible to take make-up examinations are listed below.

- Course should be taken in the same semester. Attendance of the courses in the same semester is mandatory, which means that just attending examinations is neither allowed nor accepted.

- SGPA lower limit for make-up examinations eligibility should be satisfied.

If cadet fails a course at the end of semester and does not pass the make-up exam, the course should be repeated in the first semester available.

An exception was defined for the cadets who were eligible for graduation. These cadets were proposed to take an additional make-up and upgrade examination in the second round of exams to graduate. In the new system graduation means:

- 169 credits of courses must be taken,

- mandatory courses must be taken,

- no F grades, and
- a cumulative GPA more than or equal to 2.00.

New Courses

The management of the Industrial Engineering Department recently opened a new course named Operation Research III. For that lecture Operation Research II course was decided to be a prerequisite. Also the instructor was expecting similar success and failure rates to its prerequisite lecture as indicated in this dissertation's interview. The statistics of the Operation Research-II were used since no information is currently available for the new course.

English Language Courses Rule

There were four proficiency levels (beginner, intermediate, advanced and super) in English courses. Student who showed extreme proficiency in English were categorized as super level. Super level courses were awarded by straight "AA" credit letter by the Academy Management. It was expected to increase motivation of learning English among cadets. Level changes were made possible at the beginning of each year depending on the cadet's TOEFL score.

Education of English as a foreign language needed special attention in modeling of the new system. It was also very important part of the curriculum development with its course hours, credits and continuing follow-up structure. Because of that structure each semester's English course is a prerequisite of the next semester's English course. This means that any curriculum development study or evaluation system design effort should pay special attention to organizing these courses. Because when a failure occurs it would mean a semester delay at academic graduation. The same is true for a semester early academic graduation case which is only possible when next semester courses overloaded. In order to overcome this problem, English courses were made possible to be overloaded if cadet was not in beginner proficiency level. It was also made possible for failed cadets in advanced proficiency level to take two English language courses at the same semester. This structure is designed with the approval of the Foreign Language Education Department.

Discharge Rules

In the proposed new evaluation system, cadets discharged from/dropped out of the academy under three conditions.

- If cadet is placed in the probation list at three consecutive semesters or five times at total.
- If cadet cannot reach a cumulative GPA limit (2.00) at the end of ten semesters.
- If cadet fails a course second time.

Scenario Definitions

Two alternative settings were defined for each decision variables and conducted experimental design on 16 different settings. Detailed information on scenario evaluation is given in the next chapter.

Conceptual Model

In this part of the chapter a simulation model development procedure was introduced for the new evaluation system. While developing the simulation model information was used from a clustering study and the new curriculum design study as inputs. The model consisted of six submodels.

Input Modeling

For distribution fitting of the clusters the Input Analysis tool of ARENA was used. The main reason for selecting this tool is that ARENA is the software that will be used in the later stages in the study and its easy-to-use interface.

First, all distributions used in simulation studies were fit into each course cluster. For the courses that were not used in clustering, cluster membership variable values identified for the group were used, which can be thought as projections. In ARENA's input analysis tool the quality of a curve fit is based primarily on the square error criterion, which is defined as the sum of $(f_i - f_{xi})^2$, that is summed over all histogram intervals. In this expression f_i refers to the relative frequency of the data for the *i*th interval, and f_{xi} refers to the relative frequency for the fit probability distribution function (ARENA 9.0 online help, n. d.). *p values* were also taken into consideration and selected best distribution that is giving minimum *p* value and square error term. If all of the generally used distributions rejected by the goodness of fit tests, an empirical distribution observed from the cluster sample was used. An example of the distribution procedure is given in Appendix I for CT_1. Resulting distributions for all course clusters were summarized in tables of Appendix J. Next, linear equation parameters were found for each squadron, as given in tables of Appendix K, and scores were transformed into grades.

Entities

- Cadets: Entities were cadets in the simulation model.
- Dummy entities: Used in order to assign squadron variable at each semester.

Variables and Attributes

In ARENA, a variable means a global variable that is visible to all entities. Attributes mean local variables which are specific to entities. Global variables are known by all entities however local variables (attributes) are not known by other entities. For this study both type of variables were used, as given in Appendix L.

Parameters

First the semester credits of each course, course hours of each course, grade limits, cluster membership ratios, cluster membership movements, cluster performance distributions, linear transformation functions for grades, make-up examination failure rates and distribution information were regarded as input parameters into the simulation model.

- derscredit: credit of course at the curriculum.
- ing1AA-ing1DD grade limits for letters described in Table 1 for ING101 and ING102.
- ingAA-ingDD grade limits for letters described in Table 1 for ING201, ING202, ING301, ING301, ING401 and ING402.
- tekAA-tekDD grade limits for letters described in Table 1 for technical courses (departmental courses and applied sciences courses).
- asosAA-asosDD grade limits for letters described in Table 1 for military and social sciences courses.
- Input parameters: distributions parameters.
- Course grade parameters: linear equation used in grade random variable generation for each course based on statistics obtained for each squadron.
- Transition probabilities: Probabilities obtained by tracking movements of cadets across stages.

Performance Measures

Performance measures were identified in validation of the clustering methodology and scenario analysis. If the “F” ratios and “AA” ratios were predicted within an acceptable margin the simulation model was then run. Identified variables were given in two categories.

Measures Used in Validation of Clustering Methodology to be Used in Simulation

- Number of cadets that got an "F" in a course.
- Number of cadets that got an "AA" in a course.

Measures Used in Experimentation and Simulation Scenario Analysis

- Number of graduated cadets (used in simulation experimentation).
- Graduation time (used in simulation experimentation).
- Number of a semester early academically graduated cadets (used in simulation experimentation).
- Number of discharged cadets due to probation rules (used in simulation experimentation).
- Number of discharged cadets due to failure of a course two times (used in simulation experimentation).
- Discharged time due to probation (used in experimentation).

Decision Variables

Although decision variables were categorized under different categories, because of the iterative nature of the modeling and the simulation variables, they were evaluated at each step of the study.

Decision Variables Used in Curriculum and Evaluation System Designs

- Prerequisites courses of each course.
- Number of course hours that can be overloaded.
- English language course rules.
- Social elective course rules.
- Technical elective course rules.

- Probation list entrance rules.

Decision Variables Used in Simulation Model Building and Experimentation

The last four variables in this category were used in experimentation.

- Curriculum and other outputs of curriculum and evaluation system design process.
- Course timetable.
- sGPA lower limits to be not placed in probation list.
- Cumulative GPA lower limits to be not placed in probation list.
- sGPA lower limit value required to take make-up examinations.
- Total probation list entrance counter value.

Assumptions

This research study is based on some assumptions because of the lack of information on the following subjects.

- Failed students were less likely to fail the same course.
- Instructors will not change their grading behaviors when the evaluation system is changed.
- Cadets will not change their studying behaviors when the evaluation system is changed.
- When the new evaluation system is implemented there will be enough resources to satisfy the timetable as assured by the Planning Department of Dean's Office.
- Academic graduation at seventh semester (overloading and taking courses with higher ranked cadets) and its possible tension will not affect high profile cadets' performances.

Limitations

- Limited data: Because of curriculum changes applied in 2003 and 2007 data were limited. Cadets enrolled prior to 2003 and their grades were not consistent with the database because of a curriculum changes by the department. Since 25 hours of English language education was inserted into the first semester curricula, grades of cadets enrolled later than 2007 were not used in clustering and simulation studies.

- Limited data on some of the technical complimentary courses.

- Limited data of the cadets enrolled in 2006. Eighth semester grades were not available at the time of the analysis.

- Grades for retention/repeating cadets were not stored and shown in transcripts. One of the difficulties that were experienced during the data collection and database preparation phase was the loss of repeating cadet's grades. These grades were important for the analysis of extreme students however they did not appear in the transcripts. Grades were of more value than grades of an ordinary regular cadet since these cadets were pushing the limits of the system.

One of the main boundaries that were experienced was grading and curriculum changes. Although some of the civilian universities were benchmarked, there was still no example of such an evaluation system change in the military academic environment. Transformation of such a hierarchical, centrally governed and historic organization was not experienced before. The Turkish Air Force and other Army colleges had no experience with evaluation systems that allow students take courses from other semesters with other squadrons.

Equations

Equations Used in Make-Up and Upgrade Submodel

• semcredit = semcredit + derscredit * crdactive	!! total credit earned in semester
• totalcredit = totalcredit + semcredit	!! total credit earned
• semderscredit = semderscredit + crdactive	!! course credits it the semester
• totalderscredit = totalderscredit + semderscredit	!! total course credits
• yko = semcredit / semderscredit	!! sGPA update at the end of each course taking and after the make-up/upgrade examinations
• gko = totalcredit / totalderscredit	!! cumulative GPA update before and after make-up/upgrade examination period.
• MX ((semderscredit * ykohedef) , (semderscredit * gkohedef))	!! calculates total credit that should be earned at the semester in order to reach the maximum of two GPA lower limit values

Equations Used in Course Submodels

- dersf = dersf + 1 — !! if student failed counts failures
- dersrpt = dersrpt + 1 — !! counts repetition of the course
- hds = hds + hdsactive — !! keeps record of total hours of courses in a week
- overhds = overhds + hdsactive — !! keeps record of overloaded course hours
- totalcredit = totalcredit - derscredit * crdactive — !! if course is repeated subtracts previously earned credits

Constraints

Prerequisite Courses Constraints

- *prerequisite_coursecode***rpt** >0 — !! prerequisite course should have been taken
- *coursecode***donem** <> TNOW — !! prerequisite shouldn't have been taken at the current semester
- *coursecode***f** == 0 — !! prerequisite should have been passed

Course Hours Constraints

- (hds+hdsactive) <= hdsmax — !! Ensures that cadet has enough course hours to take the course
- we3 ==0 && we4 == 0 — !! third and the fourth course hours of Wednesday shouldn't be occupied by another course

Academic eligibility for course taking

If course is to be taken for the first time

These constraints ensure regular cadets to take course at the semester specified in the curriculum. For that purpose ARENA's embedded variables TNOW and Entity.VA.Time were used. A regular student can take the course no early than the specified time if it is to be taken for the first time.

• *coursecode***rpt== 0 &&** Entity.VATime >= 15	!! these constraints satisfies that course should be taken according to curriculum (controlled by Entity.VA.Time)
• over ==1 && (overhds + hdsactive) <= overhdsmax	!! if student is eligible for overloading this constraint checks if entity still has available hours for overloading.

If course is to be taken for the second time

One of the below two constraints should be satisfied.

• *coursecode***rpt== 1** && *coursecode***f** == 1	!! course is a repeating course and a failed course
• goztkr == 2 && (Entity.VATime - dersdonem) <= 10 && (derscredit == 1 || derscredit == 1.5)	!! If student was in probation list and course credit letter was DD or DC.

An example of combination of described prerequisite constraints in a single *DECIDE block* was given below for the *Logistics* (HSA300) course. The course is opened in the first course hour of Monday. It has a prerequisite course named *Introduction to Aviation* (HVG101).

(HVG101rpt >0 && HVG101donem <> TNOW && HVG101f == 0) && we3 ==0 && we4 == 0 (hds+hdsactive) <= hdsmax && ((dersrpt == 0 && (Entity.VATime >= 15|| (over ==1 && (overhds + hdsactive) <= overhdsmax)) || (dersrpt == 1 && (dersf == 1 || (goztkr == 2 && (Entity.VATime - dersdonem) <= 10 && (derscredit == 1 || derscredit == 1.5)))))

Make-Up and Upgrade Examination Taking

At the beginnings of the make-up and upgrade examination submodel:

- yko >= make_up_limit !! sGPA should be greater than make_up lower limit credit value in order not to enter into probation list and take make_up examinations.
- *coursecode***f** == 0 !! no failure at the courses
- yko >= ykohedef && gko >= gkohedef !! student must satisfy both sGPA and cumulative GPA lower limit values otherwise put into probation list
- ekbut == 1 || ekyuk == 1 !! if student is a senior student and eligible for graduation one more make-up and upgrade examination round is conducted

At the beginnings of each course submodel in the make-up and upgrade examination submodel:

- *coursecode***donem** == TNOW !! course should be taken at the same semester
- *coursecode***f** >= 1 || (yuk == 1 && ING102 < ing1CC) !! course grade should be F *or* must be an upgrading cadet and course grade should be DD or DC

Upgrade and make-up examinations resulting conditions

• yuk == 0 && dersf == 1	!! examination is taken for only make-up purpose. Result: grdactive == 51 && derscredit == 1
• yuk == 1 && dersf == 1 && grdactive > ders	!! course is taken for both upgrade and make-up purposes and grade is higher than semester grade. !! Result: credit incremental until maximum of sGPA lower limit or cumulative GPA lower limit satisfied. !! Result: *ders* == grdactive, *ders*f == 0, *ders*credit == 0.5
• yuk == 1 && dersf == 1 && grdactive <= ders	!! failure condition and grade taken was lower than the semester grade !! Result: grdactive == 50, derscredit == 1
• yuk == 1 && dersf == 0 && grdactive <= ders	!! do nothing since make-up examination grade is smaller than the semester grade

Discharge from academy

• goztkr == 3 || goz == 5	!! if cadet stayed on the probation list three consecutive times or five times total
• *coursecode*f == 2	!! if failed two times from the same lecture

Logical Model

In this step, algorithms of the simulation model with flow diagrams were developed. The integration procedure of clustering results and simulation study is explained.

Creation of entities

Entities were cadets in the simulation model. Cluster membership proportions across "*technical stage-1 cluster membership*" (CT_{1i}, i: 1,2,3) and "*computer cluster membership*" (CC_j, j: 1,2,3) are presented in Table 23.

Table 23. Cross table with proportions between CT_1 and CC

		CC				
		1	2	3	**Total**	
CT_1	**1**	0.07	0.12	0.00	0.18	1
	2	0.07	0.38	0.09	0.54	
	3	0.01	0.15	0.12	0.28	
		0.14	0.64	0.22		

Cluster memberships of cadets were identified as "*English stage-1 cluster membership*" (CE_{1i}, i: 1,2,3) and "*English proficiency level-1*" (EL_{1j}, j: 1,2,3,4). The proportions of the observations are presented as a cross table in Table 24.

Table 24. Cross table with proportions between CE_1 and EL

		EL_1					
		Beginner	**Intermediate**	**Advanced**	**Super**	**Total**	
		1	**2**	**3**	**4**		
CE_1	**1**	0.01	0.03	0.02	0.15	0.21	1
	2	0.07	0.21	0.33	0.01	0.61	
	3	0.03	0.06	0.09	0.00	0.18	
		0.11	0.30	0.43	0.16		

The two previous tables were combined and resulting percentages were given in Table 25. Each cell represent the probability of $P\left(CT_{1i}, CC_j, CE_{1k}, EL_{1l}\right)$ *i,j,k*: 1,2,3 and *l*:1,2,3,4. Probabilities presented in this table were used while separating created entities into groups in the simulation model.

Table 25. Probabilities of cluster memberships attribute.

	CE	1				2				3		
CT	CC \ EL	1	2	3	4	1	2	3	4	1	2	3
1	1	**0.100**	0.000	0.000	**0.600**	0.000	**0.100**	**0.100**	0.000	0.000	**0.100**	0.000
	2	0.000	**0.050**	0.000	**0.050**	0.000	**0.350**	**0.450**	0.000	**0.050**	**0.050**	0.000
2	1	0.000	0.000	**0.111**	**0.333**	0.000	0.000	**0.556**	0.000	0.000	0.000	0.000
	2	0.000	**0.039**	**0.020**	**0.137**	**0.098**	**0.275**	**0.333**	**0.020**	**0.039**	0.000	**0.039**
	3	0.000	0.000	0.000	0.000	0.000	**0.444**	**0.222**	0.000	**0.111**	0.000	**0.222**
3	1	0.000	0.000	**0.500**	**0.500**	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	2	0.000	**0.100**	0.000	**0.150**	**0.050**	**0.100**	**0.350**	0.000	0.000	**0.100**	**0.150**
	3	**0.045**	0.000	0.000	**0.045**	**0.136**	**0.091**	**0.227**	0.000	0.000	**0.227**	**0.227**

Cluster movements

Since this study was based on a person-centric longitudinal approach and cadets were defined as being a member of a cluster identification of their cluster changes between stages was required. In Alexander and Murphy (1998) the movement of students within a 15-week semester was tracked in terms of cluster membership changes. Braten and Olaussen (2005) followed the same procedure in terms of membership variable changes over one whole year. The same procedure was employed in this dissertation and the movement of cadets was tracked over four years (across the eighth semester of education, in three stages for technical courses, two stages for English courses).

Technical cluster movements from first stage to second stage

The representation of changes in cluster membership from first stage to the second stage with relative proportions is given in Figure 8. Students' movements from a specific first stage cluster to a particular second-stage cluster less than 0.20 are indicated by dash lines. Solid lines indicate that the proportion is larger than 0.20.

As explained in the previous chapter, four clusters were found for the second stage and three clusters for the first stage, as shown in the Figure 8, it was observed that almost half of the cadets' move to second cluster while 40% of them retain their clusters. 10% of the cadets that were named as high profile in the first stage lost their performance and moved to the third cluster. Most of the medium profile cadets stayed in the middle clusters (%81.5) in the second stage.

Technical cluster movements from second stage to third stage

The representation of changes in cluster membership from second stage to the third stage among cadets with proportions is given in Figure 9. While analyzing movements to the third cluster, when considering the previous two stages cluster memberships, the picture becomes much clearer. Resulting transition probabilities to the third stage are written as $P\left(CT_{3,i}\middle|CT_{1,j},CT_{2,k}\right)$ for all i,j,k=1,2,3 for the first and third stages and k=1,2,3,4 for the second stage. For example, cadets who continued their memberships at the first cluster and second stages were very likely to continue (90%) membership to the first cluster at the third stage, as shown in Figure 10. One interesting finding that is shown in Figure 11 is 70% of the cadets who were members of the second clusters but moved to first cluster at second stage moved to second cluster at the third stage again. Another interesting finding is that 76% of the medium profile cadets of the first stage who retained the membership at the second stages continued second cluster membership at the third stage. 70% of the cadets who were members of the second cluster at first stage but then moved to third cluster at the second stage again moved to second cluster at the third stage. No high profile cadet moved to the low profile clusters in the next stages.

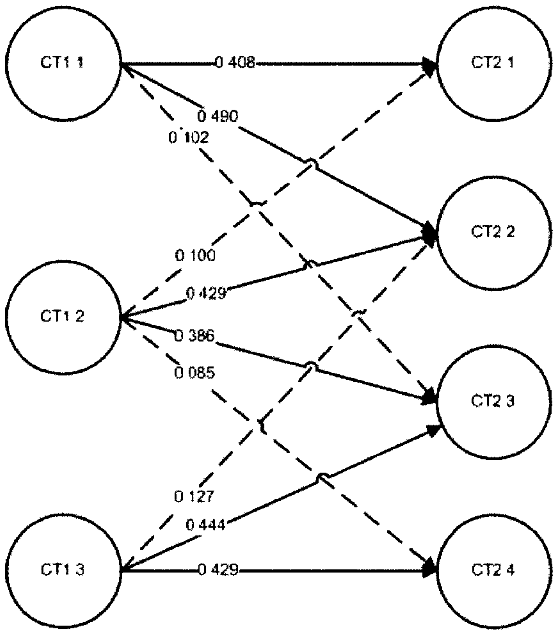

Figure 8. Cluster movements from CT_1 to CT_2.

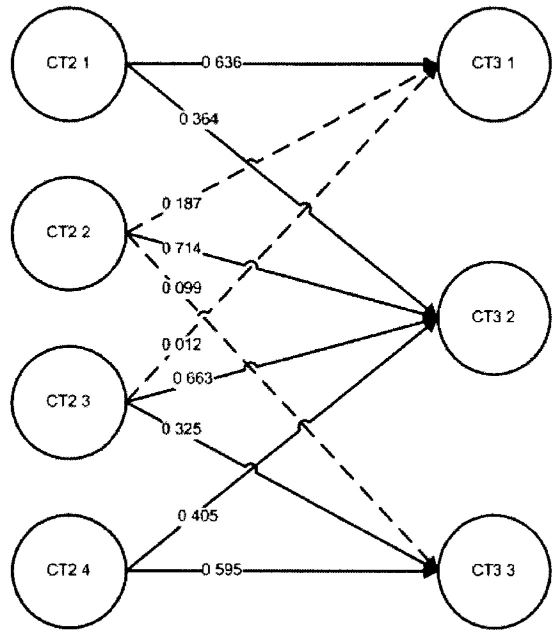

Figure 9. Cluster movements from CT_2 to CT_3.

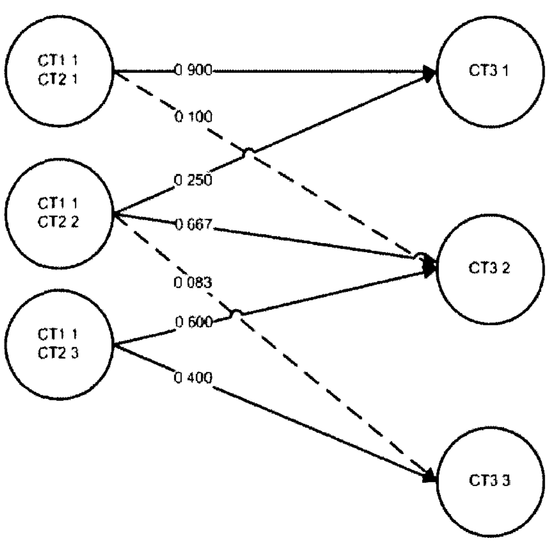

Figure 10. Cluster movements from CT_{11} to CT_3.

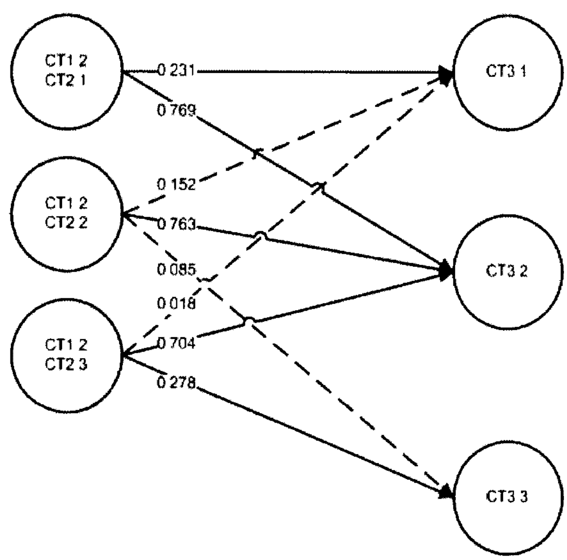

Figure 11. Cluster movements from CT_{12} to CT_3.

69% of the cadets who showed a low profile at both the first and second stages continued showing the similar academic performance as being member of the third cluster at the last stage, as shown in Figure 12. 25% of the low profile cadets at the first stage increased their academic performance across the education stages, as shown in Figure 12. They moved from third cluster to second cluster at second stage and then moved to the first cluster at the third stage. These findings indicate that cadets preserved their profiles throughout the education with small changes. One finding out of the cluster movements' analysis is is that students with high academic motivation while entering the academy were not much affected by the environmental effects.

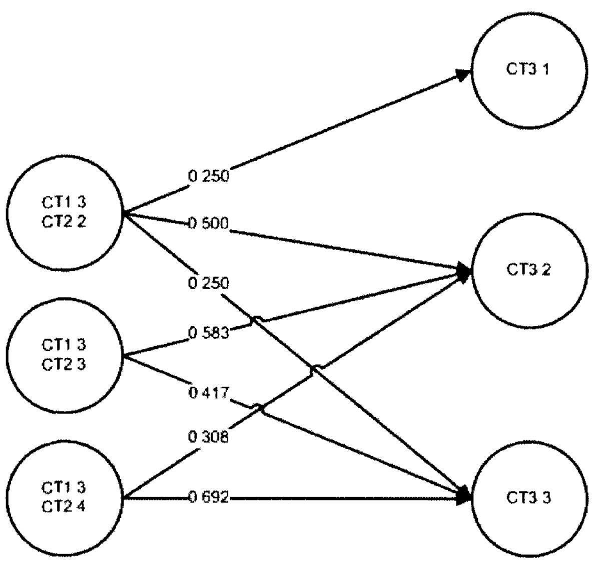

Figure 12. Cluster movements from CT_{13} to CT_3.

English cluster movements from first stage to second stage

English cluster transition probabilities are given in Figure 13. 74% of the cadets in cluster-1 remained in the same cluster at the second stage. Just explaining cluster movement is not enough to model English courses performance. As described while giving information about curriculum development and evaluation system design phase, proficiency levels and English courses design plays an important role in academic success at TuAFA because of their weight in the curriculum and continuing structure.

When cadets' proficiency level changes across two stages were examined as shown in Figure 14, it was seen that the majority of the super level cadets preserved their levels (94.7%). Also 31.4% of the cadets at the advanced level moved into the super level at the second stage (third year). Advanced or super level cadets composed 67.2% of the all cadets at the second stage.

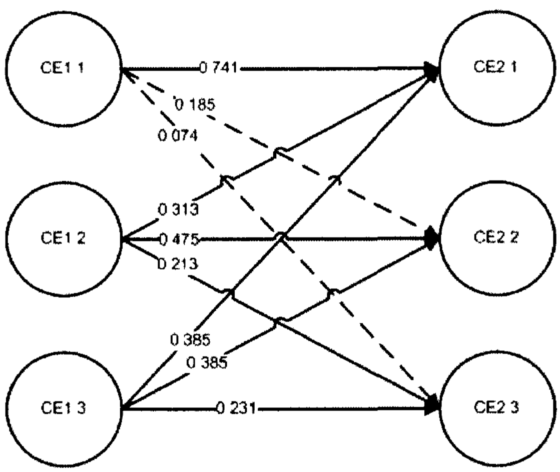

Figure 13. Cluster movements from CE_1 to CE_2 when EL not considered.

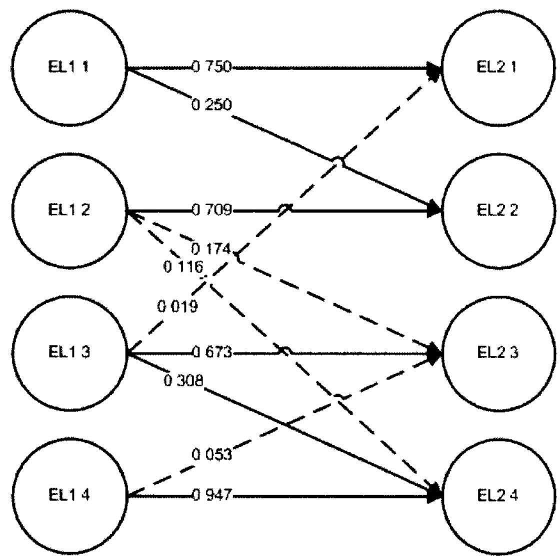

Figure 14. Movements in terms of proficiency levels from EL_1 to EL_2.

Clusters were created and separated by the EM algorithm into four proficiency levels. While analyzing cluster membership and level changes across two stages, conditional probabilities were examined and these values were used as proportions and can be formulated as $P\left(CE_{2,k}, EL_{2,l}, \middle| CE_{1,k}, EL_{1,l}\right)$ where k: 1,2,3 stands for cluster membership and l: 1,2,3,4 stands for proficiency levels. The resulting transition probabilities for beginner level cadets are given in Figure 15. In this study, the lower the cluster membership value means the higher the profile (e.g.

high profile cluster=1), the higher the proficiency level value higher the profile (e.g. super level=4). Downward lines were indicating movements toward higher cluster profiles and higher proficiency levels in the next four graphics.

As it can be seen from Figure 15, most of the beginner level students were stable and stayed at the same level. Only 25% of the cadets at the beginner level and third cluster moved to the intermediate level. Most of the intermediate level students either stayed in the same cluster or moved into a lower profile cluster even if they moved into a higher proficiency level, as shown in Figure 16.

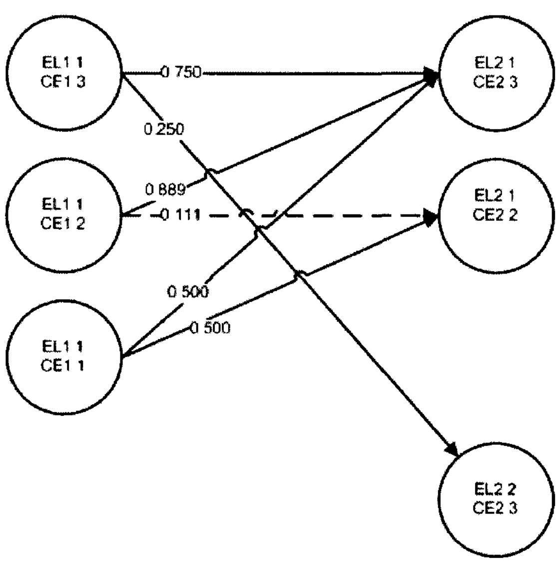

Figure 15. Cluster movement from EL_{11} to EL_2.

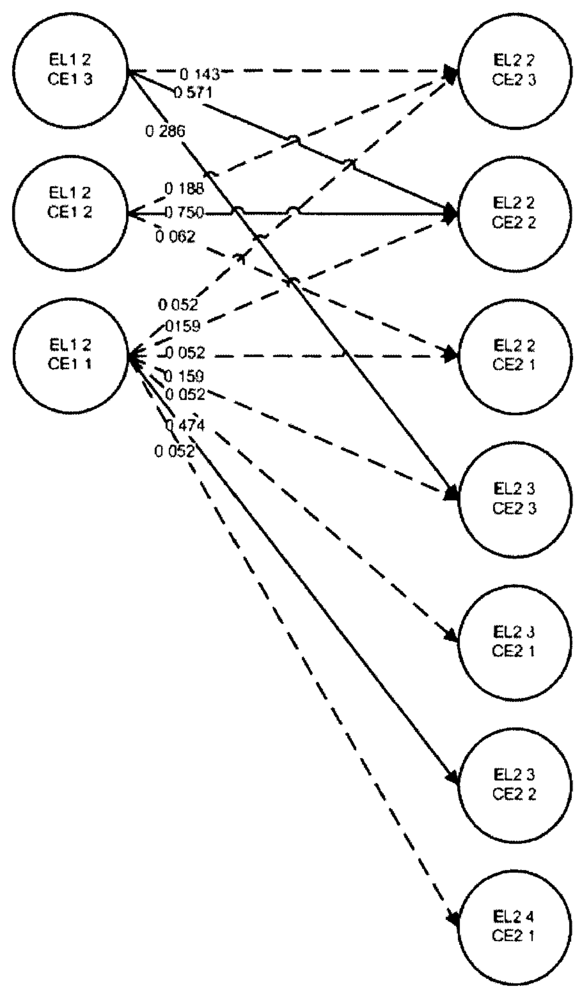

Figure 16. Cluster movement from EL_{12} to EL_2.

Only 0.06% of the cadets at the intermediate level and second cluster moved into the first cluster of the super level. One important finding in the same figure is that 73.7% (15.9% + 5.2% + 47.4% +5.2%) of the cadets at first cluster and intermediate level moved into advanced or super levels. These cadets have the potential for a semester early academic graduation.

Advanced and super level cadets' transition probabilities are given in Figure 17 and Figure 18. None of the advanced level cadets moved into lower levels and only a single cadet (5.5%) moved into advanced level while preserving the cluster membership to the first cluster.

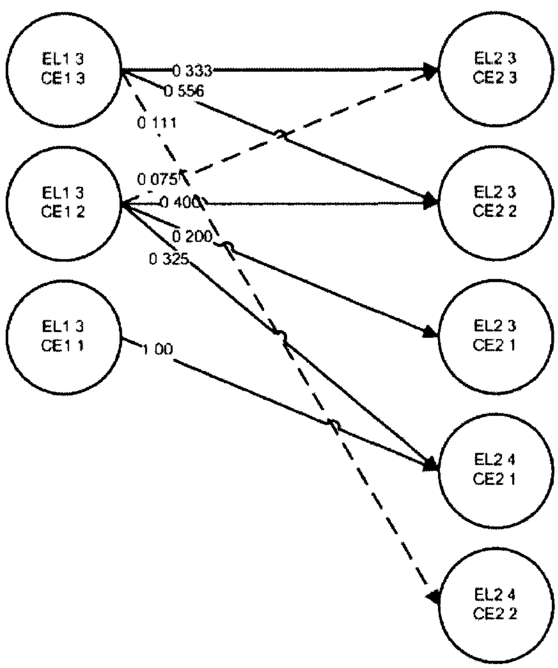

Figure 17. Cluster movement from EL_{13} to EL_2.

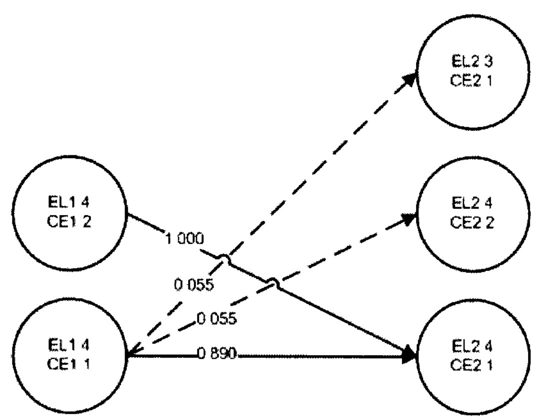

Figure 18. Cluster movement from EL_{14} to EL_2.

Submodels

The simulation model created for comparing evaluation system design alternatives was a combination of five major submodels as shown in Figure 19. These major submodels also had several submodels as required by the increasing size of the submodels in the simulation model creation phase.

In the simulation model, each five day interval represented a week and each day represented a weekday. Every ten days, a squadron of entities was created. For each squadron, 100 entities were created representing squadron of cadets. When entities spent less than seven semesters in the system, they were immediately directed to the pre-assignment submodel as shown by dash lines in Figure 19. Otherwise entities were directed to the graduation submodel as showed by solid line and if graduation conditions were satisfied entities left the system after statistics collection.

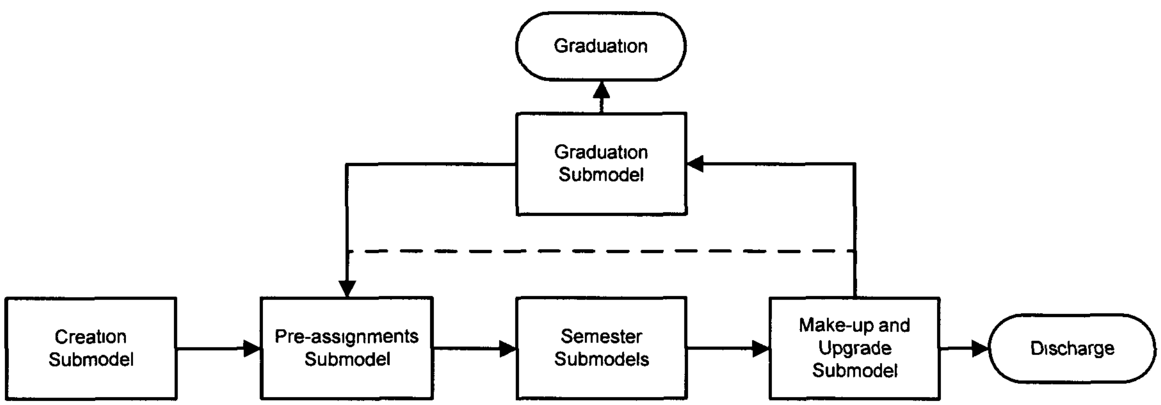

Figure 19. Main flow diagram of simulation model

Creation Submodel

In the creation submodel entities that represent cadets and a dummy entity for global variables assignments were created, as shown in Figure 20. Cluster and proficiency level assignments were made for each entity. Entities moved to pre-assignments submodel after attributes assignments.

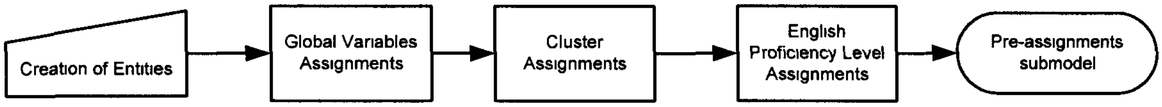

Figure 20. Flow diagram of creation submodel.

Pre-assignments Submodel

A flowchart diagram of the pre-assignments submodel is given in Figure 21. First, all temporary assignments were reset. Next, the GPA lower limit value, the sGPA lower limit value and the maximum available course hour attributes were assigned based on the curriculum entity's time spent in the system and entity's listed assignments (probation or ERDEM). Finally, the entity was directed to the next semester submodel.

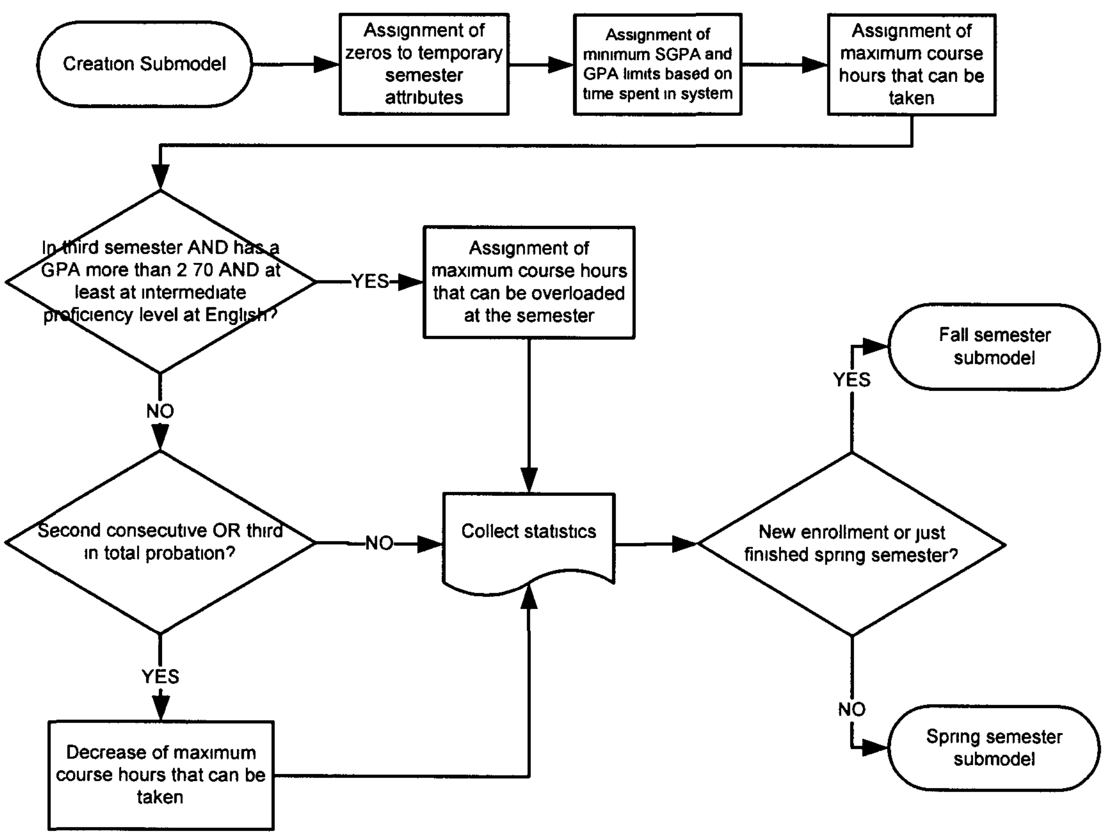

Figure 21. Pre-assignments submodel.

Semester Submodels

Two semester submodels were used in the simulation model: one for fall semester and one for spring semester. Each semester submodel has course submodels that were planned in accordance with the designed curriculum and timetable. The course taking algorithm was described according to the flow diagram, given in Figure 22. Courses were placed in accordance with hierarchy of the prerequisite structure, shown in Figure 7.

Each semester submodel had 20 day submodels (4 seasons and 5 weekdays) and each day submodel has course submodels. Courses were placed at the first day they appeared according to the timetable given in the Appendix H. When an entity was found ineligible for a course on a course submodel it was checked in the next course submodel following described hierarchy. After checking all the weekdays entities if weekly available course hours of the entity were fulfilled it moved into make-up submodel. If the entity did not fulfill course hours it moved to the next season (next year's same semester's courses) in order to find an available course that fit into its schedule. If no course was found at the end of four seasons but course hours were not fulfilled, the entity was directed to the semester submodel starting point and made another round. At the end of the second round entity was directly moved to the make-up and upgrade submodel.

Each course submodel in the day submodels of the semester submodels had following parts:

- *Temporary assignment of course attributes*: course hours, credits and course timetable information were stored temporarily and used while checking eligibility to take the course.

- *Temporary assignment of grades*: Grades were stored temporarily and used while checking eligibility to repeat the course.

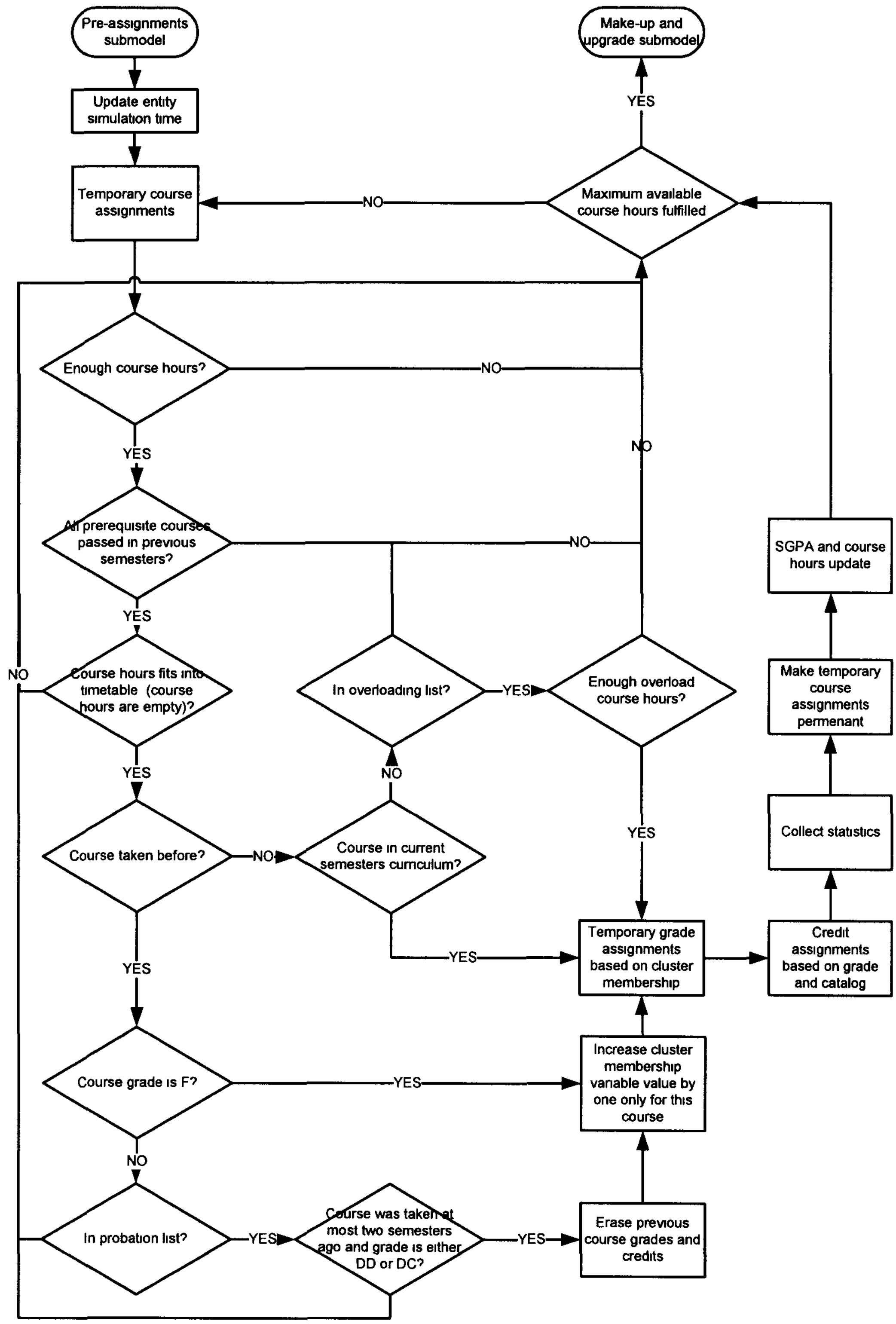

Figure 22. Semester, day and course submodels integrated flow diagram.

- *Prerequisite check submodels*: Since each course has different prerequisite setting, logic gates with "Decision" blocks of ARENA were used while checking the following constraints:
    - Prerequisite courses constraints.
    - Weekly course hour availability check.
    - Timetable availability check
    - Curriculum fit check if course is to be taken for the first time.
    - Overloading course hours' availability check if cadet is listed in ERDEM and if course is to be taken for the first time.
    - Repeating course check: if course is to be taken for the second time and course letter is "F".
- *Distribution and grade assignment submodel*: In this submodel, the following are checked and assigned:
    - Random variable of course score assignment based on cluster distributions and grade assignments.
    - Cluster upgrade to one step higher profile if course is repeated and reset at the course submodel exit.
    - *course*f was reset to "0" if course is passed
    - Other assignments based on success/failure.
- *Credit assignment submodel*: In this assignment grades were converted into credit letters and course credits. Since different credits are given to different course groups, as given in Table 1, different grade assignment blocks used for each type of course.

- *Statistics collection submodel*:

At the end of the each course submodels temporary assignments were transformed into permanent assignments and statistics were collected using *Record* and *Read-Write* blocks of ARENA. Statistics of "AA" and "F" ratios were used for validation purposes.

Make-up and Upgrade Examinations Submodel

The flow diagram of make-up and upgrade examination submodel is given in Figure 23. As shown by the diagram, first eligibility for make-up, upgrade and additional make-up examinations taking were checked. In the figure, the GPA lower limit was shown as 1.2 as an example. If the entity was not available for the examinations, the rules of discharge were checked.

Courses were grouped and each credit subgroup had courses with the same credits. Each credit submodel composed of course submodels. At the entrance of the course submodels eligibility of course make-up/upgrade examination taking was checked.

Failures at make-up examinations were modeled with binomial distributions obtained from historic regardless of cadets' cluster membership values. If the examination was taken and passed, the grade is changed. GPA upgrading was done with 0.5 credit increments only enough to reach maximum of two lower limit GPA values. When entities spent seven or more semesters in the system, they were directed to the graduation submodel. Otherwise they were directed to pre-assignment submodel.

Graduation Submodel

In the graduation submodel graduation conditions were checked. These conditions were:

1. success in all mandatory courses,

2. success in each technical course category or its replacement(s),

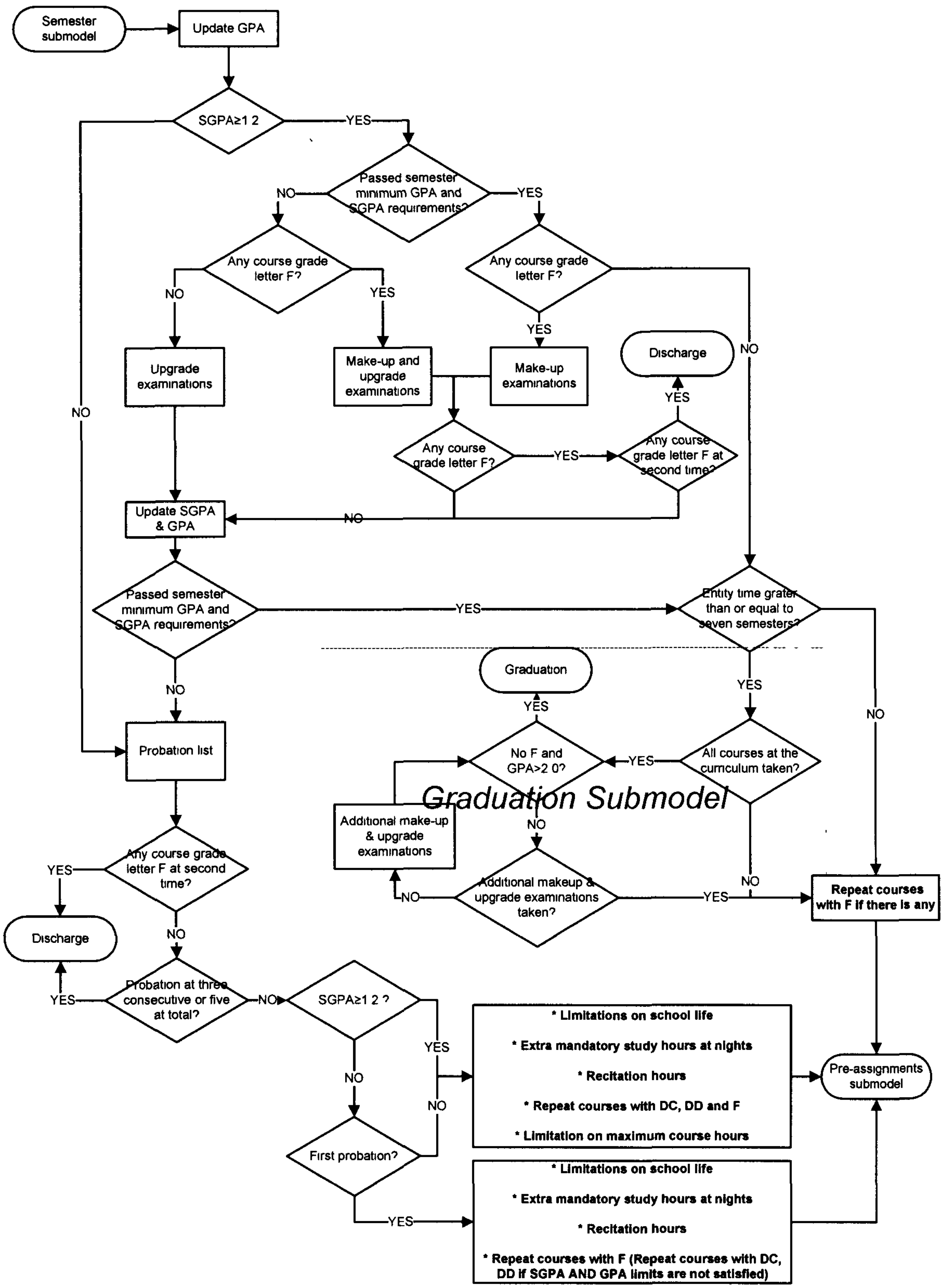

Figure 23. Make-up and upgrade examinations submodel in addition with graduation submodel

3. 2.00 cumulative GPA, and

4. 169 credit course hours.

Any entity satisfying these conditions left the system with dispose block after statistics collection. Entities not satisfying graduation conditions were redirected to the make-up and upgrade submodel for an extra make-up and upgrade examination turn if first and second conditions were satisfied. After extra examination period entities not satisfying graduation condition were directed to the pre-assignment block.

Simulation Model

First a simulation model was developed for tor the validation of clustering modeling methodology's integration in order to estimate "AA" and "F" ratios. The simulation model developed for validation and calibration had five major submodel types listed below:

- Creation blocks (Figure 34 in Appendix M). The first block created dummy entities needed for squadron variable changes and second block created entities representing cadets
- Cluster assignment submodel (Figure 35 in Appendix M)
- Score distribution assignment submodel (Figure 36 in Appendix M)
- Grade assignment submodel (Figure 37 in Appendix M)
- Counter submodels used for ratio statics. (Figure 38 in Appendix M)

The validated model is later integrated as the creation submodel into the evaluation system simulation model. In Appendix N, screen captures of the submodels in the evaluation system simulation ARENA model are presented. The simulation model consists of six submodels. These submodels are listed below:

- Creation submodel (Figure 40 in Appendix N).
- Pre-assignment submodel (Figure 41 in Appendix N)
- Two semester submodels (Figure 42, Figure 43, Figure 44, Figure 45, and Figure 46 in Appendix N)
- Make-up and upgrade submodel (Figure 47, Figure 48, and Figure 49 in Appendix N)
- Graduation submodel (Figure 50 in Appendix N)

Verification and Validation of Simulation Model

Verification

Verification is concerned with building the model correctly that satisfies the developer's conceptual model and descriptions. Thus the verification check was stated if the ARENA model behaved the way it was intended.

The first step of the verification process was asking someone other the model developer to check the model, as recommended by Banks et al. (2005). Colleagues from the Industrial and Computer Engineering Departments and Planning Department of Dean's office of TuAFA were consulted.

Creating flow diagrams also helped develop a verified simulation model. The trace and step function in ARENA was also used and entity sequences were followed. Statistics were collected with output analysis of ARENA and also the outputs obtained from Read-Write blocks of ARENA. Logical and syntax errors were corrected that were discovered by the software. Entity tracing was used to examine outputs in Excel and ARENA.

Validation

After obtaining a syntax error free and verified model, the next step was validating the model. In this step first, face validation was conducted. The Planning Department of Dean's Office at TuAFA, Industrial Engineering Department Head, and the Dean of TuAFA were consulted.

Testing Model Validity by Input-Output Transformation

For the calibration and the validation of clustering methodology, a validation/calibration model was developed. Two variables were chosen and named fail ratio and high-success ratio of a given lecture. A Monte-Carlo simulation model was developed in ARENA in order to validate if "F" and "AA" ratios are predicted within an acceptable margins. The main reason for choosing these variables was management's approach to the problem as described in the research questions and hypotheses part. Management wanted to know how many cadets would finish academic courses in seven semesters and how much failure would happen at the end of the semester in different evaluation system settings using historical data. The acceptable margin was identified by the Dean's Office as 0.02. This was necessary in order to understand if clustering analysis and simulation can be integrated.

The diagram given in Figure 24 summarizes general steps of calibration and validation steps by input-output transformation.

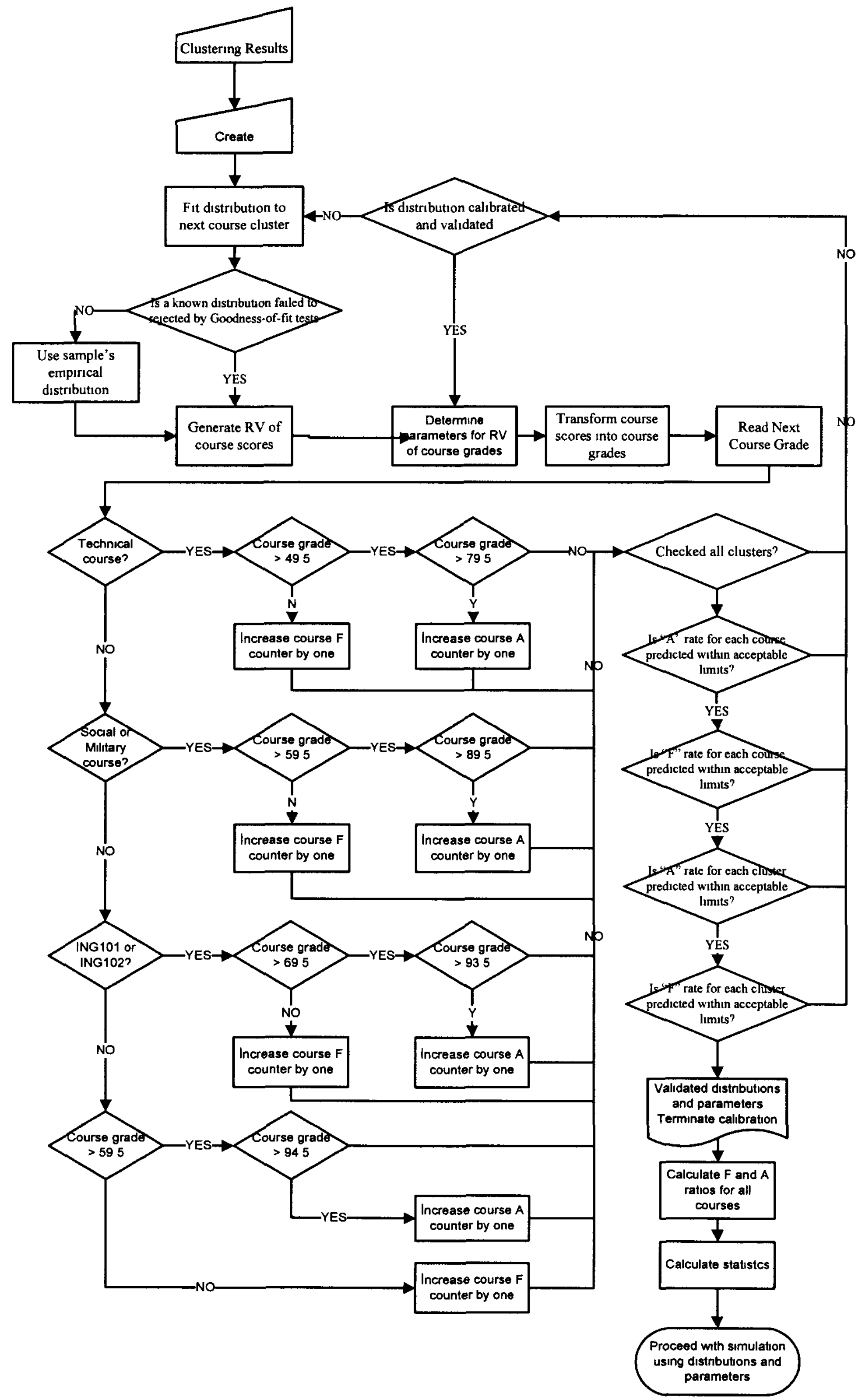

Figure 24. Validation and calibration flow diagram of clustering by Monte-Carlo simulation

Two ratio variables could be specified as:

p_i overall fail ratio of given course "j" and,

q_j overall AA ratio of given course "j".

The above two ratios can be calculated with the following equation using the random variables.

$$p_{jk} = \frac{1}{mn}\sum_{ik} X_{ijk} \quad \forall j \quad i = 1,\ldots,n\; j = 1,\ldots,l \quad k = 1,\ldots,m \tag{3}$$

In the above formula i is the cadet, k is the semester and j is the course. The ratio averages were obtained by making required replication to approximate the ratio average by normal distribution. Results of above equation from each replication are then used in the calculation of the below statistic for overall simulation model.

$$p_j = \frac{1}{n}\sum_{ik} p_{jk} \quad \forall j \quad i = 1,\ldots,n\; j = 1,\ldots,l \quad k = 1,\ldots,m \tag{4}$$

The overall replication averages were given in ARENA's output with the required half widths in order to construct confidence intervals. These measurements are tested based on the hypothesis given below: $\hat{p}_j$ is the proportion of "AA" and "F" getting cadets to the total number of cadets in the course j;

$$H_0 : \hat{p}_j = \pi_{0j}$$

$$H_a : \hat{p}_j \neq \pi_{0j}$$

In above test hypothesis π_0 is the hypothesized ratio of the course; $\hat{p}$ is the overall ratio replication average from simulation output of each course. 100 replications of the simulation model were made. In ARENA half widths of the confidence intervals on performance measures were calculated and given in the output. These half widths were computed by Equation (5) using independent replications (Kelton et al., 2007).

$$\text{half width} = t_{n-1,\alpha/2} \frac{s}{\sqrt{R}} \tag{5}$$

Although the model produced good approximations to the most of the courses some difficulties were experienced because of the sensitivity of the linear equations. Especially in the later stage courses 19 overestimations and 12 underestimations were found at the beginning of calibration procedures which were 22.4% of total 138 estimated values.

Linear standardization and linear transformation procedures needed adjustment since both procedures were known to be sensitive to the extreme values. Also since the cases were related with human behavior, extreme values were not rare.

For example during the validation efforts, the expected percentage of the failure at the course named "Planning for Engineers" (END342) was found to be overestimated. The course grade distributions of this course were based on course scores obtained by Min-Max standardization methodology. As given in the clustering chapter Min-Max linear transformation that was used, transforming student scores into the course grades creates values respective to the minimum and the maximum values of the squadrons and is very sensitive to these parameter values. The reason of overestimation found to be because of a student labeled as "case-18" grades. This student was the only student failed from that lecture over four years of our analysis spectrum. In other words only a single student failed from that lecture and that student got 11 over 100. In a deeper search it was found out that that student not only failed from that lecture but also from three other lectures and then left the academy after final examinations. One solution to that problem could be the deletion of that outlier however these outliers were the one that has a value and what was being looked for in this analysis. In terms of a failure, 11 is no different than 45. The minimum of the linear transformation equation was changed to 45, and model produced good approximations.

Half widths obtained after calibration steps for each course's "F" and "AA" ratios are given in Table 98 of Appendix O. It was showed that the clustering methodology is able to produce good predictions to both "F" and "AA" percentages except the one for the ING302 course "AA" ratio among 138 ratios.

Summary

In this chapter, cluster analyses results conducted on courses at separate stages of the education were used as an input to the simulation model. Transition probabilities between clusters throughout the education were calculated based on cluster membership variable change ratios. A distribution was fit into the scores of each cluster at each course. These scores were transformed into the grades and using these grades course credits was assigned. Then results of the simulation model and clustering procedures were validated using "F" and "AA" ratios at each course. In the final, a validated simulation model was developed in ARENA for newly designed evaluation system to the case of TuAFA. Results of the clustering methodology and simulation model were evaluated and used in order to answer the research questions. The hypothesis that was tested in this chapter and results obtained are summarized in Table 26.

Table 26: Summary of the result of hypothesis-3 and hypothesis-4

Hypothesis 3: By a new curriculum and timetable design, graduation at seventh semester could be made possible.	Decision: By careful planning and organization with appropriate timetables, graduation at seventh semester can be achieved under given assumptions.
Hypothesis 4: A modeling technique based on cluster analysis and Monte-Carlo simulation can be used in modeling "F" and "AA" rates within management`s acceptance limits.	Decision: The simulation model is successful in predicting "AA" and "F" rates within acceptable margins after calibration and adjustments of linear equations used in the model.

CHAPTER V

SIMULATION EXPERIMENT AND RESULTS

In this chapter, the assumptions of the simulation study were evaluated. Next, parameter settings and decision variables were defined. Finally simulation experiments were conducted and the results were interpreted.

Evaluation of the Assumptions Used in Simulation

The first assumption was stated as "*Industrial Engineering program is a representative of overall academic performance at the TuAFA*". In order to validate this assumption cadet performances were examined in the first semester and in overall semester averages.

Validation of First Assumption

Performance in Terms sGPA and Failures

While examining the validity of the first assumption sGPA and failed number of courses were examined. The ANOVA table for two performance measures of the first semester is given in Table 27. Since significance values are greater than 0.05, it can be concluded that cadet performance among four departments in terms of both sGPA and total number of failed courses at the first semester was different. This result was expected because the departments that cadets were assigned were not chosen before registration to the academy. They were first selected as cadets then later assigned to departments. Cadets fill a list of their departmental choices and Academy management assigns them to the departments. Although this might be seen as a problematic since not all cadets were assigned to their first choices it ensures uniformity among cadets and accepted as a good way of keeping balance. 2010 graduates were used in the database for that analysis.

Table 27. ANOVA table for the first semester performances among departments

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
sGPA1	Between Groups	1.353	3	.451	.786	.503
	Within Groups	163.527	285	.574		
	Total	164.879	288			
F1	Between Groups	.612	3	.204	.228	.877
	Within Groups	254.551	285	.893		
	Total	255.163	288			

The second group of statistics that was examined was cadets' overall performance in the academy in terms of average failure (averageF) and average semester GPA (asGPA). Four departments were compared using ANOVA. It was found that departments were different in terms semester GPAs but not on the average failures, as shown in Table 28. This is probably because of the departmental differences of the curriculums. For a further analysis, departmental differences were examined using independent samples t-test in pairs and results are provided in Appendix P.

Table 28. ANOVA table for the overall performances averages among departments

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
asGPA	Between Groups	1.691	3	.564	3.170	**.025**
	Within Groups	40.010	225	.178		
	Total	41.701	228			
averageF	Between Groups	.335	3	.112	1.086	**.356**
	Within Groups	23.119	225	.103		
	Total	23.454	228			

Validation of Second Assumption

The second assumption that was used in the simulation model was about moving failed cadets into an upper profile cluster at the failed courses. There was not enough data on that statistic to validate this assumption. According to colleagues from the Planning Department of Dean's Office of TuAFA around only 10% of the cadets failed from the same course in their retention year.

Another difficulty that was experienced while validating this assumption was the cadets who left the system after failure and retention. Cadets who needed to repeat year as retention generally left the system either by their own will or by disciplinary rules. In TuAFA when a cadet academically fails, he/she is always a semester behind of his/her previous colleagues. This is often seen as unacceptable if parents of the cadet were capable of paying the fines due to the discharge/drop out of the academy.

Parameter Settings

After the validation of the simulation assumptions, an experimental design analysis was undertaken. In the rest of this chapter, alternative scenarios were analyzed using different parameter settings. In the experimental analysis part of this study four parameters are defined that can be adjusted with two levels. These parameters and settings were;

1. Cumulative GPA lower limits for probation list placement at the end of the make-up and upgrade examinations.
2. sGPA lower limits for probation list placement at the end of the make-up and upgrade examinations.
3. Make-up examinations taking lower limit.
4. Dropping out of the academy due total probation number.

Levels of "cumulative GPA lower limits" factor were presented in Table 29. As the low setting USAFA's limits were used, as the high setting limits were increased around 0.05-0.10 credits.

Table 29. Design settings of the cumulative GPA factor.

	Setting	
Semester	-	+
1	1.50	1.50
2	1.70	1.75
3	1.80	1.90
4	1.90	2.00
5	1.95	2.00
6	2.00	2.00
7	2.00	2.00
>=8	2.00	2.00

Levels of "sGPA lower limits" factor were presented in and Table 30. As the low setting USAFA's limits were used, as the high setting limits were increased around 0.10-0.20 credits starting with the third semester.

Table 30. Design settings of the sGPA factor.

	Setting	
Semester	-	+
1	1.50	1.50
2	1.50	1.50
3	1.50	1.60
4	1.50	1.60
5	1.50	1.70
6	1.60	1.70
7	1.70	1.80
>=8	1.80	1.80

As indicated in the previous chapter, in order to take make-up and upgrade examinations cadets should have at least predefined sGPA otherwise placed in the probation list directly and repeat courses with "F", "DD" and "DC" at the next semester. Levels of this factor are presented in Table 31.

Table 31. Design settings of the make-up examination taking lower limit factor.

	Setting	
Semester	-	+
all	1.2	1.3

When a cadet is placed on the probation list for a predefined total number of times, the cadet is discharged and removed from the academy. Levels of the "probation list total entrance" factor are presented in Table 32. The rule indicates that cadets are allowed to be placed on the list three times total in the low setting, four times total in the high setting.

Table 32. Design settings of the probation list total entrance factor

	Setting	
Semester	-	+
all	4	5

Performance Measures

Performance changes were evaluated for the following performance measures:

1. Average number of cadets graduated
2. Average graduation time
3. Average number of cadets academically graduated in seven semesters
4. Average number of cadets discharged from the academy due to probation list rules
5. Average time of cadets discharged from the academy due to probation list rules
6. Average number of cadets discharged from the academy due to time constraints (not finished in 10 semesters)

2^k Factorial Design

Experiments with 2^k full factorial design were conducted. 2^k factorial design requires choosing two levels for each factor and simulation runs for each design points (Law and Kelton, 1991). After defining factor levels, experiments were conducted for 16 design points that are shown in Table 33.

Table 33. Design Settings of Factor Levels

Design Point	Source of variation		Response	Settings of Factor Levels			
				Cumulative GPA Settings	sGPA Settings	Make-up Examination taking lower limit	Probation list counter
1	0	Intercept	R_1	-	-	-	-
2	1	{1}C_GPA	R_2	+	-	-	-
3	2	{2}S_GPA	R_3	-	+	-	-
5	3	{3}MU_L	R_5	-	-	+	-
9	4	{4}P_L	R_9	-	-	-	+
4	12	C_GPA*S_GPA	R_4	+	+	-	-
6	13	C_GPA*MU_L	R_6	+	-	+	-
7	23	S_GPA*MU_L	R_7	-	+	+	-
10	14	C_GPA*P_L	R_{10}	+	-	-	+
11	24	S_GPA*P_L	R_{11}	-	+	-	+
13	34	MU_L*P_L	R_{13}	-	-	+	+
8	123	C_GPA*S_GPA*MU_L	R_8	+	+	+	-
12	124	C_GPA*S_GPA*P_L	R_{12}	+	+	-	+
14	134	C_GPA*MU_L*P_L	R_{14}	+	-	+	+
15	234	S_GPA*MU_L*P_L	R_{15}	-	+	+	+
16	1234	1*2*3*4	R_{16}	+	+	+	+

For each setting, 10 replications were made and at each replication 20 entity creations were made (representing squadron enrollments). At each creation 100 entities were created (representing cadets). At each replication a total of 2,000 entities were created and the results of replications are given in Appendix Q. In the simulation model, each semester was five days and each year was ten days. These time variables were not making the simulation dynamic they were just used for the determination of times spent in the system and increased by a simple "Delay" block at the beginnings of each semester submodel. Another attribute for this variable could have been used but was chosen because it was embedded in ARENA and provided easy to understand calculations and animations. The effects at every design point were computed using Statistica 8.0 software and evaluated significance of the factors using ANOVA procedure.

Interpretation of Effects for the Number of Graduated Cadets

The number of graduated cadets was always a very important measure for the TuAF because the TuAFA was the only source of fighter pilot training. As indicated in the introduction chapter, commanders are very much interested in the failure numbers. They want to see the possible number of failures under new evaluation system implementation. They always closely followed success/failure rates and attended the meetings after each examination period. In that sense TuAFA has a very strong feedback mechanisms and corrective action capabilities. For example if failure form a course found to be over 25% at a midterm examination immediately a recitation period of three hours was to be planned.

In this analysis, the sGPA lower limits factor and make-up examination taking lower limit factor were found to be significant (indicated by bold letters), as shown in the ANOVA test result in Table 34. Also the interaction between GPA lower limit factor and make-up limit factor was found to be significant.

The effects of the significant main factors were analyzed in the diagrams shown in Figure 25 and Figure 26. Figure 25 shows that when sGPA lower limit setting is set to high, there is a low number of graduated cadets. Under the same conditions this is meaningful because increased limits put more cadets in the probation list which is causing either discharge due to total or consecutive probation list constraints or time constraint. It was also interesting to see when make-up limit in high setting number of graduated cadets increased. The main reason for that is the repeating of the courses is increased by the probation listings and that increased GPA's and that caused increased number of graduation.

Table 34. Effects and result of analysis of variance for "the number of graduated cadets" statistic

source of var.	SSx	df	MSx	F	p	Partial eta-squared	Observed power (alpha=0.05) and significance	
I	**583810606.0**	**1**	**583810606.0**	**2045966.0**	**0.000**	**1.000**	**1.000**	
1	1.0	1	1.0	0.0	0.963	0.000	0.050	insignificant
2	**2176.0**	**1**	**2176.0**	**8.0**	**0.007**	**0.050**	**0.783**	**significant**
3	**1156.0**	**1**	**1156.0**	**4.0**	**0.046**	**0.027**	**0.516**	**significant**
4	276.0	1	276.0	1.0	0.327	0.007	0.164	insignificant
12	681.0	1	681.0	2.0	0.125	0.016	0.335	insignificant
13	**2176.0**	**1**	**2176.0**	**8.0**	**0.007**	**0.050**	**0.783**	**significant**
23	16.0	1	16.0	0.0	0.815	0.000	0.056	insignificant
14	51.0	1	51.0	0.0	0.674	0.001	0.070	insignificant
24	601.0	1	601.0	2.0	0.149	0.014	0.302	insignificant
34	**1156.0**	**1**	**1156.0**	**4.0**	**0.046**	**0.027**	**0.516**	**significant**
123	106.0	1	106.0	0.0	0.544	0.003	0.093	insignificant
124	226.0	1	226.0	1.0	0.375	0.005	0.143	insignificant
134	16.0	1	16.0	0.0	0.815	0.000	0.056	insignificant
234	391.0	1	391.0	1.0	0.244	0.009	0.213	insignificant
1234	181.0	1	181.0	1.0	0.428	0.004	0.124	insignificant
Error	41090.0	144	285.0					

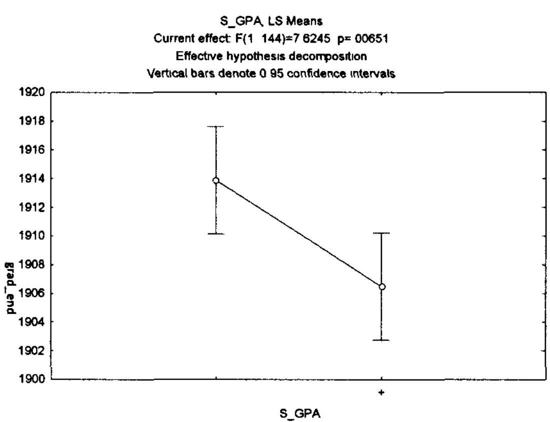

Figure 25. Effect diagram of sGPA factor on the total number of graduated cadets

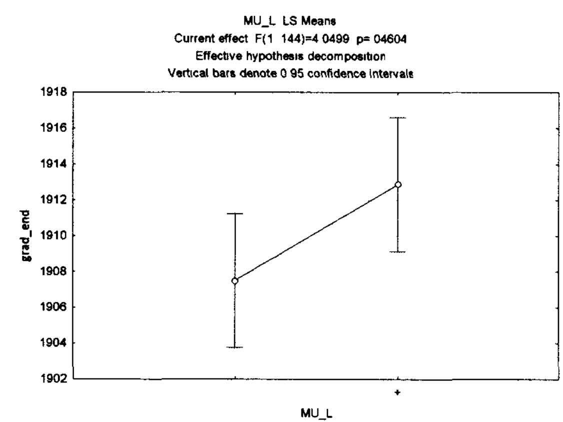

Figure 26. Effect diagram of make-up lower limit factor on the total number of graduated cadets

Other significant interaction factors were examined with the diagrams given in Figure 27 and Figure 28. In Figure 27 it can be observed that when make-up limit (dotted line) and cumulative

GPA limit are both is set to high the total number of graduated cadet increases. But when cumulative GPA limit is kept high and make-up limit low (solid line) the total number of graduated cadets decreases. In Figure 28, it can be observed that when probation list entrance counter is set to high (dotted line) total number of graduation increases. But when the probation counter list entrance counter is set to high (high=5: which looses the constraint compared to low=4) but the make-up limit is set to low, the number of graduates decreases.

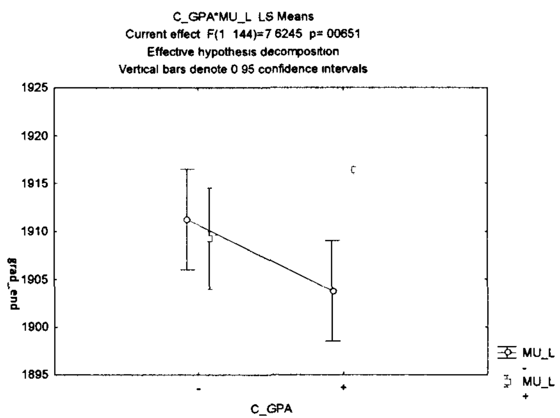

Figure 27. Effect diagram of interaction of cumulative GPA and make-up limit

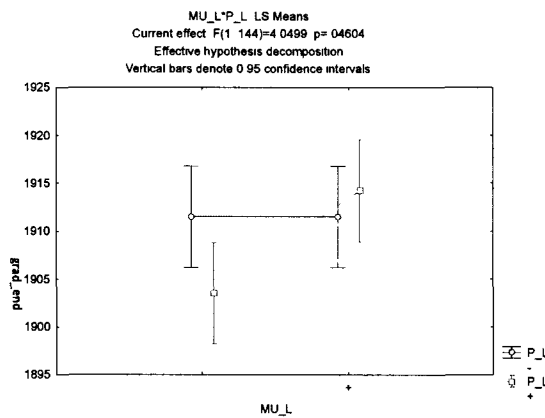

Figure 28. Effect diagram of interaction of make-up limit and probation list entrance counter

Interpretation of Effects for the Average Graduation Time

In Table 35 the results of the ANOVA for the effects of factors on average graduation time is presented. Only the interaction between sGPA limit and probation limit is found to be significant.

The dotted line in Figure 29 shows the change in the number of graduated cadets when the make-up examination taking limit is set to a higher level (1.3) and sGPA limits setting shifts from a higher setting to a lower setting. It may imply an increase in the semester and cumulative GPA by increased make-up examination taking limit and listing as probation without taking make-up examinations.

Table 35. Effects and result of analysis of variance for the graduation time statistic

source of var.	SSx	df	MSx	F	p	Partial eta-squared	Observed power (alpha=0,05) and significance	
I	**264395.7**	**1**	**264395.7**	**11327874.2**	**0.000**	**1.000**	**1.000**	
1	0.0	1	0.0	0.6	0.439	0.004	0.120	insignificant
2	0.0	1	0.0	0.6	0.439	0.004	0.120	insignificant
3	0.1	1	0.1	3.3	0.072	0.022	0.436	insignificant
4	0.0	1	0.0	1.7	0.198	0.011	0.250	insignificant
12	0.0	1	0.0	2.0	0.165	0.013	0.284	insignificant
13	0.0	1	0.0	0.1	0.718	0.001	0.065	insignificant
23	0.0	1	0.0	1.2	0.279	0.008	0.190	insignificant
14	0.0	1	0.0	0.2	0.642	0.002	0.075	insignificant
24	**0.2**	**1**	**0.2**	**6.4**	**0.012**	**0.043**	**0.712**	**significant**
34	0.0	1	0.0	0.0	0.959	0.000	0.050	insignificant
123	0.0	1	0.0	0.3	0.570	0.002	0.087	insignificant
124	0.1	1	0.1	3.3	0.072	0.022	0.436	insignificant
134	0.0	1	0.0	0.3	0.570	0.002	0.087	insignificant
234	0.0	1	0.0	0.8	0.380	0.005	0.141	insignificant
1234	0.0	1	0.0	0 6	0.439	0.004	0.120	insignificant
Error	3.4	144	0.0					

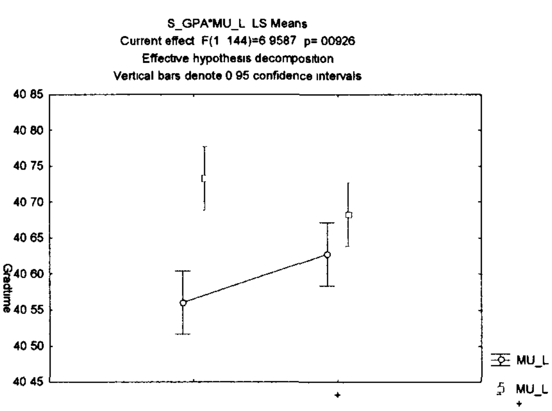

Figure 29. Effect diagram of interaction of make-up limit and sGPA setting entrance counter

Interpretation of Effects for the Number of Academically Graduated Cadets at Seventh Semester

In Table 36 the results of the ANOVA for the effects of factors on the number of graduated cadets at seventh semester are given. This was one of the main questions of this dissertation. It was found that cumulative GPA limits setting and interaction between sGPA and probation counter limit is significant.

Table 36. Effects and result of ANOVA for the number of graduated cadets at seventh semester statistic

source of var.	**SSx**	**df**	**MSx**	**F**	**p**	**Partial eta-squared**	**Observed power (alpha=0.05) and significance**	
I	**41652728.0**	**1**	**41652728.0**	**47227.4**	**0.000**	**0.997**	**1.000**	
1	**5736.0**	**1**	**5736.0**	**6.5**	**0.012**	**0.043**	**0.717**	**significant**
2	3367.0	1	3367.0	3.8	0.053	0.026	0.492	insignificant
3	1392.0	1	1392.0	1.6	0.211	0.011	0.239	insignificant
4	297.0	1	297.0	0.3	0.563	0.002	0.089	insignificant
12	1440.0	1	1440.0	1.6	0.203	0.011	0.245	insignificant
13	1452.0	1	1452.0	1.7	0.202	0.011	0.247	insignificant
23	141.0	1	141.0	0.2	0.690	0.001	0.068	insignificant
14	624.0	1	624.0	0.7	0.402	0.005	0.133	insignificant
24	**8585.0**	**1**	**8585.0**	**9.7**	**0.002**	**0.063**	**0.873**	**significant**
34	837.0	1	837.0	1.0	0.332	0.007	0.162	insignificant
123	73.0	1	73.0	0.1	0.774	0.001	0.059	insignificant
124	1703.0	1	1703.0	1.9	0.167	0.013	0.281	insignificant
134	325.0	1	325.0	0.4	0.545	0.003	0.093	insignificant
234	865.0	1	865.0	1.0	0.324	0.007	0.166	insignificant
1234	18.0	1	18.0	0.0	0.886	0.000	0.052	insignificant
Error	127002.0	144	882.0					

The analysis showed that around 25% of the cadets might have a potential for a semester early academic graduation. When cumulative GPA settings are set to higher, more graduated cadets at seventh semester would be expected, as shown in Figure 30.

In Figure 31, the solid line implies the change in seventh semester graduation number when probation list entrance counter is set to low limit (4) and sGPA setting is shifted from a low setting to a high setting. When the semester probation list entrance counter is set to low a GPA limit is set to low and a less number of graduation in seven semesters. The figure also shows that numbers are more sensitive to the sGPA setting when probation list counter set to low level. When the probation list counter level set to high level (dotted line), the number of a semester early graduated cadets is less sensitive to the sGPA setting and the effect is just the opposite side.

This means that, if cadets had chance to be listed as probation one more semester (increased from 4 to 5), sGPA limits change would have less effect.

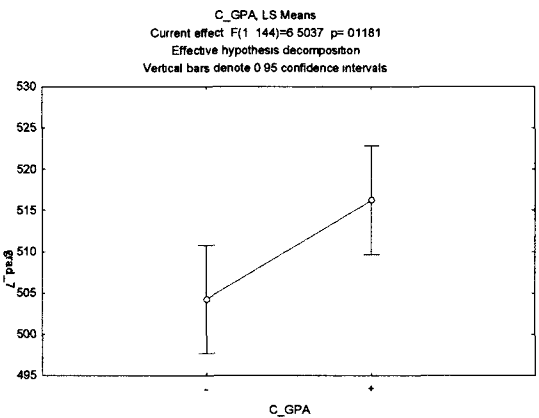

Figure 30. Effect diagram of cumulative GPA on graduation at seventh semester.

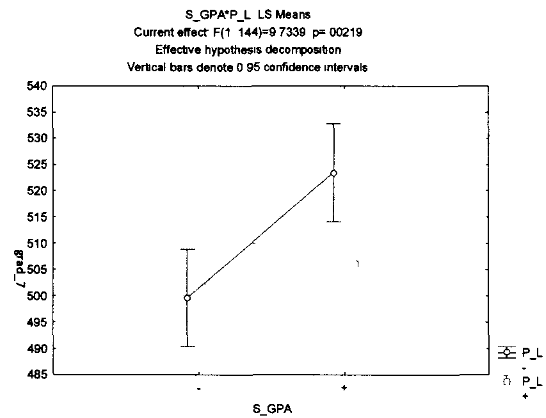

Figure 31. Effect diagram of interaction of sGPA and probation list entrance counter on graduation at seventh semester.

Interpretation of Effects for the Number of Discharged Cadets by Probation Rules

When the effects of factors are interpreted on the number discharges due to probation rules, as shown in Table 37, it was observed that only the sGPA setting has a significant effect as a main factor. In Figure 32, the effect of sGPA setting can be seen. When cumulative GPA setting is set to a higher level, an increased number of discharges due to more probation list placement are expected.

Also the interaction between cumulative GPA and make-up examination taking limit has significant effect. When make-up examination taking lower limit is kept same the number of discharges due to probation rules is sensitive to the changes in cumulative GPA, as shown in Figure 33.

Table 37. Effects and result of ANOVA for the number of discharges by probation rules statistic

source of var.	SSx	df	MSx	F	p	Partial eta-squared	Observed power (alpha=0.05) and significance	
I	**272085.0**	**1**	**272085.0**	**1361.5**	**0.000**	**0.904**	**1.000**	
1	0.9	1	0.9	0.0	0.947	0.000	0.051	insignificant
2	**2295.2**	**1**	**2295.2**	**11.5**	**0.001**	**0.074**	**0.920**	**significant**
3	250.0	1	250.0	1.3	0.265	0.009	0.199	insignificant
4	87.0	1	87.0	0.4	0.510	0.003	0.100	insignificant
12	57.6	1	57.6	0.3	0.592	0.002	0.083	insignificant
13	**950.6**	**1**	**950.6**	**4.8**	**0.031**	**0.032**	**0.582**	**significant**
23	1.6	1	1.6	0.0	0.929	0.000	0.051	insignificant
14	48.4	1	48.4	0.2	0.623	0.002	0.078	insignificant
24	354.0	1	354.0	1.8	0.185	0.012	0.262	insignificant
34	547.6	1	547.6	2.7	0.100	0.019	0.376	insignificant
123	2.0	1	2.0	0.0	0.920	0.000	0.051	insignificant
124	0.4	1	0.4	0.0	0.964	0.000	0.050	insignificant
134	255.0	1	255.0	1.3	0.260	0.009	0.202	insignificant
234	22.5	1	22.5	0.1	0.738	0.001	0.063	insignificant
1234	75.6	1	75.6	0.4	0.539	0.003	0.094	insignificant
Error	28776.4	144	199.8					

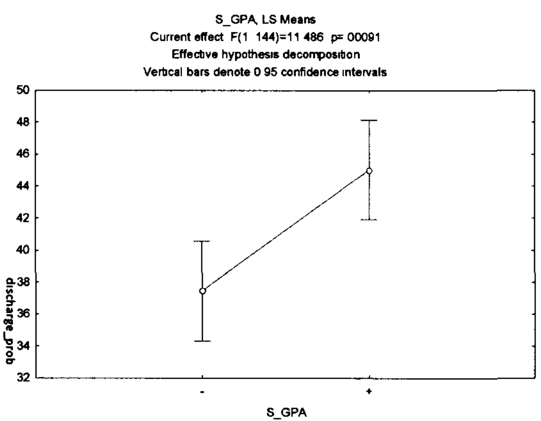

Figure 32. Effect diagram of sGPA setting to the discharges by probation rules.

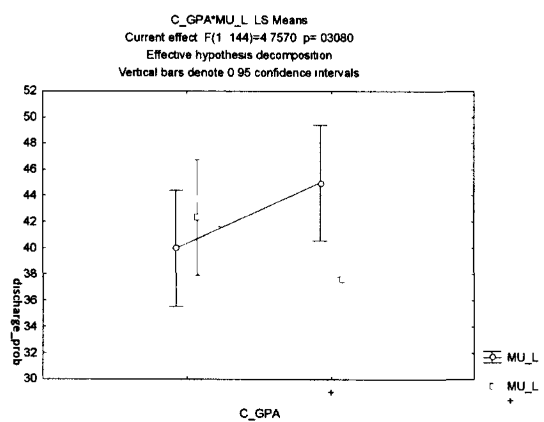

Figure 33. Effect diagram of interaction of cumulative GPA setting and the make-up examination lower limit to the discharges by probation rules.

Interpretation of Effects for the Time of the Discharged Cadets by Probation Rules and Time Constraint

When Table 38 and Table 39 were examined, no significant factors could be found. This means that the average is the best predictor of the time of the discharges due to probation rules and the number of discharges due to time constraint.

Table 38. Effects and result of ANOVA for the time of discharged by probation rules statistic.

source of var.	SSx	df	MSx	F	p	Partial eta-squared	Observed power (alpha=0.05) and significance	
I	**94468.7**	**1**	**94468.7**	**15894.9**	**0.000**	**0.991**	**1.000**	
1	6.2	1	6.2	1.0	0.310	0.007	0.173	insignificant
2	9.0	1	9.0	1.5	0.220	0.010	0.232	insignificant
3	1.3	1	1.3	0.2	0.637	0.002	0.076	insignificant
4	3.1	1	3.1	0.5	0.473	0.004	0.110	insignificant
12	11.2	1	11.2	1.9	0.171	0.013	0.277	insignificant
13	4.0	1	4.0	0.7	0.411	0.005	0.130	insignificant
23	3.0	1	3.0	0.5	0.477	0.004	0.109	insignificant
14	4.6	1	4.6	0.8	0.383	0.005	0.140	insignificant
24	0.4	1	0.4	0.1	0.806	0.000	0.057	insignificant
34	0.0	1	0.0	0.0	0.974	0.000	0.050	insignificant
123	0.1	1	0.1	0.0	0.928	0.000	0.051	insignificant
124	0.1	1	0.1	0.0	0.897	0.000	0.052	insignificant
134	15.0	1	15.0	2.5	0.114	0.017	0.352	insignificant
234	4.8	1	4.8	0.8	0.372	0.006	0.144	insignificant
1234	7.2	1	7.2	1.2	0.272	0.008	0.195	insignificant
Error	855.8	144	5.9					

Table 39. Effects and result of ANOVA for the number of discharged due to time constraint statistic.

source of var.	SSx	df	MSx	F	p	Partial eta-squared	Observed power (alpha=0.05) and significance	
I	**15800.6**	**1**	**15800.6**	**898.9**	**0.000**	**0.862**	**1.000**	
1	0.1	1	0.1	0.0	0.940	0.000	0.051	insignificant
2	50.6	1	50.6	2.9	0.092	0.020	0.392	insignificant
3	60.0	1	60.0	3.4	0.067	0.023	0.451	insignificant
4	22.5	1	22.5	1.3	0.260	0.009	0.203	insignificant
12	8.1	1	8.1	0.5	0.498	0.003	0.103	insignificant
13	32.4	1	32.4	1.8	0.177	0.013	0.271	insignificant
23	46.2	1	46.2	2.6	0.107	0.018	0.364	insignificant
14	50.6	1	50.6	2.9	0.092	0.020	0.392	insignificant
24	0.1	1	0.1	0.0	0.940	0.000	0.051	insignificant
34	6.4	1	6.4	0.4	0.547	0.003	0.092	insignificant
123	14.4	1	14.4	0.8	0.367	0.006	0.146	insignificant
124	2.0	1	2.0	0.1	0.735	0.001	0.063	insignificant
134	11.0	1	11.0	0.6	0.430	0.004	0.123	insignificant
234	1.6	1	1.6	0.1	0.763	0.001	0.060	insignificant
1234	38.0	1	38.0	2.2	0.144	0.015	0.309	insignificant
Error	2531.2	144	17.6					

Proposed Evaluation System Parameter Settings

The main purpose of this system is to understand the evaluation system changes effects on to the cadets graduation times, graduation numbers and discharge times and discharge numbers when other factors like instructor's effect and management's effects were continued as it was. Since this is not a production system and human behavior is complex there is no attempt to optimize any parameters. Management did not want to increase the number of graduates but were much concerned with the discharge numbers being over acceptable limits. With these thoughts in mind the following parameter setting for the new evaluation system was proposed. The proposed setting corresponds to the design point 10 in the experimental design settings.

Cumulative GPA lower limit for probation list placement at the end of the make-up and upgrade examinations were set to high (+) level. sGPA lower limits for probation list placement at the end of the make-up and upgrade examinations were set to low (-) level. Make-up examinations taking lower limit set to low (-) level. Dropping out of the academy due total probation number set to high (+) level.

Make-up and upgrade examinations taking lower limit is currently used as 1.2 as proposed. Increasing sGPA limits has a significant effect on the number of graduated cadets. During the analysis it was seen that interaction of cumulative GPA and make-up limit is significant on number of graduated cadets. Increasing both limits decreasing the graduation number. By doing that the number of cadets that were eligible cadets for taking make-up examinations decreased. Since success rates are high at these examinations cadets miss a chance to increase their GPA and this leads to more discharges.

Under these conditions the 95% long term expected levels of performance variables and confidence intervals of these variables can be constructed using equation (5).

Table 40. Confidence intervals on performance measures

performance measure	average	st.dev.	CI	
graduation time	40.56	0.12	40.47	40.89
total number of graduations	1930.00	10.54	1922.05	1927.95
graduation at seventh semester	522.50	30.55	499.47	502.03
discharges due to probation rules	27.60	7.92	21.63	35.97
discharge time due to probation rules	25.58	1.56	24.40	26.18
discharge time due to time constraint	7.70	2.54	5.78	8.92

Summary

In this chapter, the experimental design procedure and the simulation results were explained. 16 design points for four decision variables were defined. Ten replications were conducted for each setting. The effects of factors with ANOVA and effect diagrams were examined. It was found that sGPA lower limit setting is found to be more effective on the performance measures, than the cumulative GPA settings. Make-up examination limit is also found to effective on half of the performance measures examined either as a single factor or with an interaction. However make-up examination credit limit is not always causes a decrease on performance measures because cadets were forced to repeat courses with DD and DC and increased their GPAs. The hypothesis that was tested in this chapter and results obtained are summarized in Table 41.

Table 41: Summary of the result of hypothesis-5

Hypothesis 5:	Decision:
A Monte-Carlo simulation model can be used in order to understand possible causes of decision variables on performance measures such as graduation time and number of graduated cadets in a newly designed evaluation system.	It was shown that simulation model developed in the previous chapter provided insights by an experimental design. Setting both cumulative GPA and sGPA on the high setting is not very effective. sGPA is more effective on the performances of the system compared to other variables. A 25% graduation rate is expected in the seventh semester. Around 96% academic graduation ratio is expected in the long run under given conditions.

CHAPTER VI

CONCLUSIONS AND IMPLICATIONS

Complex and an unpredictable human behavior and its interactions with educational environment make the study topic a very demanding task. Academic performance is affected by many cognitive, noncognitive and demographic variables. Another classification of the variables could also be made as endogenous and exogenous. This study showed endogenous variables are important since student profile do not change much over time. It was observed that academic performance in one field also plays a significant role in other study fields. It was shown that high profile cadets in technical courses also continue to get high scores in other courses.

One limitation of this study concerning longitudinal academic performance is instructor changes. Although contents of each course are predefined by the TuAFA; the styles of instructors, grading and approaches to cadets are different. Unfortunately it is often becoming hard to find courses that were given by same instructor over a long period of time.

However, any curriculum or evaluation system development aiming managing student discharge study should focus on these differences and the difficulties due to variation among students.

In this study courses were first clustered based on cadet's scores and context of the courses. Next courses were separated into stages. Then students were clustered based on their scores and their movements were tracked throughout the education stages. A curriculum and timetable were developed that provided enough room for repeating courses and overloading courses for a semester early graduation. A new evaluation system was developed and rules were created to examine the effects of these rules using factor analysis on the developed Monte-Carlo simulation model.

Existing patterns of academic performance were explored with longitudinal cluster-analytic study in a military academic environment over a four year undergraduate education time. Alexander and Murphy (2004) indicated that little is still known about the nature of academic development, and more longitudinal explorations of student profiles are certainly needed. The findings from this study add an important part of research of cadets in a military academic environment and fills existing literature gaps.

In this study, academic performance in a Military Academy which is a very complex phenomenon is tried to be understood rather than making point estimation. In this case, for students enrolled at TuAFA being an engineer is not accepted as the primary objective of the cadets. Motivating students toward increasing their performances on academic courses is not an easy job. Cadet's educational quality prior to academy is shown to be playing a very big role in their academic performance. Because of the complexity of the system, predictions methodologies are lacking in making estimations (Witten & Frank, 2005). This is one of the major advantages of clustering methodologies as shown in this study. A 2-step clustering methodology based on hierarchical and EM clustering algorithms was used. As shown in the clustering chapter, the hypothesis on the student profiles existence and changes over time were proven.

Positive correlations between some courses showed us some important clues that could be used in clustering studies. Following these clues supported by the findings of the clustering study and tracking of cluster membership variable changes over four years, it is understood that if a cadet ossified his/her approach toward academic courses he/she continued showing similar performances throughout the education. This gave great insight about cadet profiles at TuAFA. One finding of tracking the movement of the cadets is that: description of cadets with high potential and motivation them for an increasing performance by providing a semester early graduation. Also the negative side is true - TuAFA needs to treat low academic profile students carefully primarily on core courses. Additional consultation and recitation hours would be a solution because these cadets also preserve their attitudes. The aim is to encourage low profile students during semester studies by not providing them an additional upgrade and make-up examination option.

As described in third and fourth chapters, English language education is one of the important aspects of education in TuAFA. It is a credit course group with a very large weight at each semester. English as a foreign language courses occupies around 14% of the total credits in the current and proposed curricula. One primary reason for such a structure is making cadets understand the importance of English as a foreign language. English is the prime language in all tower conversations around the world in the aviation sector and air forces. That is why starting from 2009 the curriculum was updated and 25 course hours of English education per week is stated at TuAFA. English has a follow-up structure and must be handled promptly in any evaluation system designs.

Any curriculum that is based on credit system and without retention must focus on prerequisites and difficulties of the courses. During this study, there was enough time to think about disadvantages of the current system of TuAFA. Cadets do not pay enough attention to organizing their lives due to predetermined timetables and curriculum. The proposed system is expected to encourage cadet's self efficacy and improve system performance by reducing inefficient time.

Developing an optimal curriculum and timetable was not one of the primary objectives of this study at the beginning. However examples of these tables were needed to show the possibility of a semester early academic graduation. It was also demanded from the management in order to show how the system could be manageable in the academic context. Developed example timetables were used for just validation purposes.

In the current system academic assistance by departments is very weak. There is an organization for academic consultation but the feasibility of the system is questionable. Cadets and instructors are all in favor of the current implementation. Knowing that problem, a close watch of every cadet in means of academic performance is required by a feasible assistance since a very flexible timetable and curriculum is proposed in the new system, Starting from 2009-2010 education year an example of assistance started for academically weak cadets. An instructor is appointed to every three cadets. It is believed that this mechanism should be improved and developed in the new system. Cadets in groups of three will be assigned an advisor by the Executive Committee of the relevant department. The courses that the student will take each semester and any changes in the student's program must be approved by the advisor, taking into consideration the student's academic development, prerequisites, and related articles of these regulations.

Future Work and Final Remarks

Several directions for a future research can be suggested from this study. The focus of this study was academic performance of cadets in a military academic environment. The methodology can be exemplified in other studies in civilian universities. Also motivational aspects of cadets/students can be inserted into a clustering analysis. An experimental study that focuses on student profile changes would be very beneficial for future works.

In this study the causes of variability and mean differences among squadrons were not exhaustively addressed. This remains a completely new research area especially to the academicians in the field of psychological education. Another clustering effort concerning instructor behaviors can be integrated in a future study.

A detailed agent based modeling approach would be another alternative for analyzing an academic life and changes over time. In such setting human interactions can be modeled.

Also additions to the simulation model can be done by adding double major and double minor options. Although it is made possible in the system we did not evaluate and simulate this option in the model and left it as a topic for another study.

Studies on military cadets are extremely limited especially in the countries other than USA. It is strongly suggested to examine cadet profiles using cognitive and noncognitive variables in other countries. Unfortunately the effects of an advisory commander were not considered in the model because of the lack of data. This could be also another insertion in future studies.

This work showed a detailed study on curriculum and student profiles would be beneficial if cadet discharge due to academic failure is the scope of a future research. It was shown that clusters created are statistically significant and different in means. Clustering results were validated by discriminant functions analysis. The correct prediction rate was around 94%.

It is believed that commanders at different stages in addition to Academy commanders can benefit from the outputs of this study when defining evaluation strategies and understanding academic performance of cadets. Although the author of this dissertation very much benefited by the experience of instructors, the Office of the Dean of TuAFA, his knowledge[4] and that of other colleagues, the ideas, comments, interpretations and future implications were personal thoughts and TuAF and TuAFA cannot be kept responsible.

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[4] The author of this dissertation is a graduate of TuAFA and has nine years of experience as an instructor at the Academy.

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APPENDICES

Appendix A: Proposed Curriculum

FRESHMAN YEAR CURRICULUM (INDUSTRIAL ENGINEERING DEPARTMENT) (SIMULATION SCENARIO)				
FIELD OF THE COURSE	COURSE CODE	COURSE NAME	SEMESTER 1ST CREDITS	SEMESTER 2ND CREDITS
MILITARY & SOCIAL SCIENCES	HRT100	MAPPING	2.0	
	BGL100	PERSONAL DEVELOPMENT-1	1.0	
	HVG101	INTRODUCTION TO AVIATION	1.0	
	IST100	INTELLIGENCE	1.0	
	ITA101 ITA102	REVOLUTION HISTORY OF TURKISH REPUBLIC AND KEMALISM-I-II	2.0	2.0
	TRK100	TURKISH	2.0	
	LOJ201	LOGISTICS		1.0
ENGLISH	ING101 ING102	ENGLISH-I-II	5.0	5.0
APPLIED SCIENCES	FIZ101 FIZ102	PHYSICS-I-II	4.5	4.5
	KIM100	CHEMISTRY	2.5	
	MAT101 MAT102	CALCULUS-I-II	4.5	4.5
INDUSTRIAL ENGINEERING	BLG100	INTRODUCTION TO COMPUTERS	0.5	
	END211	INTRODUCTION TO INDUSTRIAL ENGINEERING		2.0
	BLG101	COMPUTER PROGRAMMING		3.5
	HVC285	COMPUTER AIDED TECHNICAL DRAWING		2.5
		TOTAL	**25.0**	**25.0**

SOPHOMORE YEAR CURRICULUM (INDUSTRIAL ENGINEERING DEPARTMENT) (SIMULATION SCENARIO)				
FIELD OF THE COURSE	**COURSE CODE**	**COURSE NAME**	**SEMESTER**	
			3RD	**4TH**
			CREDITS	
MILITARY & SOCIAL SCIENCES	BGL200	PERSONAL DEVELOPMENT-2	2.0	
	EKO201 EKO202	ECONOMY I-II	2.0	2.0
	HSA300	AIR WEAPONRY AND EQUIPMENT TECHNOLOGIES	2.0	
	ISL216	COST ACCOUNTING	2.5	
	HUK301	LAW-I		2.0
	THU301	FUNDAMENTALS OF AERONAUTICS &FLIGHT - I		1.0
ENGLISH	ING201 ING202	ENGLISH-III-IV	3.0	3.0
APPLIED SCIENCE S	MAT201	LINEAR ALGEBRA	4.0	
	MAT202	DIFFERENTIAL EQUATIONS		4.0
INDUSTRIAL ENGINEERING	END251	PROBABILITY THEORY	3.0	
	BLG206	VISUAL COMPUTER PROGRAMMING	3.0	
	HVC282	MATERIAL SCIENCES	2.5	
	END252	STATISTICS		3.5
	END303	OPERATIONS RESEARCH - I		3.0
	HVC287	ENGINEERING MECHANICS		3.0
	HVC391	MANUFACTURING PROCESSES		2.5
		TOTAL	**24.0**	**24.0**

JUNIOR YEAR CURRICULUM (INDUSTRIAL ENGINEERING DEPARTMENT) (SIMULATION SCENARIO)				
FIELD OF THE COURSE	**COURSE CODE**	**COURSE NAME**	**SEMESTER**	
			5TH	**6TH**
			CREDITS	
MILITARY & SOCIAL SCIENCES	HUK302	LAW-II	2.0	
	PSK301	PSYCHOLOGY	1.0	
	LID402	LEADERSHIP		2.0
ENGLISH	ING301 ING302	ENGLISH V-VI	2.0	2.0
INDUSTRIAL ENGINEERING	END304 END305	OPERATIONS RESEARCH II-III	3.0	3.0
	HVC381 HVC382	INTRODUCTION TO AERONAUTICAL SCIENCES I-II	3.0	3.0
	END341	ENGINEERING ECONOMICS	3.0	
	END342	PLANNING FOR ENGINEERS	3.0	
	END382	QUALITY PLANNING AND CONTROL	3.0	
	END322	FACILITY LAYOUT AND PLANNING		3.0
	END332	WORK STUDY AND ERGONOMICS		3.0
	END361	SYSTEM SIMULATION		3.5
		TOTAL	**20.0**	**19.5**

SENIOR YEAR CURRICULUM (INDUSTRIAL ENGINEERING DEPARTMENT) (SIMULATION SCENARIO)				
FIELD OF THE COURSE	**COURSE CODE**	**COURSE NAME**	**SEMESTER**	
			7TH	**8TH**
			CREDITS	
MILITARY & SOCIAL SCIENCES	HRK401	OPERATION - I	2.0	
	HTR400	WAR HISTORY	2.0	
	SYT400	POLITICAL HISTORY	2.0	
	AYZ400	MILITARY CORRESPONDENCE		1.0
	SOS4X2	SOCIAL COMPLEMENTARY COURSE		2.0
ENGLISH	ING401 ING402	ENGLISH-VII-VIII	2.0	2.0
INDUSTRIAL ENGINEERING	END423	PRODUCTION PLANNING AND CONTROL	3.0	
	END4X1	COMPLEMENTARY COURSE - I	2.5	
	END4X2	COMPLEMENTARY COURSE - II	2.5	
	END472	MANAGEMENT INFORMATION SYSTEMS		3
	END492	GRADUATION PROJECT		2.5
	END4X3	COMPLEMENTARY COURSE - III		2.5
	END4X4	COMPLEMENTARY COURSE - IV		2.5
		TOTAL	**16.0**	**15.5**

Complementary Courses:

END4X1

END4X1.1: Systems Analyses and Evaluation (END413)

END4X1.2: Statistical Decision Making (END452)

END4X2

END4X2.1: Supply Chain Management (END414)

END4X2.2: Computer Integrated Manufacturing Systems-I (CIM-I) (END425)

END4X3

END4X3.1: Decision Theory (END402)

END4X3.2: Scheduling (END422)

END4X4

END4X4.1: Group Technology and Flexible Manufacturing Systems (END424)

END4X4.2: Just In Time (JIT) Manufacturing (END429)

Social Complementary Courses:

SOS4X2.1: Management and Organization (YON304)

SSO4X2.2: International Relations (ISL402)

Appendix B: Summary of Levene's Test, ANOVA and Normality Test Results

Table 42. Levene's test, ANOVA and normality tests results of "technical" courses

Course Code	Homogeneity of variances	Equal Means	Normality	Course Code	Homogeneity of variances	Equal Means	Normality
END211	Not Rejected	Rejected	Not Rejected	**END429**	Rejected	Rejected	Not Rejected
END251	Not Rejected	Rejected	Not Rejected	**END452**	Rejected	Rejected	Not Rejected
END252	Not Rejected	Rejected	Not Rejected	**END472**	Rejected	Rejected	Not Rejected
END303	Not Rejected	Rejected	Not Rejected	**END492**	Not Rejected	Not Rejected	Rejected
END304	Not Rejected	Rejected	Rejected	**FIZ101**	Not Rejected	Rejected	Not Rejected
END322	Rejected	Not Rejected	Not Rejected	**FIZ102**	Not Rejected	Rejected	Rejected
END332	Not Rejected	Rejected	Not Rejected	**HVC282**	Not Rejected	Rejected	Not Rejected
END341	Not Rejected	Not Rejected	Not Rejected	**HVC285**	Not Rejected	Rejected	Not Rejected
END342	Not Rejected	Rejected	Not Rejected	**HVC287**	Rejected	Not Rejected	Not Rejected
END361	Not Rejected	Not Rejected	Not Rejected	**HVC381**	Rejected	Rejected	Not Rejected
END382	Rejected	Rejected	Not Rejected	**HVC382**	Not Rejected	Rejected	Not Rejected
END402	Rejected	Rejected	Rejected	**HVC391**	Not Rejected	Rejected	Not Rejected
END413	NA	NA	NA	**KIM100**	Not Rejected	Rejected	Not Rejected
END414	NA	NA	NA	**MAT101**	Not Rejected	Rejected	Not Rejected
END422	Not Rejected	Rejected	Not Rejected	**MAT102**	Rejected	Rejected	Not Rejected
END423	Not Rejected	Rejected	Not Rejected	**MAT201**	Not Rejected	Rejected	Not Rejected
END424	NA	NA	NA	**MAT202**	Not Rejected	Rejected	Not Rejected
END425	NA	NA	NA				

NA: not applicable

Table 43. Levene's test, ANOVA and normality tests results of "social and military sciences" courses

Course Code	Homogeneity of variances	Equal Means	Normality	Course Code	Homogeneity of variances	Equal Means	Normality
AYZ400	Rejected	Rejected	Rejected	**ISL402**	Rejected	Rejected	Not Rejected
BGL100	Rejected	Rejected	Not Rejected	**IST100**	Not Rejected	Rejected	Not Rejected
BGL200	Rejected	Rejected	Not Rejected	**ITA101**	Rejected	Rejected	Not Rejected
EKO201	Not Rejected	Rejected	Not Rejected	**ITA102**	Rejected	Rejected	Not Rejected
EKO202	Not Rejected	Not Rejected	Rejected	**LID402**	Not Rejected	Not Rejected	Not Rejected
HRK401	Not Rejected	Rejected	Rejected	**LOJ201**	Rejected	Rejected	Not Rejected
HRT100	Not Rejected	Rejected	Not Rejected	**PSK301**	Rejected	Rejected	Not Rejected
HSA300	Rejected	Rejected	Not Rejected	**SYT400**	Rejected	Rejected	Not Rejected
HTR400	Rejected	Rejected	Not Rejected	**THU301**	Rejected	Rejected	Not Rejected
HUK301	Not Rejected	Rejected	Not Rejected	**TRK100**	Not Rejected	Rejected	Rejected
HUK302	Not Rejected	Rejected	Not Rejected	**YON304**	Rejected	Rejected	Rejected
HVG101	Rejected	Rejected	Rejected				

Table 44. Levene's test, ANOVA and normality tests results of "computer sciences" courses

Course Code	Homogeneity of variances	Equal Means	Normality
BLG100	Rejected	Rejected	Rejected
BLG101	Not Rejected	Rejected	Not Rejected
BLG206	Not Rejected	Rejected	Not Rejected

Table 45. Levene's test, ANOVA and normality tests results of "English" language courses

Course Code	Homogeneity of variances	Equal Means	Normality
ING101	Not Rejected	Rejected	Not Rejected
ING102	Not Rejected	Rejected	Not Rejected
ING201	Not Rejected	Rejected	Not Rejected
ING202	Rejected	Rejected	Rejected
ING301	Not Rejected	Rejected	Not Rejected
ING302	Not Rejected	Rejected	Not Rejected
ING401	Rejected	Rejected	Rejected
ING402	Rejected	Rejected	Rejected

Appendix C: ANOVA Test Results of the Clusters

Table 46: ANOVA tables of the clusters of CT_I

ANOVA

CT_1		Sum of Squares	df	Mean Square	F	Sig.
FIZ101Z	Between Groups	186.485	2	93.243	297.671	.000
	Within Groups	85.515	273	.313		
	Total	272.000	275			
KIM100Z	Between Groups	123.783	2	61.892	113.998	.000
	Within Groups	148.216	273	.543		
	Total	272.000	275			
MAT101Z	Between Groups	154.321	2	77.160	179.001	.000
	Within Groups	117.679	273	.431		
	Total	272.000	275			

ANOVA

CT_2		Sum of Squares	df	Mean Square	F	Sig.
MAT201Z	Between Groups	131.121	3	43.707	92.739	.000
	Within Groups	116.879	248	.471		
	Total	248.000	251			
MAT202Z	Between Groups	155.343	3	51.781	140.507	.000
	Within Groups	90.658	246	.369		
	Total	246.001	249			
END251Z	Between Groups	126.268	3	42.089	85.746	.000
	Within Groups	121.733	248	.491		
	Total	248.001	251			
END252Z	Between Groups	135.557	3	45.186	101.151	.000
	Within Groups	109.444	245	.447		
	Total	245.001	248			

ANOVA

CT_3		Sum of Squares	df	Mean Square	F	Sig.
END341Z	Between Groups	116.711	2	58.355	114.070	.000
	Within Groups	123.290	241	.512		
	Total	240.001	243			
END361Z	Between Groups	140.505	2	70.252	170.172	.000
	Within Groups	99.493	241	.413		
	Total	239.997	243			
END303Z	Between Groups	108.863	2	54.431	100.033	.000
	Within Groups	131.137	241	.544		
	Total	240.000	243			
END342Z	Between Groups	49.997	2	24.998	32.003	.000
	Within Groups	182.003	233	.781		
	Total	231.999	235			
HVC391Z	Between Groups	58.066	2	29.033	39.044	.000
	Within Groups	173.258	233	.744		
	Total	231.324	235			

Table 47: ANOVA tables of the clusters CE_i

ANOVA

CE_1		Sum of Squares	df	Mean Square	F	Sig.
ING101Z	Between Groups	108.140	2	54.070	203.139	.000
	Within Groups	38.861	146	.266		
	Total	147.001	148			
ING102Z	Between Groups	81.793	2	40.896	96.705	.000
	Within Groups	59.206	140	.423		
	Total	140.998	142			

ANOVA

CE_2		Sum of Squares	df	Mean Square	F	Sig.
ING301Z	Between Groups	93.656	2	46.828	185.254	.000
	Within Groups	31.344	124	.253		
	Total	125.001	126			
ING302Z	Between Groups	65.406	2	32.703	71.283	.000
	Within Groups	54.594	119	.459		
	Total	119.999	121			

Table 48: ANOVA tables of the clusters *CC*

ANOVA

CC		Sum of Squares	df	Mean Square	F	Sig.
BLG101Z	Between Groups	163.026	2	81.513	212.622	.000
	Within Groups	101.977	266	.383		
	Total	265.003	268			
BLG206Z	Between Groups	144.731	2	72.366	176.505	.000
	Within Groups	101.268	247	.410		
	Total	246.000	249			

Appendix D: Kruskal-Wallis Test Results

Table 49. Kruskal-Wallis test results of CT_1

Test Statistics(a)

	FIZ101Z	KIM100Z	MAT101Z	HRT100Z	HVG101Y
Chi-Square	190.543	127.899	159.798	81.808	21.748
df	2	2	2	2	2
Asymp. Sig.	.000	.000	.000	.000	.000
	FIZ102Y	**MAT102Z**	**ITA101Z**	**TRK100Y**	
Chi-Square	104.361	88.640	24.946	13.431	
df	2	2	2	2	
Asymp. Sig.	.000	.000	.000	.001	

a Grouping Variable: **tech.cluster.1**

Table 50. Kruskal-Wallis test results of CT_2

Test Statistics(a)

	HVC285Z	END211Z	MAT201Z	HVC287Z	END251Z	BGL100Y
Chi-Square	19.529	56.742	118.887	61.552	134.970	29.841
df	3	3	3	3	3	3
Asymp. Sig.	.000	.000	.000	.000	.000	.000
	EKO201Z	**ITA102Z**	**MAT202Z**	**END252Z**	**HVC282Z**	**EKO202Y**
Chi-Square	62.591	38.195	156.853	143.319	53.304	58.568
df	3	3	3	3	3	3
Asymp. Sig.	.000	.000	.000	.000	.000	.000
	IST100Z	**THU301Z**				
Chi-Square	45.700	14.051				
df	3	3				
Asymp. Sig.	.000	.003				

a Grouping Variable: **tech.cluster.2**

Table 51. Kruskal-Wallis test results of CC

Test Statistics(a)

	BLG100Y	BLG101Z	BLG206Z
Chi-Square	29.941	154.940	125.648
df	2	2	2
Asymp. Sig.	.000	.000	.000

a Grouping Variable: **comp.cluster**

Table 52. Kruskal-Wallis test results of CT_3

Test Statistics(a)

	END341Z	END361Z	END303Z	END472Z	BGL200Z	HSA300Z
Chi-Square	112.566	131.169	111.129	44.169	10.389	9.786
df	2	2	2	2	2	2
Asymp. Sig.	.000	.000	.000	.000	.006	.007
	HUK301Z	**LOJ201Z**	**PSK301Z**	**SYT400Z**	**HVC391Z**	**END332Z**
Chi-Square	31.270	35.392	43.534	19.706	50.323	44.140
df	2	2	2	2	2	2
Asymp. Sig.	.000	.000	.000	.000	.000	.000
	END382Z	**END342Z**	**END322Z**	**END304Y**	**HUK302Z**	**YON304Y**
Chi-Square	56.073	50.017	51.447	61.492	31.371	19.622
df	2	2	2	2	2	2
Asymp. Sig.	.000	.000	.000	.000	.000	.000
	HVC381Z	**END452Z**	**END429Z**	**END423Z**	**AYZ400Y**	**HRK401Y**
Chi-Square	32.737	39.647	31.434	33.516	14.865	6.715
df	2	2	2	2	2	2
Asymp. Sig.	.000	.000	.000	.000	.001	.035
	HTR400Z	**END492Y**	**END402Z**	**HVC382Z**	**END422Z**	**LID402Y**
Chi-Square	22.940	2.031	43.513	40.126	36.667	3.748
df	2	2	2	2	2	2
Asymp. Sig.	.000	**.362**	.000	.000	.000	**.153**
	ISL402Z					
Chi-Square	19.457					
df	2					
Asymp. Sig.	.000					

a Grouping Variable: **tech.cluster.3**

Table 53. Kruskal-Wallis test results of CE_1 and CE_2

Test Statistics(a)

	ING101Z	ING102Z	ING201Z	ING202Y
Chi-Square	96.199	84.417	52.728	27.467
df	2	2	2	2
Asymp. Sig.	.000	.000	.000	.000

a Grouping Variable: **ing.cluster.1**

Test Statistics(a)

	ING301Z	ING302Z	ING401Y	ING402Y
Chi-Square	85.677	81.183	27.427	17.499
df	2	2	2	2
Asymp. Sig.	.000	.000	.000	.000

a Grouping Variable: **ing.cluster.2**

Appendix E: Kruskal-Wallis Test Mean Ranks

Table 54. Mean ranks of CT_1

Ranks

	tech. cluster.1	N	Mean Rank		tech. cluster.1	N	Mean Rank		tech. cluster.1	N	Mean Rank
FIZ101Z	1	51	243.79	HRT100Z	1	51	208.23	ITA101Z	1	50	173.49
	2	149	148.97		2	149	144.87		2	145	138.03
	3	76	47.31		3	76	79.22		3	74	103.05
	Total	276			Total	276			Total	269	
KIM100Z	1	51	230.03	HVG101Y	1	51	171.13	MAT102Z	1	50	202.03
	2	149	143.42		2	149	143.87		2	145	144.33
	3	76	67.43		3	76	106.08		3	74	71.42
	Total	276			Total	276			Total	269	
MAT101Z	1	51	224.13	FIZ102Y	1	50	215.99	TRK100Y	1	50	169.72
	2	149	154.70		2	145	139.59		2	145	131.18
	3	76	49.28		3	74	71.28		3	74	119.03
	Total	276			Total	269			Total	269	

Table 55. Mean ranks of CT_2

Ranks

	tech. cluster.2	N	Mean Rank		tech. cluster.2	N	Mean Rank		tech. cluster.2	N	Mean Rank
HVC285Z	1	34	157.13	BGL100Y	1	34	168.00	HVC282Z	1	33	184.39
	2	92	139.45		2	92	131.36		2	91	143.44
	3	87	116.53		3	87	127.57		3	86	96.22
	4	39	91.50		4	39	76.46		4	37	86.91
	Total	252			Total	252			Total	247	
END211Z	1	34	194.62	EKO201Z	1	34	192.43	EKO202Y	1	34	189.62
	2	92	141.41		2	92	145.37		2	92	140.02
	3	87	104.60		3	87	104.63		3	85	107.49
	4	39	80.79		4	39	73.31		4	38	69.99
	Total	252			Total	252			Total	249	
MAT201Z	1	34	212.93	ITA102Z	1	34	180.00	IST100Z	1	34	177.43
	2	92	145.52		2	92	135.59		2	92	142.04
	3	87	113.88		3	87	117.66		3	85	107.41
	4	39	34.45		4	39	78.15		4	38	76.18
	Total	252			Total	252			Total	249	
HVC287Z	1	32	170.45	MAT202Z	1	34	228.57	THU301Z	1	32	138.80
	2	91	150.76		2	92	153.68		2	89	136.19
	3	84	100.89		3	86	93.84		3	85	109.84
	4	38	65.45		4	38	36.70		4	35	93.21
	Total	245			Total	250			Total	241	
END251Z	1	34	205.93	END252Z	1	34	211.91				
	2	92	168.30		2	92	163.67				
	3	87	76.94		3	85	75.88				
	4	39	69.21		4	38	63.47				
	Total	252			Total	249					

Table 56. Mean ranks of CT_3

Ranks

	tech. cluster. 3	N	Mean Rank		tech. cluster. 3	N	Mean Rank		tech. cluster .3	N	Mean Rank
END341Z	1	39	205.7	END382Z	1	39	180.1	HTR400Z	1	28	112.2
	2	147	128.1		2	141	118.2		2	100	78.7
	3	58	52.3		3	55	73.5		3	31	55.1
	Total	244			Total	235			Total	159	
END361Z	1	39	214.7	END342Z	1	39	173.9	END492Y	1	28	90.2
	2	147	127.3		2	141	121.0		2	100	76.5
	3	58	48.4		3	56	73.7		3	31	82.1
	Total	244			Total	236			Total	159	
END303Z	1	39	202.3	END322Z	1	39	172.3	HVC382Z	1	28	125.3
	2	147	129.6		2	141	122.4		2	100	76.3
	3	58	50.9		3	56	71.3		3	31	50.9
	Total	244			Total	236			Total	159	
END472Z	1	39	185.2	END304Y	1	39	180.1	END402Z	1	28	125.6
	2	147	117.8		2	141	121.1		2	100	77.4
	3	57	89.6		3	56	69.0		3	31	47.3
	Total	243			Total	236			Total	159	
BGL200Z	1	28	107.6	HUK302Z	1	39	169.4	END422Z	1	25	105.8
	2	104	85.9		2	141	113.0		2	83	61.4
	3	38	68.2		3	54	91.8		3	24	43.4
	Total	170			Total	234			Total	132	
HSA300Z	1	39	153.2	YON304Y	1	39	159.1	LID402Y	1	28	94.3
	2	147	119.7		2	141	117.0		2	100	78.5
	3	58	108.9		3	57	96.5		3	31	71.9
	Total	244			Total	237			Total	159	
HUK301Z	1	39	170.4	HVC381Z	1	28	120.1	ISL402Z	1	28	109.4
	2	147	123.1		2	101	78.4		2	100	79.0
	3	58	88.7		3	31	51.6		3	31	56.6
	Total	244			Total	160			Total	159	
LOJ201Z	1	39	181.8	END452Z	1	28	124.7	HRK401Y	1	28	101.1
	2	147	116.2		2	101	77.7		2	101	76.4
	3	58	98.5		3	31	49.7		3	31	75.2
	Total	244			Total	160			Total	160	
PSK301Z	1	39	185.8	END429Z	1	28	121.8	END332Z	1	39	176.5
	2	147	118.1		2	101	76.4		2	141	118.1
	3	58	91.0		3	31	56.5		3	57	81.9
	Total	244			Total	160			Total	237	
SYT400Z	1	39	161.5	END423Z	1	28	120.0	AYZ400Y	1	28	107.8
	2	144	111.6		2	101	78.8		2	101	78.6
	3	52	103.2		3	31	50.4		3	31	62.0
	Total	235			Total	160			Total	160	
HVC391Z	1	39	180.0								
	2	141	117.1								
	3	56	79.2								
	Total	236									

Table 57. Mean ranks of CE_1, and CE_2

Ranks

	ing.cluster.1	N	Mean Rank		ing.cluster.2	N	Mean Rank
ING101Z	1	32	125.28	ING301Z	1	45	96.57
	2	91	74.87		2	53	62.84
	3	26	13.58		3	29	15.59
	Total	149			Total	127	
ING102Z	1	32	124.81	ING302Z	1	45	98.59
	2	86	65.60		2	48	44.92
	3	25	26.40		3	29	31.40
	Total	143			Total	122	
ING201Z	1	30	104.68	ING401Y	1	19	41.71
	2	82	62.26		2	23	20.02
	3	20	26.60		3	11	16.18
	Total	132			Total	53	
ING202Y	1	30	91.27	ING402Y	1	19	37.13
	2	80	63.44		2	23	25.15
	3	20	35.08		3	11	13.36
	Total	130			Total	53	

Table 58. Mean ranks of CC

Ranks

	comp. cluster	N	Mean Rank
BLG100Y	1	38	182.39
	2	172	137.30
	3	58	94.82
	Total	268	
BLG101Z	1	38	217.14
	2	173	151.94
	3	58	30.65
	Total	269	
BLG206Z	1	38	230.33
	2	164	121.78
	3	48	55.22
	Total	250	

Appendix F: Discriminant Functions Analysis Results

Table 59. Discriminant function results of CT_1.

Classification Results(b,c)

		tech.cluster.1	Predicted Group Membership			Total
			1	2	3	1
Original	Count	1	51	0	0	51
		2	9	135	5	149
		3	0	0	76	76
	%	1	100.0	.0	.0	100.0
		2	6.0	90.6	3.4	100.0
		3	.0	.0	100.0	100.0
Cross-validated(a)	Count	1	51	0	0	51
		2	9	135	5	149
		3	0	0	76	76
	%	1	100.0	.0	.0	100.0
		2	6.0	90.6	3.4	100.0
		3	.0	.0	100.0	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b 94.9% of original grouped cases correctly classified.

c 94.9% of cross-validated grouped cases correctly classified.

Table 60. Discriminant function results of CT_2.

Classification Results(b,c)

		tech.cluster.2	Predicted Group Membership				Total
			1	2	3	4	1
Original	Count	1	34	0	0	0	34
		2	3	88	1	0	92
		3	0	3	70	12	85
		4	0	0	5	33	38
	%	1	100.0	.0	.0	.0	100.0
		2	3.3	95.7	1.1	.0	100.0
		3	.0	3.5	82.4	14.1	100.0
		4	.0	.0	13.2	86.8	100.0
Cross-validated(a)	Count	1	34	0	0	0	34
		2	4	87	1	0	92
		3	0	3	69	13	85
		4	0	0	6	32	38
	%	1	100.0	.0	.0	.0	100.0
		2	4.3	94.6	1.1	.0	100.0
		3	.0	3.5	81.2	15.3	100.0
		4	.0	.0	15.8	84.2	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b 90.4% of original grouped cases correctly classified.

c 89.2% of cross-validated grouped cases correctly classified.

Table 61. Discriminant function results of CT_3.

Classification Results(b,c)

		tech.cluster.3	Predicted Group Membership			Total
			1	2	3	1
Original	Count	1	38	1	0	39
		2	4	132	5	141
		3	0	1	55	56
	%	1	97.4	2.6	.0	100.0
		2	2.8	93.6	3.5	100.0
		3	.0	1.8	98.2	100.0
Cross-validated(a)	Count	1	38	1	0	39
		2	4	130	7	141
		3	0	2	54	56
	%	1	97.4	2.6	.0	100.0
		2	2.8	92.2	5.0	100.0
		3	.0	3.6	96.4	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
b 95.3% of original grouped cases correctly classified.
c 94.1% of cross-validated grouped cases correctly classified.

Table 62. Discriminant function results of CC.

Classification Results(b,c)

		comp.cluster	Predicted Group Membership			Total
			1	2	3	1
Original	Count	1	38	0	0	38
		2	13	137	14	164
		3	0	0	48	48
	%	1	100.0	.0	.0	100.0
		2	7.9	83.5	8.5	100.0
		3	.0	.0	100.0	100.0
Cross-validated(a)	Count	1	38	0	0	38
		2	14	135	15	164
		3	0	0	48	48
	%	1	100.0	.0	.0	100.0
		2	8.5	82.3	9.1	100.0
		3	.0	.0	100.0	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
b 89.2% of original grouped cases correctly classified.
c 88.4% of cross-validated grouped cases correctly classified.

Table 63. Discriminant function results of CE_1.

Classification Results(b,c)

		ing.cluster.1	Predicted Group Membership			Total
			1	2	3	1
Original	Count	1	32	0	0	32
		2	9	75	1	85
		3	0	0	25	25
		Ungrouped cases	39	58	29	126
	%	1	100.0	.0	.0	100.0
		2	10.6	88.2	1.2	100.0
		3	.0	.0	100.0	100.0
		Ungrouped cases	31.0	46.0	23.0	100.0
Cross-validated(a)	Count	1	32	0	0	32
		2	9	75	1	85
		3	0	0	25	25
	%	1	100.0	.0	.0	100.0
		2	10.6	88.2	1.2	100.0
		3	.0	.0	100.0	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
b 93.0% of original grouped cases correctly classified.
c 93.0% of cross-validated grouped cases correctly classified.

Table 64. Discriminant function results of CE_2.

Classification Results(b,c)

		ing.cluster.2	Predicted Group Membership			Total
			1	2	3	1
Original	Count	1	45	0	0	45
		2	4	44	0	48
		3	0	3	26	29
		Ungrouped cases	46	40	29	115
	%	1	100.0	.0	.0	100.0
		2	8.3	91.7	.0	100.0
		3	.0	10.3	89.7	100.0
		Ungrouped cases	40.0	34.8	25.2	100.0
Cross-validated(a)	Count	1	45	0	0	45
		2	4	44	0	48
		3	0	3	26	29
	%	1	100.0	.0	.0	100.0
		2	8.3	91.7	.0	100.0
		3	.0	10.3	89.7	100.0

a Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
b 94.3% of original grouped cases correctly classified.
c 94.3% of cross-validated grouped cases correctly classified.

Appendix G: Evaluation System Examples

Bogazici University (BOUN)

At BOUN, students must take all the courses in the first two semesters of their program when these courses are first offered. Students cannot drop required courses that must be taken in the first two semesters. Students cannot take more credits than allowed in their program during their first two semesters; however, they can take non-credit courses.

If the instructor is not convinced of the success or failure of the student, the student can be given “E” credit letter and examined one more time. There is no official make-up examination period at the end of the semesters. Instead students are free to repeat courses with DC and DD credit letters. Courses with F credit letter should be repeated. A summer semester may be offered during an academic year and students may take courses in the summer school as well.

Students can repeat up to six of the courses in which they have received DD or DC, within three semesters following the semester these courses have first been taken, if approved by the advisor

A student whose GPA is lower than 2.00 at the end of any semester, is "on probation". A student who is "on probation" is not allowed to carry extra credit hours. A student whose GPA is lower than 2.00 is considered an "underachieving" student if his/her sGPA remains lower than 2.00 for two consecutive semesters. In addition to repeating the course in which he/she has received a grade of F, he/she can repeat a DD or DC course and/or take a maximum of two new courses. Underachieving students can take up to 3 courses or 10 credits in the summer term. They can repeat the course for which they have received a grade of F, DD, or DC, and may take no more than 2 new courses. The maximum period of study is 14 semesters in undergraduate programs

(For further information please refer to Bogazici University, 2010, *Undergraduate Program Regulations*, available at http://www.boun.edu.tr/government/undergrad_regulations.html, last accessed on 01 October 2010)

Middle East Technical University (METU)

A prerequisite course is a course which a student must pass before being allowed to take another course. Students' normal course load at each semester may be reduced by up to 2 courses at most with the approval of the Chairman of the Department. Underloading made possible if student's cumulative GPA is less than 2.00 (calculated by using catalog given in Table 65), student course program necessitates it or there exists other genuine and valid reasons.

Table 65. Grading catalog at METU

Percentage	Course Grade	Coefficient
90-100	AA	4
85-89	BA	3.5
80-84	BB	3
75-79	CB	2.5
70-74	CC	2
65-69	DC	1.5
60-64	DD	1
50-59	FD	0.5
49 and below	FF	0

Students with a cumulative GPA of at least 2.00 who have fallen behind in their program and want to catch up or want to retake courses to improve their cumulative GPA, may increase their course load by only 1 course on the recommendation of their advisor and with the approval of the chairman of the department. Course loads of students whose cumulative GPA is at least 2.50 can be increased, if they wish, by 2 courses at most if recommended by their advisor.

Students whose cumulative GPA and /or GPA are below 2.00 have failed. Failing students enrolled in their second or later terms have to increase their cumulative GPA to minimum 1.80

for the term in which they are enrolled. Otherwise, they cannot continue their studies. Second or higher term students with a cumulative GPA lower than 1.80 in the term they are enrolled in have to raise their cumulative GPA to 1.80 in order to be able to register for courses they have not taken before. These students repeat courses previously taken until their cumulative GPA rises to the required minimum. Repeating students cannot register for courses withdrawn and for courses not taken in the regular term.

Students can repeat courses from which they previously obtained a passing grade on the condition that they repeat the courses within 3 semesters following the semester when they first obtained the passing grade.

Students who have received grades of FF or FD from at most two credit courses will be given an additional period until the beginning of the next coming semester in order to complete their deficiencies or to take an extra examination. The grade received within this period replaces the final examination grade, and is evaluated as the final examination grade. Students' standing at the end of the semester is calculated using the grades received at the end of the additional period.

Even if students have not received the grades of FF or FD in their last semester, if their cumulative GPA is less than 2.00, they can be given an additional period for the courses in which the grades of DD, DC or CC were received in the last semester under the conditions prescribed above.

(For further information please refer to: Middle East Technical University 2004, *Academic Rules and Regulations*, available at http://www.oidb.metu.edu.tr/english/regulations/oidb41a.htm, last accessed on 01 October 2010).

Istanbul Technical University (ITU)

A probation rule exists as a warning to the student. Lower limits for each semester are declared at the starting of each year. If student is placed in the probation list for three different times student is dropped out of the university. A regular graduating student must complete following assignments.

- 153 total credits,
- 25% of the total credits to be fulfilled with Basic Sciences courses,
- 20% of the total credits to be fulfilled with Basic Engineering courses,
- 20% of the total credits to be fulfilled with Social Sciences courses,
- 25%-35% of the total credits to be fulfilled with Vocational or Vocation Oriented Design courses,
- At least 17% of the total credits to be fulfilled with Elective and Compulsory courses.

Istanbul University (IU)

In the regulations updated in 21 September 2010 students whose cumulative GPA and /or GPA is below 2.00 fail. Failing students enrolled in their second or later terms have to increase their cumulative GPA to minimum 2.00 in the next term they are enrolled in.

If a student fails a course (F letter) he/she is given a make-up examination at the end of the semester. If a student is conditionally successful at a course (DD or DC letter) he/she is given a chance to take a make-up/upgrade examination at the end of the semester.

If student is in the last semester but failed a single course an extra single course make-up examination is given after the 15 days of regular make-up examination period. When students have not failed a course in their last semester or cumulative GPA is less than 2.00, they can be given an additional period for the courses in which the grades of DD, DC or CC were received in the last semester under the conditions prescribed above.

(For further information please refer to: Istanbul University, 2010, *Undergraduate Education Regulations,* available in Turkish at http://www.istanbul.edu.tr/genel/idari/Ogrenciisleri/onlisans_lisans_yonetmelik.htm, last accessed on 01 October 2010)

United States Air Force Academy (USAFA)

The information about USAFA's evaluation system was collected from three different resources. The first resource was the USAFA curriculum handbook, the second was their website and the last one was interviews with the TuAFA officers who visited USAFA. In the USAFA there are three semesters of education mid-semester, end of semester and summer term. Semester GPA and cumulative GPA are determined by dividing the total quality points (Table 66) earned in all graded courses by the total semester hours attempted. They calculate and use different GPA levels for major courses and core courses in addition to cumulative GPA in their evaluation system. Every cadet at the USAFA must choose a major from 32 offered majors. Cadets have to choose a major degree until the first semester of sophomore year.

Cadets must fulfill the 3.25 GPA requirement if they exceed their maximum course load by adding a course for audit. Course load for all cadets is five academic courses at minimum (must be a minimum of 15.5 semester hours) and maximum of 7 academic courses, or 22 semester hours per semester. Cadets who are in good standing may exceed 22 semester hours if they have a minimum 3.25 cumulative or previous sGPA.

Table 66. Grades and associated quality points at USAFA

Grade	Quality Points
A	4.0
A-	3.7
B+	3.3
B	3.0
B-	2.7
C+	2.3
C	2.0
C-	1.7
D	1.0
F	0.0

The departments offer two types of majors: disciplinary and divisional. Cadets are allowed to repeat at most 13 hours of course at a semester. Repeated or replaced elective course grades are replaced by the new grade but both grades (the previous and the new) are showed on transcript.

The cadet listed and stayed on academic probation if the combined sGPA is below a 2.0. Students must pass "F" graded course at the first semester it is opened. They can repeat a course and can get an "F" again. In this case both "F" grades will count in the cumulative GPA. When a cadet takes a course for a third time and receives a passing grade, the newest grade will replace only the grade from the second attempt; the grade from the first attempt will remain factored into the cumulative GPA.

Cadets who earn a sGPA of at least 3.0 in academic courses enter the Dean's list.

A cadet is deficient in studies at the mid-semester progress report or the end of a semester under the following conditions in two categories.

Category-1 (serious deficient)

- A grade of "F" or a controllable incomplete "I" grade in one or more courses, whether graded or pass/fail.

- Semester, core, and/or cumulative GPAs less than 2.00. Deficiencies in core GPA will not be tracked for academic probation status until a cadet's 4th semester.

- First-class cadets are deficient and may be placed on academic probation if their majors' GPAs are less than 2.00.

Category-2: (Deficient):

- Semester, core, and/or cumulative GPA less than 2.00 but greater than the GPA defined in Table 67.

- Single "F" grade. One "F" grade in an academic major, core, or elective course.

- Senior cadets are deficient and may be placed on academic probation if their majors' GPAs are less than 2.00

Discharge from the Academy may happen in three ways by the recommendation of Academic Review Committee (ARC):

- Multiple Failures. More than one "F" grade in one semester.

- Repeat Failure. Repeat failure ("F" grade) in the same course, whether core or elective and regardless of the number of semester hours.

- Very low GPA with any of the GPAs showed in the Table 67.

- Two sequential semesters of either low or very low semester and/or cumulative GPA.

- Failure to achieve a 2.00 semester or cumulative GPA in 3 sequential semesters.

- Multiple deficient semesters. Deficiency in three of their first four semesters.

Table 67. GPA lower limit values at USAFA

total semesters	cumulative GPA lower limit	sGPA lower limit	cumulative core GPA lower limit
1	1.50	1.50	
2	1.70	1.50	
3	1.80	1.50	
4	1.90	1.50	2.00
5	1.95	1.50	2.00
6	2.00	1.60	2.00
7	2.00	1.70	2.00
≥8	2.00	1.80	2.00

They have a probation placement rule to all academically deficient cadets at mid-semester, end-of-semester, and at the end of a summer term. Cadets will be removed from all conditions of academic probation when their semester, core and cumulative (and major's GPA for first-class cadets) performance meet the minimum GPA of 2.00 with no "F".

ARC is a very powerful organization that reviews cadets all academic progress. It can recommend or direct, continuation, assistance, course drop, course hour underload, course hour overload, course repeat, limit participation in extracurricular, athletic and military activities. For further information please refer to: United States Air Force Academy, Curriculum Handbook 2010-2011, available at www.usafa.edu/df/dfr/curriculum/CHB.pdf (last accessed on 01.10.2010).

Appendix H: Example Timetables

Table 68. Example Timetable used in system simulation

COURSE HOUR	1ST SEMESTER				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING101	MAT101	ING101	MAT101	FIZ101
2	ING101	MAT101	ING101	MAT101	FIZ101
3	ING101	MAT101	FIZ101	HVG101	HRT100
4	KIM100	TRK100	FIZ101	ITA101	HRT100
5	KIM100	TRK100	FIZ101	ITA101	BLG100
6	KIM100	COEFF. C.	MILITARY T.	IST100	BGL100
7		PHYSICAL T.	MILITARY T.		
8		PHYSICAL T.	MILITARY T.		
COURSE HOUR	**2ND SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING102	MAT102		MAT102	FIZ102
2	ING102	MAT102		MAT102	FIZ102
3	ING102	MAT102	FIZ102	BLG101	BLG101
4	ING102	END211	FIZ102	BLG101	HVC285
5	ING102	END211	FIZ102	BLG101	HVC285
6	LOJ201	HVC285	COEFF. C.	ITA102	
7		PHYSICAL T.	MILITARY T.	ITA102	
8		PHYSICAL T.	MILITARY T.		
COURSE HOUR	**2ND SEMESTER (additional courses)**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING101	MAT101		MAT101	FIZ101
2	ING101	MAT101		MAT101	FIZ101
3	ING101	MAT101	FIZ101	BLG100	
4	ING101		FIZ101		
5	ING101		FIZ101		
6			COEFF. C.	ITA101	IST100
7	HRT100	PHYSICAL T.	MILITARY T.	ITA101	TRK100
8		PHYSICAL T.	MILITARY T.		TRK100
COURSE HOUR	**3RD SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING201	MAT201	HVC282	MAT201	END251
2	ING201	MAT201	HVC282	MAT201	END251
3	ING201			BLG206	END251
4			HSA300	BLG206	EKO201
5			HSA300	BLG206	EKO201
6		HVC282	COEFF. C.		ISL216
7		PHYSICAL T.	MILITARY T.	BGL200	ISL216
8		PHYSICAL T.	MILITARY T.	BGL200	ISL216

Table 68. Example Timetable used in system simulation **(continued)**

COURSE HOUR	3RD SEMESTER (additional courses)				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING102	MAT102		MAT102	
2	ING102	MAT102		MAT102	
3	ING102	FIZ102	MAT102	BLG101	
4	ING102	FIZ102		BLG101	
5	ING102	FIZ102		BLG101	
6	HVC285		COEFF. C.		
7	HVC285	PHYSICAL T.	MILITARY T.	FIZ102	
8	HVC285	PHYSICAL T.	MILITARY T.	FIZ102	
COURSE HOUR	**4TH SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1		MAT202	END252	MAT202	HVC287
2		MAT202		MAT202	HVC287
3		END303	HVC391	END252	HVC287
4	EKO202	END303	HVC391	END252	
5	EKO202	END303	HVC391	END252	
6	ING202		COEFF. C.		THU301
7	ING202	PHYSICAL T.	MILITARY T.	BGL200	HUK301
8	ING202	PHYSICAL T.	MILITARY T.	BGL200	HUK301
COURSE HOUR	**4TH SEMESTER (additional courses)**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING201				
2	ING201		HVC282		
3	ING201	MAT201		END251	
4		MAT201		END251	HVC282
5		MAT201		END251	HVC282
6		MAT201	COEFF. C.		
7		PHYSICAL T.	MILITARY T.		
8		PHYSICAL T.	MILITARY T.		
COURSE HOUR	**5TH SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING301				END304
2	ING301				END304
3	ING301	HVC381	END342		END304
4		HVC381	END342		HUK302
5		HVC381	END342	END382	HUK302
6			COEFF. C.	END382	END341
7		PHYSICAL T.	MILITARY T.	END382	END341
8		PHYSICAL T.	MILITARY T.	PSK301	END341

Table 68. Example Timetable used in system simulation **(continued)**

COURSE HOUR	5^{TH} SEMESTER (additional courses)				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1			MAT202		END303
2		LOJ201	MAT202		END303
3			MAT202		END303
4	HUK301		MAT202	END252	
5	HUK301			END252	
6	ING202		COEFF. C.	END252	
7	ING202	PHYSICAL T.	MILITARY T.	END252	
8	ING202	PHYSICAL T.	MILITARY T.		
COURSE HOUR	**6^{TH} SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1		END332		END322	END305
2		END332		END322	END305
3		END332		END322	END305
4		HVC382		END361	END361
5		HVC382		END361	END361
6	ING302	HVC382	COEFF. C.	LID402	
7	ING302	PHYSICAL T.	MILITARY T.	LID402	
8	ING302	PHYSICAL T.	MILITARY T.		
COURSE HOUR	**6^{TH} SEMESTER (additional courses)**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING301				END304
2	ING301				END304
3	ING301				END304
4			HUK302		
5			HUK302		
6			COEFF. C.		
7		PHYSICAL T.	MILITARY T.		
8		PHYSICAL T.	MILITARY T.	PSK301	
COURSE HOUR	**7^{TH} SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING401	END4X1.2	END4X2.2		
2	ING401	END4X2.2	END4X2.2		
3	ING401	END423	END4X2.1	END4X1.2	
4	HRK401	END423	END4X2.1	HTR400	HTR400
5	HRK401	END423	END4X2.1		SYT400
6			COEFF. C..		SYT400
7			MILITARY T.		END4X1.1
8			MILITARY T.	END4X1.2	END4X1.1
9					END4X1.1

Table 68. Example Timetable used in system simulation **(continued)**

COURSE HOUR	7TH SEMESTER (additional courses)				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	END4X3.3			END305 SOS4X2.1	END361 SOS4X2.2
2	END4X3.3			END305 SOS4X2.1	END361 SOS4X2.2
3	END4X3.3		END472	END305	END361
4			END472		END361
5			END472		
6	ING302 ING402	HVC382	COEFF. C..	AYZ400	
7	ING302 ING402	HVC382	MILITARY T.	LID402	
8	ING302 ING402	HVC382	MILITARY T.	LID402	
9					
COURSE HOUR	**8TH SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1		END4X3.2			
2		END4X3.2			
3		END4X3.2	END4X3.1		
4	END4X3.1	END4X4.2	END4X4.1		
5	END4X3.1	END4X4.2	END4X4.1	AYZ400	
6	ING402	END4X4.2	COEFF. C.	END472	END4X4.1
7	ING402	SOS4X2.2	MILITARY T.	END472	SOS4X2.1
8	ING402	SOS4X2.2	MILITARY T.	END472	SOS4X2.1
COURSE HOUR	**8TH SEMESTER (additional courses)**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING401		HTR400	END423	
2	ING401		HTR400	END423	
3	ING401			END423	
4					SYT400
5					SYT400
6			COEFF. C.		
7			MILITARY T.		
8			MILITARY T.		

MILITARY T.: Military Training
COEFF. C.: Coefficient course
PHYSICAL T : Physical Training

Courses underlined are already opened at TuAFA under other department's curriculums.

Table 69. An example of a semester early graduating cadet's timetable

COURSE HOUR	**4TH SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	ING202	MAT202	END252	MAT202	HVC287
2	ING202	MAT202		MAT202	HVC287
3	ING202	END303	HVC391	END252	HVC287
4	EKO202	END303	HVC391	END252	SYT400
5	EKO202	END303	HVC391	END252	SYT400
6	***ING301***		COEFF. C.	***LID402***	THU301
7	***ING301***	PHYSICAL T.	MILITARY T.	***LID402***	HUK301
8	***ING301***	PHYSICAL T.	MILITARY T.		HUK301
COURSE HOUR	**5TH SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1	***ING401***				END304
2	***ING401***				END304
3	***ING401***	HVC381	END342		END304
4	***HRK401***	HVC381	END342		HUK302
5	***HRK401***	HVC381	END342	END382	HUK302
6	ING302		COEFF. C.	END382	END341
7	ING302	PHYSICAL T.	MILITARY T.	END382	END341
8	ING302	PHYSICAL T.	MILITARY T.	PSK301	END341
COURSE HOUR	**6TH SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1		END332	HTR400	END322	END305
2		END332	HTR400	END322	END305
3		END332	***END4X3.1***	END322	END305
4	***END4X3.1***	HVC382	***END4X4.1***	END361	END361
5	***END4X3.1***	HVC382	***END4X4.1***	END361	END361
6	ING402	HVC382	COEFF. C.	END472	***END4X4.1***
7	ING402	PHYSICAL T.	MILITARY T.	END472	***SOS4X2***
8	ING402	PHYSICAL T.	MILITARY T.	END472	***SOS4X2***
COURSE HOUR	**7TH SEMESTER**				
	MONDAY	**TUESDAY**	**WEDNESDAY**	**THURSDAY**	**FRIDAY**
1		END4X1.2	END4X2.2		
2		END4X2.2	END4X2.2		
3		END423	END472	END4X1.2	
4		END423	END472	HTR400	HTR400
5		END423	END472		SYT400
6			COEFF. C.	***AYZ400***	SYT400
7			MILITARY T.		
8			MILITARY T.	END4X1.2	

Overloaded courses:
4th semester: LID402, ING301; 5th semester: ING401, HRK401;
6th semester: END4X3.1: END402, END4X4.1: END424; SOS4X2; 7th semester: END492, AYZ400

Appendix I: Distribution Analysis of CT_1 Clustering Courses' Clusters

Table 70. Distribution Fitting for CT_1 Clustering Courses

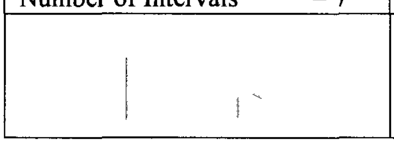
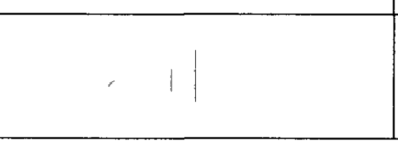
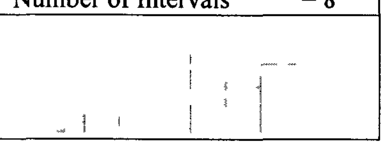
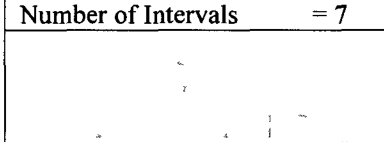
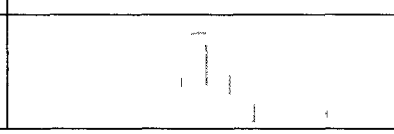
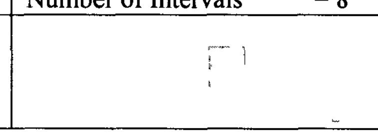
FIZ101 - Physics I		
Cluster 1	**Cluster 2**	**Cluster 3**
Distribution Summary Distribution: Weibull Expression: 0.49 + WEIB(0.946, 2.02) Square Error: 0.023692 Chi Square Test Number of intervals = 4 Degrees of freedom = 1 Test Statistic = 2.25 Corresponding p-value = 0.15 Kolmogorov-Smirnov Test Test Statistic = 0.0677 Corresponding p-value > 0.15 Data Summary Number of Data Points = 51 Min Data Value = 0.662 Max Data Value = 2.32 Sample Mean = 1.33 Sample Std Dev = 0.442 Histogram Summary Histogram Range = 0.49 to 2.5 Number of Intervals = 7	Distribution Summary Distribution: Beta Expression: -1.49 + 3.49 * BETA(3.71, 4.36) Square Error: 0.007328 Chi Square Test Number of intervals = 7 Degrees of freedom = 4 Test Statistic = 6.54 Corresponding p-value = 0.178 Kolmogorov-Smirnov Test Test Statistic = 0.0572 Corresponding p-value > 0.15 Data Summary Number of Data Points = 149 Min Data Value = -1.19 Max Data Value = 1.77 Sample Mean = 0.116 Sample Std Dev = 0.577 Histogram Summary Histogram Range = -1.49 to 2 Number of Intervals = 12	Distribution Summary Distribution: Beta Expression: -2.82 + 3.1 * BETA(3.16, 2.6) Square Error: 0.010846 Chi Square Test Number of intervals = 5 Degrees of freedom = 2 Test Statistic = 3.53 Corresponding p-value = 0.188 Kolmogorov-Smirnov Test Test Statistic = 0.0926 Corresponding p-value > 0.15 Data Summary Number of Data Points = 76 Min Data Value = -2.56 Max Data Value = 0.0155 Sample Mean = -1.12 Sample Std Dev = 0.593 Histogram Summary Histogram Range = -2.82 to 0.28 Number of Intervals = 8
		

Table 70. Distribution Fitting for CT1 Clustering Courses **(continued)**

KIM100 - Chemistry		
Cluster 1	**Cluster 2**	**Cluster 3**
Distribution Summary Distribution: Erlang Expression: -0.26 + ERLA(0.227, 6) Square Error: 0.005219 Chi Square Test Number of intervals = 4 Degrees of freedom = 1 Test Statistic = 0.451 Corresponding p-value = 0.503 Kolmogorov-Smirnov Test Test Statistic = 0.0932 Corresponding p-value > 0.15 Data Summary Number of Data Points = 51 Min Data Value = -0.0126 Max Data Value = 2.43 Sample Mean = 1.1 Sample Std Dev = 0.526 Histogram Summary Histogram Range = -0.26 to 2.68 Number of Intervals = 7	Distribution Summary Distribution: Normal Expression: NORM(0.0778, 0.761) Square Error: 0.001141 Chi Square Test Number of intervals = 7 Degrees of freedom = 4 Test Statistic = 1.41 Corresponding p-value > 0.75 Kolmogorov-Smirnov Test Test Statistic = 0.0389 Corresponding p-value > 0.15 Data Summary Number of Data Points = 149 Min Data Value = -1.96 Max Data Value = 2.15 Sample Mean = 0.0778 Sample Std Dev = 0.764 Histogram Summary Histogram Range = -2 to 2.57 Number of Intervals = 12	Distribution Summary Distribution: Weibull Expression: -3.61 + WEIB(3, 3.89) Square Error: 0.009320 Chi Square Test Number of intervals = 5 Degrees of freedom = 2 Test Statistic = 4.06 Corresponding p-value = 0.144 Kolmogorov-Smirnov Test Test Statistic = 0.0828 Corresponding p-value > 0.15 Data Summary Number of Data Points = 76 Min Data Value = -3.18 Max Data Value = 0.983 Sample Mean = -0.894 Sample Std Dev = 0.8 Histogram Summary Histogram Range = -3.61 to 1 Number of Intervals = 8

Table 70. Distribution Fitting for CT_1 Clustering Courses **(continued)**

MAT101 - Calculus I		
Cluster 1	**Cluster 2**	**Cluster 3**
Distribution Summary Distribution: Triangular Expression: TRIA(0, 0.946, 2.65) Square Error: 0.027542 Chi Square Test Number of intervals = 5 Degrees of freedom = 3 Test Statistic = 3.06 Corresponding p-value = 0.4 Kolmogorov-Smirnov Test Test Statistic = 0.135 Corresponding p-value > 0.15 Data Summary Number of Data Points = 51 Min Data Value = 0.0314 Max Data Value = 2.41 Sample Mean = 1.04 Sample Std Dev = 0.581 Histogram Summary Histogram Range = 0 to 2.65 Number of Intervals = 7	Distribution Summary Distribution: Weibull Expression: -1.59 + WEIB(2.01, 2.95) Square Error: 0.003278 Chi Square Test Number of intervals = 8 Degrees of freedom = 5 Test Statistic = 2.49 Corresponding p-value > 0.75 Kolmogorov-Smirnov Test Test Statistic = 0.0406 Corresponding p-value > 0.15 Data Summary Number of Data Points = 149 Min Data Value = -1.28 Max Data Value = 1.84 Sample Mean = 0.207 Sample Std Dev = 0.671 Histogram Summary Histogram Range = -1.59 to 2 Number of Intervals = 12	Distribution Summary Distribution: Weibull Expression: -4.47 + WEIB(3.61, 5.95) Square Error: 0.003592 Chi Square Test Number of intervals = 4 Degrees of freedom = 1 Test Statistic = 1.18 Corresponding p-value = 0.291 Kolmogorov-Smirnov Test Test Statistic = 0.0702 Corresponding p-value > 0.15 Data Summary Number of Data Points = 76 Min Data Value = -4.02 Max Data Value = 0.481 Sample Mean = -1.1 Sample Std Dev = 0.675 Histogram Summary Histogram Range = -4.47 to 0.94 Number of Intervals = 8
		

Appendix J: Distribution Information of Course Clusters

Table 71. Distribution Information of CT_{11}

	Cluster 1
FIZ101	0.49 + WEIB(0.946, 2.02)
FIZ102	0.33 + 0.671 * BETA(2.38, 1.32)
HRT100	CONT (0.000, -0.850, 0.039, -0.443, 0.196, -0.036, 0.235, 0.371, 0.353, 0.779, 0.647, 1.186, 0.902, 1.593, 1.000, 2.000)
HVG101	0.09 + 0.911 * BETA(2.28, 0.833)
ITA101	NORM(0.493, 0.815)
KIM100	-0.26 + ERLA(0.227, 6)
MAT101	TRIA(0, 0.946, 2.65)
MAT102	-2 + 4 * BETA(3.84, 1.61)
TRK100	NORM(0.715, 0.15)

Table 72. Distribution Information of CT_{12}

	Cluster 2
FIZ101	-1.49 + 3.49 * BETA(3.71, 4.36)
FIZ102	NORM(0.556, 0.159)
HRT100	-3.74 + WEIB(4.15, 5.68)
HVG101	CONT (0.000, 0.000, 0.118, 0.124, 0.171, 0.249, 0.237, 0.375, 0.316, 0.500, 0.539, 0.625, 0.750, 0.750, 0.921, 0.876, 1.000, 1.000)
ITA101	-4.63 + WEIB(4.57, 4.35)
KIM100	NORM(0.0778, 0.761)
MAT101	-1.59 + WEIB(2.01, 2.95)
MAT102	-2.55 + WEIB(2.97, 3.85)
TRK100	TRIA(0.000, 0.722, 1)

Table 73. Distribution Information of CT_{13}

	Cluster 3
FIZ101	-2.82 + 3.1 * BETA(3.16, 2.6)
FIZ102	NORM(0.357, 0.19)
HRT100	-5 + 6 * BETA(4.67, 1.94)
HVG101	BETA(2.4, 1.11)
ITA101	-2.91 + ERLA(0.297, 10)
KIM100	-3.61 + WEIB(3, 3.89)
MAT101	-4.47 + WEIB(3.61, 5.95)
MAT102	-3.56 + 5.31 * BETA(4.98, 4.59)
TRK100	TRIA(0.000, 0.722, 1)

Table 74. Distribution Information of CT_{21}

	Cluster 1
BGL100	CONT (0.000, 0.000, 0.029, 0.199, 0.176, 0.400, 0.265, 0.600, 0.618, 0.801, 1.000, 1.000)
EKO201	TRIA(-1.69, 1.43, 3)
EKO202	TRIA(0.38, 0.878, 1)
END211	TRIA(-1, 0.863, 3.47)
END251	CONT (0.000, -0.538, 0.061, 0.022, 0.152, 0.581, 0.545, 1.141, 0.939, 1.700, 1.000, 2.260)
END252	CONT (0.00, -0.530, 0.059, 0.176, 0.265, 0.882, 0.765, 1.588, 0.971, 2.294, 1.0, 3)
HVC282	0.19 + BETA(2.91, 2.03)
HVC285	TRIA(-2, 1.21, 2.59)
HVC287	CONT (0, -1.41, 0.03, -0.53, 0.406, 0.354, 0.656, 1.236, 0.969, 2.118, 1.000, 3.000)
IST100	CONT (0.000, -2.000, 0.118, -0.800, 0.353, 0.400, 0.794, 1.600, 0.971, 2.800, 1.000, 4.000)
ITA102	CONT (0.000, -1.510, 0.059, -0.714, 0.265, 0.082, 0.500, 0.878, 0.794, 1.674, 1.000, 2.470)
MAT201	CONT (0.000, 0.000, 0.029, 0.458, 0.412, 0.916, 0.853, 1.374, 0.941, 1.832, 1.000, 2.290)
MAT202	TRIA(0.73, 1.37, 2)
THU301	-2 + 4 * BETA(1.58, 1.26)

Table 75. Distribution Information of CT_{22}

	Cluster 2
BGL100	CONT (0.000, 0.000, 0.087, 0.110, 0.141, 0.222, 0.207, 0.333, 0.272, 0.444, 0.391, 0.556, 0.674, 0.667, 0.815, 0.778, 0.924, 0.890, 1.000, 1.000)
EKO201	CONT (0.000, -2.000, 0.022, -1.452, 0.109, -0.904, 0.239, -0.357, 0.435, 0.191, 0.707, 0.739, 0.946, 1.287, 0.978, 1.834, 0.989, 2.382, 1.000, 2.930)
EKO202	0.05 + WEIB(0.624, 3.55)
END211	-2.67 + WEIB(3.15, 3.78)
END251	-1.87 + WEIB(2.65, 4.56)
END252	TRIA(-1, 0.5, 2)
HVC282	BETA(2.37, 1.31)
HVC285	TRIA(-2, 0.547, 2)
HVC287	NORM(0.363, 0.868)
IST100	-2.78 + WEIB(3.27, 4.03)
ITA102	-2.36 + 4.23 * BETA(3.53, 2.48)
MAT201	-1.83 + 3.79 * BETA(3.95, 3.09)
MAT202	CONT (0.000, -1.360, 0.011, -0.987, 0.033, -0.613, 0.109, -0.240, 0.337, 0.133, 0.554, 0.507, 0.870, 0.880, 0.967, 1.253, 0.989, 1.627, 1.000, 2.000)
THU301	TRIA(-2.71, 0.692, 2)

Table 76. Distribution Information of CT_{23}

	Cluster 3
BGL100	BETA(1.36, 1.18)
EKO201	NORM(-0.266, 0.79)
EKO202	TRIA(0, 0.611, 1)
END211	TRIA(-2.44, -0.172, 1.82)
END251	-2.53 + 3.53 * BETA(3.6, 2.98)
END252	-1.92 + ERLA(0.195, 7)
HVC282	NORM(0.544, 0.239)
HVC285	-2 + 4 * BETA(1.36, 1.56)
HVC287	NORM(-0.292, 0.809)
IST100	CONT (0, -2.85, 0.012, -2.311, 0.035, -1.772, 0.118, -1.233, 0.259, -0.694, 0.529, -0.156, 0.847, 0.383, 0.918, 0.922, 0.965, 1.461, 1.000, 2.000)
ITA102	CONT (0, -3.80, 0.011, -3.156, 0.034, -2.511, 0.057, -1.867, 0.161, -1.222, 0.264, -0.578, 0.540, 0.067, 0.828, 0.711, 0.954, 1.356, 1.000, 2.000)
MAT201	-1.71 + 3.48 * BETA(2.42, 2.74)
MAT202	NORM(-0.361, 0.691)
THU301	NORM(-0.119, 0.875)

Table 77. Distribution Information of CT_{24}

	Cluster 4
BGL100	EXPO(0.33)
EKO201	-4 + WEIB(3.57, 3.41)
EKO202	CONT (0.000, 0.000, 0.158, 0.166, 0.395, 0.333, 0.632, 0.500, 0.947, 0.667, 0.974, 0.834, 1.000, 1.000)
END211	CONT (0.000, -4.670, 0.026, -3.612, 0.026, -2.553, 0.205, -1.495, 0.615, -0.437, 0.949, 0.622, 1.000, 1.680)
END251	CONT (0.000, -3.000, 0.077, -2.235, 0.333, -1.470, 0.641, -0.705, 0.744, 0.060, 0.974, 0.825, 1.000, 1.590)
END252	-3.52 + WEIB(2.82, 2.5)
HVC282	TRIA(0, 0.466, 0.8)
HVC285	TRIA(-2.54, -0.736, 1.79)
HVC287	CONT (0.000, -3.000, 0.026, -2.167, 0.289, -1.333, 0.684, -0.500, 0.895, 0.333, 0.974, 1.167, 1.000, 2.000)
IST100	TRIA(-2.84, -1.19, 2)
ITA102	TRIA(-2.54, -0.265, 1.36)
MAT201	NORM(-1.46, 0.862)
MAT202	-3.96 + 3.96 * BETA(3.62, 1.81)
THU301	CONT (0, -4.76, 0.029, -3.42, 0.06, -2.08, 0.4, -0.74, 0.80, 0.60, 1, 1.940)

Table 78. Distribution Information of CT_{31}

	Cluster 1
AYZ400	CONT (0.000, 0.000, 0.036, 0.199, 0.036, 0.400, 0.179, 0.600, 0.571, 0.801, 1, 1)
BGL200	TRIA(-1.79, 0.785, 2.36)
END303	CONT (0.000, -0.450, 0.026, 0.037, 0.128, 0.523, 0.513, 1.010, 0.718, 1.497, 0.974, 1.983, 1.000, 2.470)
END304	0.26 + 0.741 * BETA(1.56, 1.01)
END322	-1.48 + 4.11 * BETA(2.58, 2.08)
END332	-0.47 + 2.47 * BETA(1.77, 1.69)
END341	-1 + 3.37 * BETA(3.2, 1.73)
END342	NORM(0.642, 0.221)
END361	0.33 + 0.671 * BETA(2.05, 0.681)
END382	CONT (0, -1.43, 0.026, -0.692, 0.154, 0.047, 0.41, 0.785, 0.846, 1.523, 0.923, 2.26, 1, 3)
END402	CONT (0.000, -1.000, 0.036, -0.400, 0.143, 0.200, 0.357, 0.800, 0.714, 1.400, 1.000, 2.000)
END422	UNIF(-0.27, 2.47)
END423	CONT (0.000, -0.920, 0.071, -0.236, 0.357, 0.448, 0.607, 1.132, 0.964, 1.816, 1.000, 2.500)
END429	TRIA(-1, 0.985, 2.71)
END452	TRIA(-0.76, 1.04, 1.81)
END472	NORM(0.873, 0.735)
END492	CONT (0.000, 0.000, 0.071, 0.199, 0.179, 0.400, 0.250, 0.600, 0.429, 0.801, 1, 1)
HRK401	0.14 + 0.861 * BETA(1.49, 0.828)
HSA300	CONT (0.000, -1.840, 0.103, -0.955, 0.282, -0.070, 0.615, 0.815, 0.923, 1.700, 0.974, 2.585, 1.000, 3.470)
HTR400	CONT (0.000, -1.680, 0.036, -0.784, 0.179, 0.112, 0.679, 1.008, 0.929, 1.904, 1, 2.8)
HUK301	CONT (0, -1, 0.128, -0.333, 0.282, 0.333, 0.718, 1, 0.872, 1.667, 0.974, 2.333, 1, 3)
HUK302	TRIA(-1.42, 0.786, 3)
HVC381	TRIA(-1.75, 1.92, 2.66)
HVC382	CONT (0.000, -0.720, 0.107, -0.036, 0.393, 0.648, 0.607, 1.332, 0.857, 2.016, 1.000, 2.700)
HVC391	-1.53 + WEIB(2.82, 2.83)
ISL402	TRIA(-2, 1.29, 2.57)
LID402	TRIA(0, 0.991, 1)
LOJ201	TRIA(-1.95, 1.52, 3)
PSK301	TRIA(-0.66, 1.34, 2)
SYT400	-1 + 4.6 * BETA(1.71, 2.97)
YON304	CONT (0, 0.23, 0.03, 0.36, 0.13, 0.49, 0.23, 0.62, 0.62, 0.74, 0.87, 0.87, 1, 1)

Table 79. Distribution Information of CT_{32}

	Cluster 2
AYZ400	NORM(0.628, 0.217)
BGL200	-3.54 + WEIB(3.9, 4.48)
END303	NORM(0.111, 0.773)
END304	CONT (0, 0, 0.01, 0.09, 0.06, 0.18, 0.17, 0.27, 0.234, 0.364, 0.390, 0.455, 0.532, 0.546, 0.730, 0.637, 0.872, 0.728, 0.979, 0.819, 0.993, 0.910, 1, 1)
END322	-2.48 + 4.48 * BETA(3.76, 2.85)
END332	-2.68 + 5.22 * BETA(3.72, 3.44)
END341	CONT (0.000, -1.990, 0.000, -1.608, 0.041, -1.227, 0.109, -0.845, 0.224, -0.463, 0.388, -0.082, 0.565, 0.300, 0.803, 0.682, 0.952, 1.063, 0.980, 1.445, 0.993, 1.827, 1, 2.208)
END342	-0.16 + 1.16 * BETA(3.22, 2.94)
END361	0.12 + 0.88 * BETA(3.57, 4.33)
END382	-2.78 + ERLA(0.309, 9)
END402	CONT (0, -2.61, 0.02, -2.10, 0.06,-1.60, 0.19, -1.09, 0.29, -0.58, 0.44,-0.08, 0.67, 0.43, 0.88, 0.94, 0.95, 1.45, 0.99, 1.95, 1, 2.46)
END422	NORM(-0.118, 0.789)
END423	CONT (0, -2, 0.05, -1.6, 0.1, -1.2, 0.17, -0.8, 0.3, -0.4, 0.55, -0, 0.69, 0.4, 0.77, 0.8, 0.92, 1.2, 0.99, 1.6, 1, 2)
END429	-2 + WEIB(2.17, 2.19)
END452	-3.67 + 5.57 * BETA(4.53, 2.43)
END472	NORM(-0.025, 0.851)
END492	1.21 * BETA(2.02, 1.66)
HRK401	BETA(1.72, 1.34)
HSA300	-5 + WEIB(5.33, 6.28)
HTR400	TRIA(-2.89, 0.122, 2.66)
HUK301	NORM(0.0251, 0.881)
HUK302	-3 + 5.92 * BETA(4.87, 4.93)
HVC381	TRIA(-2.4, 0.02, 2)
HVC382	CONT (0, -1.97, 0.01, -1.50, 0.15, -1.03, 0.28, -0.58, 0.57, -0.1, 0.72, 0.37, 0.83, 0.84, 0.93, 1.31, 0.98, 1.77, 0.99, 2.24, 1, 2.7)
HVC391	NORM(-0.0235, 0.774)
ISL402	-3 + WEIB(3.31, 3.59)
LID402	BETA(1.37, 1.02)
LOJ201	NORM(-0.0532, 0.823)
PSK301	CONT (0, -3, 0.007, -2.586, 0.027, -2.172, 0.041, -1.758, 0.095, -1.343, 0.170, -0.929, 0.252, -0.515, 0.388, -0.101, 0.619, 0.31, 0.83, 0.73, 0.92, 1.14, 1, 1.56, 1, 1.97)
SYT400	-3 + WEIB(3.21, 3.55)
YON304	NORM(0.582, 0.197)

Table 80. Distribution Information of CT_{33}

	Cluster 3
AYZ400	TRIA(0, 0.7, 1)
BGL200	TRIA(-2.68, -0.218, 2)
END303	CONT (0.000, -3.890, 0.017, -3.199, 0.052, -2.507, 0.069, -1.816, 0.448, -1.124, 0.776, -0.433, 0.948, 0.259, 0.948, 0.950)
END304	CONT (0.000, 0.000, 0.268, 0.128, 0.429, 0.256, 0.589, 0.385, 0.768, 0.514, 0.964, 0.643, 0.982, 0.771, 1.000, 0.900)
END322	CONT (0.000, -5.000, 0.018, -4.019, 0.018, -3.037, 0.071, -2.056, 0.357, -1.074, 0.732, -0.093, 0.946, 0.889, 1.000, 1.870)
END332	-3.73 + 5.47 * BETA(3.73, 2.74)
END341	-3.38 + WEIB(2.62, 3.37)
END342	-0.21 + ERLA(0.101, 5)
END361	CONT (0.000, 0.000, 0.190, 0.113, 0.379, 0.228, 0.569, 0.342, 0.862, 0.457, 0.966, 0.571, 0.983, 0.686, 1.000, 0.800)
END382	NORM(-0.666, 0.89)
END402	CONT (0.000, -2.000, 0.194, -1.400, 0.516, -0.800, 0.677, -0.200, 0.935, 0.400, 1.000, 1.000)
END422	CONT (0.000, -3.610, 0.083, -2.536, 0.167, -1.462, 0.625, -0.388, 0.875, 0.686, 1, 1.760)
END423	-3 + 4 * BETA(1.52, 1.21)
END429	CONT (0.000, -3.700, 0.032, -2.760, 0.032, -1.820, 0.258, -0.880, 0.774, 0.060, 1, 1)
END452	CONT (0.000, -3.500, 0.032, -2.506, 0.097, -1.512, 0.548, -0.518, 0.871, 0.476, 1, 1.470)
END472	TRIA(-3.47, 0.192, 1.68)
END492	TRIA(0, 0.901, 1)
HRK401	TRIA(0, 0.7, 1)
HSA300	TRIA(-2.79, 0.208, 2)
HTR400	TRIA(-2.57, -0.409, 1.46)
HUK301	NORM(-0.469, 0.976)
HUK302	-2.5 + ERLA(0.36, 6)
HVC381	TRIA(-2.43, -0.715, 1)
HVC382	TRIA(-3, -0.613, 1.55)
HVC391	CONT (0.000, -3.000, 0.054, -2.286, 0.161, -1.571, 0.446, -0.857, 0.625, -0.143, 0.911, 0.571, 0.964, 1.286, 1.000, 2.000)
ISL402	CONT (0.000, -3.000, 0.065, -2.200, 0.097, -1.400, 0.419, -0.600, 0.774, 0.200, 1, 1)
LID402	BETA(1.28, 1.10546)
LOJ201	-2.93 + 4.72 * BETA(2.17, 1.83)
PSK301	TRIA(-3.74, 0.496, 1.75)
SYT400	NORM(-0.231, 1.08)
YON304	NORM(0.509, 0.228)

Table 81. Distribution Information of CC_1

	Cluster 1
BLG100	BETA(1.89, 1.04)
BLG101	TRIA(-0.86, 1.85, 2.75)
BLG206	CONT (0.000, 0.550, 0.079, 1.000, 0.289, 1.450, 0.789, 1.900, 0.947, 2.350, 0.974, 2.800, 1.000, 3.250)

Table 82. Distribution Information of CC_2

	Cluster 2
BLG100	WEIB(0.565, 2.89)
BLG101	-1.38 + WEIB(1.79, 2.7)
BLG206	NORM(-0.0946, 0.668)

Table 83. Distribution Information of CC_3

	Cluster 3
BLG100	NORM(0.382, 0.197)
BLG101	TRIA(-2.43, -1.05, -0.61)
BLG206	NORM(-0.957, 0.671)

Table 84. Distribution Information of Single Cluster Courses

END413	CONT (0.000, -2.560, 0.111, -1.738, 0.167, -0.916, 0.389, -0.094, 0.778, 0.728, 1.000, 1.550)
END414	TRIA(-2.81, 0.85, 1.96)
END424	NORM(0, 0.992)
END425	-2.49 + 4.49 * BETA(2.21, 1.77)

Table 85. Distribution Information of CE_{11}

	Cluster 1
ING101	TRIA(0.2, 0.725, 1.95)
ING102	CONT (0.000, 0.490, 0.125, 0.822, 0.406, 1.154, 0.906, 1.486, 0.969, 1.818, 1, 2.150)
ING201	CONT (0.000, -0.860, 0.067, -0.288, 0.200, 0.284, 0.233, 0.856, 0.767, 1.428, 1.000, 2.000)
ING202	CONT (0.000, 0.390, 0.100, 0.512, 0.133, 0.634, 0.233, 0.757, 0.333, 0.879, 1.000, 1.000)

Table 86. Distribution Information of CE_{12}

	Cluster 2
ING101	-1 + 2.8 * BETA(1.96, 2.98)
ING102	NORM(-0.0875, 0.626)
ING201	CONT (0.000, -3.000, 0.024, -2.476, 0.024, -1.951, 0.098, -1.427, 0.159, -0.902, 0.268, -0.378, 0.598, 0.147, 0.866, 0.671, 0.976, 1.196, 1.000, 1.720)
ING202	CONT (0.000, 0.000, 0.013, 0.125, 0.038, 0.250, 0.063, 0.375, 0.300, 0.500, 0.387, 0.626, 0.550, 0.751, 0.712, 0.876, 1, 1)

Table 87. Distribution Information of CE_{13}

	Cluster 3
ING101	CONT (0.000, -3.340, 0.038, -2.808, 0.115, -2.276, 0.346, -1.744, 0.885, -1.212, 1, -0.680)
ING102	CONT (0.000, -3.710, 0.120, -2.674, 0.280, -1.638, 0.800, -0.602, 0.960, 0.434, 1, 1.470)
ING201	CONT (0.000, -2.930, 0.050, -2.344, 0.150, -1.758, 0.350, -1.172, 0.700, -0.586, 1.000, 0.000)
ING202	CONT (0.000, 0.000, 0.200, 0.199, 0.350, 0.399, 0.650, 0.600, 0.950, 0.800, 1.000, 1.000)

Table 88. Distribution Information of CE_{21}

	Cluster 1
ING301	CONT (0.000, 0.000, 0.022, 0.270, 0.156, 0.540, 0.667, 0.810, 0.889, 1.080, 0.956, 1.350, 1.000, 1.620)
ING302	CONT (0.000, 0.770, 0.044, 0.809, 0.111, 0.847, 0.156, 0.885, 0.422, 0.924, 0.822, 0.962, 1.000, 1.000)
ING401	CONT (0.000, 0.700, 0.053, 0.760, 0.158, 0.820, 0.316, 0.881, 0.684, 0.941, 1.000, 1.000)
ING402	CONT (0.000, 0.540, 0.053, 0.632, 0.158, 0.724, 0.211, 0.817, 0.842, 0.909, 1, 1)

Table 89. Distribution Information of CE_{22}

	Cluster 2
ING301	NORM(0.195, 0.51)
ING302	0.14 + 0.79 * BETA(3.76, 1.98)
ING401	TRIA(0, 0.871, 1)
ING402	CONT (0.000, 0.000, 0.174, 0.199, 0.217, 0.399, 0.435, 0.600, 0.652, 0.800, 1, 1)

Table 90. Distribution Information of CE_{23}

	Cluster 3
ING301	-3.38 + 3.2 * BETA(2.38, 1.7)
ING302	BETA(1.12, 1.1)
ING401	CONT (0.000, 0.140, 0.091, 0.286, 0.182, 0.432, 0.455, 0.578, 0.727, 0.724, 1.000, 0.870)
ING402	CONT (0.000, 0.000, 0.182, 0.183, 0.364, 0.367, 0.818, 0.552, 0.909, 0.736, 1, 0.920)

Appendix K: Linear Equations

Table 91. Linear Equations of CT_1

	Squadron1	Squadron2
FIZ101	FIZ101.TEMP*10.1517+58	FIZ101.TEMP*10.8756+63.9444
FIZ102	51*FIZ102.TEMP+36	44*FIZ102.TEMP+42
HRT100	HRT100.TEMP*8.2677+67.8519	HRT100.TEMP*9.4659+78.4444
HVG101	33*HVG101.TEMP+63	35*HVG101.TEMP+64
ITA101	ITA101.TEMP*5.4675+73.7407	ITA101.TEMP*7.2096+71.2778
KIM100	KIM100.TEMP*11.6238+61.0185	KIM100.TEMP*12.8187+72.1389
MAT101	MAT101.TEMP*13.2685+72.277	MAT101.TEMP*15.4765+63.513
MAT102	MAT102.TEMP*14.434+62	MAT102.TEMP*12.7972+62.25
TRK100	43*TRK100.TEMP+55	25*TRK100.TEMP+74
	Squadron3	**Squadron4**
FIZ101	FIZ101.TEMP*12.0332+54.8132	FIZ101.TEMP*11.4248+66.4407
FIZ102	46*FIZ102.TEMP+38	54*FIZ102.TEMP+34
HRT100	HRT100.TEMP*8.8155+79.3297	HRT100.TEMP*10.5775+78.661
HVG101	29*HVG101.TEMP+67	23*HVG101.TEMP+75
ITA101	ITA101.TEMP*4.2666+79.3412	ITA101.TEMP*6.9797+75.0517
KIM100	KIM100.TEMP*13.054+63.1648	KIM100.TEMP*10.6714+68.016
MAT101	MAT101.TEMP*13.9927+60.263	MAT101.TEMP*15.5702+70.86
MAT102	MAT102.TEMP*10.1901+64.682	MAT102.TEMP*11.1843+73.70
TRK100	35*TRK100.TEMP+51	29*TRK100.TEMP+67

Table 92. Linear Equations of CT_2

	Squadron1	Squadron2
BGL100	33*BGL100.TEMP+65	38*BGL100.TEMP+60
EKO201	EKO201.TEMP*12.223+73.6731	EKO201.TEMP*10.7195+81.25
EKO202	39*EKO202.TEMP+58	43*EKO202.TEMP+56
END211	END211.TEMP*9.6893+72.8654	END211.TEMP*10.7163+73.8971
END251	END251.TEMP*12.7434+56.1923	END251.TEMP*10.4056+81.5882
END252	END252.TEMP*10.5947+67.4118	END252.TEMP*12.2583+63.8235
HVC282	56*HVC282.TEMP+28	49*HVC282.TEMP+50
HVC285	HVC285.TEMP*13.0241+75.4615	HVC285.TEMP*11.9854+68.6912
HVC287	HVC287.TEMP*11.6066+58.3529	HVC287.TEMP*13.1786+59.6452
IST100	IST100.TEMP*7.3752+77.3529	IST100.TEMP*6.6252+71.5441
ITA102	ITA102.TEMP*10.6925+78.9423	ITA102.TEMP*7.9337+69.1618
MAT201	MAT201.TEMP*11.0157+82.7885	MAT201.TEMP*11.194+74.6471
MAT202	MAT202.TEMP*12.6888+64.2308	MAT202.TEMP*13.155+68.4265
THU301	THU301.TEMP*8.6214+86.1538	THU301.TEMP*3.6981+87.8971
	Squadron3	**Squadron4**
BGL100	21*BGL100.TEMP+73	16*BGL100.TEMP+82
EKO201	EKO201.TEMP*11.7265+72.1688	EKO201.TEMP*10.0137+66.85
EKO202	50*EKO202.TEMP+50	42*EKO202.TEMP+56
END211	END211.TEMP*8.7876+69.3247	END211.TEMP*8.3771+66.163
END251	END251.TEMP*13.0384+67.026	END251.TEMP*15.5182+67.76
END252	END252.TEMP*13.5131+69.48	END252.TEMP*10.1582+83.81
HVC282	51*HVC282.TEMP+23	57*HVC282.TEMP+27
HVC285	HVC285.TEMP*11.6387+75.3247	HVC285.TEMP*11.0138+77.74
HVC287	HVC287.TEMP*16.2476+61.8312	HVC287.TEMP*15.653+63.945
IST100	IST100.TEMP*6.8192+79.28	IST100.TEMP*7.8587+81.0182
ITA102	ITA102.TEMP*4.8298+87.6753	ITA102.TEMP*7.0477+78.1818
MAT201	MAT201.TEMP*12.4493+69.6753	MAT201.TEMP*11.2955+86.07
MAT202	MAT202.TEMP*13.4303+70.2933	MAT202.TEMP*12.6626+74.34
THU301	THU301.TEMP*5.4643+87.4627	THU301.TEMP*7.7559+77.814

Table 93. Linear Equations of CT_3

	Squadron1	Squadron2
AYZ400	20*AYZ400.TEMP+80	23*AYZ400.TEMP+75
BGL200	BGL200.TEMP*5.8356+88.1538	BGL200.TEMP*9.0392+83.0152
END303	END303.TEMP*14.3388+56.1961	END303.TEMP*11.9347+60.5303
END304	48*END304.TEMP+34	48*END304.TEMP+36
END322	END322.TEMP*12.2637+66.3725	END322.TEMP*13.3111+69.5714
END332	END332.TEMP*7.7011+75.6667	END332.TEMP*7.9744+80.6923
END341	END341.TEMP*11.1021+72.9412	END341.TEMP*12.5786+75.197
END342	54*END342.TEMP+45	36*END342.TEMP+62
END361	56*END361.TEMP+33	46*END361.TEMP+35
END382	END382.TEMP*16.2396+73.7255	END382.TEMP*8.5712+71.9524
END402	END402.TEMP*9.723+78.186	END402.TEMP*12.097+70.381
END422	END422.TEMP*8.9916+60.2326	END422.TEMP*14.0837+64.4762
END423	END423.TEMP*8.7208+82.25	END423.TEMP*10.1804+69.4603
END429	END429.TEMP*6.7714+67.9091	END429.TEMP*10.5262+62.5397
END452	END452.TEMP*13.0857+77.2045	END452.TEMP*13.7897+77.5079
END472	END472.TEMP*10.7692+64.5098	END472.TEMP*7.2204+71.0769
END492	30*END492.TEMP+70	40*END492.TEMP+60
HRK401	24*HRK401.TEMP+76	32*HRK401.TEMP+64
HSA300	HSA300.TEMP*6.4844+70.4118	HSA300.TEMP*7.3855+75.2985
HTR400	HTR400.TEMP*6.7786+84.8372	HTR400.TEMP*4.4557+76.2222
HUK301	HUK301.TEMP*7.6425+75.4118	HUK301.TEMP*6.1471+70.7206
HUK302	HUK302.TEMP*5.0616+76.82	HUK302.TEMP*7.6021+76.9063
HVC381	HVC381.TEMP*6.2257+80.5909	HVC381.TEMP*9.7958+66.5714
HVC382	HVC382.TEMP*10.3383+68.976	HVC382.TEMP*11.2859+58.825
HVC391	HVC391.TEMP*8.8743+56.0784	HVC391.TEMP*8.7277+57.2769
ISL402	ISL402.TEMP*7.5028+86.3953	ISL402.TEMP*8.3611+78.6508
LID402	32*LID402.TEMP+68	29*LID402.TEMP+68
LOJ201	LOJ201.TEMP*6.2524+78.451	LOJ201.TEMP*5.3405+86.5441
PSK301	PSK301.TEMP*7.7861+85.2353	PSK301.TEMP*5.361+87.5758
SYT400	SYT400.TEMP*4.3346+89.9545	SYT400.TEMP*8.2748+71.8594
YON304	51*YON304.TEMP+33	30*YON304.TEMP+66
	Squadron3	**Squadron4**
AYZ400	22.33*AYZ400.TEMP+75	24*AYZ400.TEMP+70
BGL200	BGL200.TEMP*6.8027+84.3456	BGL200.TEMP*5.5332+84.8679
END303	END303.TEMP*11.0676+60.2917	END303.TEMP*10.2639+68.363
END304	56*END304.TEMP+37	49*END304.TEMP+40
END322	END322.TEMP*8.4778+66.6471	END322.TEMP*10.0701+68.907
END332	END332.TEMP*8.5252+78.0882	END332.TEMP*8.2508+82
END341	END341.TEMP*11.1838+74.7778	END341.TEMP*11.1137+73.490
END342	35*END342.TEMP+54	39*END342.TEMP+51
END361	51*END361.TEMP+37	54*END361.TEMP+35
END382	END382.TEMP*8.1792+78.3582	END382.TEMP*14.3149+75.092
END402	END402.TEMP*10.28+74.63	END402.TEMP*9.0315+75.3208
END422	END422.TEMP*11.23+65.03	END422.TEMP*10.6059+72.384
END423	END423.TEMP*10.41+76.65	END423.TEMP*12.3396+78.245

Table 99. Linear Equations of CT_3 **(continued)**

	Squadron3	Squadron4
END429	END429.TEMP*9.86+67.51	END429.TEMP*12.2895+72.075
END452	END452.TEMP*12.22+81.02	END452.TEMP*9.7959+88.3396
END472	END472.TEMP*8.9767+78.8056	END472.TEMP*4.701+90.2909
END492	40*END492.TEMP+65	55*END492.TEMP+45
HRK401	30*HRK401.TEMP+66.67	34*HRK401.TEMP+60
HSA300	HSA300.TEMP*5.505+91.5694	HSA300.TEMP*8.8332+76.7818
HTR400	HTR400.TEMP*5.4364+78.7871	HTR400.TEMP*5.0748+81.3019
HUK301	HUK301.TEMP*5.7664+77.2917	HUK301.TEMP*7.4072+73.1455
HUK302	HUK302.TEMP*5.7247+73.9851	HUK302.TEMP*6.8783+82.5
HVC381	HVC381.TEMP*8.74+70.61	HVC381.TEMP*10.196+65.6604
HVC382	HVC382.TEMP*9.83+67.2	HVC382.TEMP*7.8644+73.8113
HVC391	HVC391.TEMP*11.2088+51.403	HVC391.TEMP*9.7885+56.8148
ISL402	ISL402.TEMP*6.8072+83.0783	ISL402.TEMP*4.5576+84.1887
LID402	30.66*LID402.TEMP+67.67	31*LID402.TEMP+67
LOJ201	LOJ201.TEMP*5.0323+86.6667	LOJ201.TEMP*7.9535+84.2364
PSK301	PSK301.TEMP*5.7304+88.0833	PSK301.TEMP*3.9366+89.9455
SYT400	SYT400.TEMP*5.9816+73.0972	SYT400.TEMP*5.3332+74.0364
YON304	39*YON304.TEMP+60	24*YON304.TEMP+74

Table 94. Linear Equations of *CC*

	Squadron1	Squadron2
BLG100	30*BLG100.TEMP+57	46*BLG100.TEMP+47
BLG101	BLG101.TEMP*10.7953+64.6296	BLG101.TEMP*11.6546+67.4861
BLG206	BLG206.TEMP*10.7227+67.6538	BLG206.TEMP*11.1446+62.3529
	Squadron3	**Squadron4**
BLG100	51*BLG100.TEMP+42	62*BLG100.TEMP+34
BLG101	BLG101.TEMP*13.908+56.6	BLG101.TEMP*11.2734+72.586
BLG206	BLG206.TEMP*9.8965+76.2933	BLG206.TEMP*10.2376+75.072

Table 95. Linear Equations of CE_1

	Squadron1	Squadron2
ING101	ING101.TEMP*7.7101+83.3704	ING101.TEMP*8.102+82.1389
ING102	ING102.TEMP*8.4226+83.2407	ING102.TEMP*6.8023+84.1944
ING201	ING201.TEMP*7.3387+87.5455	ING201.TEMP*7.7469+84.5294
ING202	28*ING202.TEMP+71	35*ING202.TEMP+65
	Squadron3	**Squadron4**
ING101	ING101.TEMP*7.5035+87.3667	ING101.TEMP*7.7493+86.016
ING102	ING102.TEMP*10.4458+83.2	ING102.TEMP*8.7384+79.482
ING201	ING201.TEMP*7.3387+87.5455	ING201.TEMP*8.9+84.2909
ING202	22*ING202.TEMP+75	44*ING202.TEMP+55

Table 96. Linear Equations of CE_2

	Squadron1	Squadron2
ING301	ING301.TEMP*4.3602+92.5556	ING301.TEMP*10.7934+87.8545
ING302	36*ING302.TEMP+60	44*ING302.TEMP+52
ING401	43*ING401.TEMP+56	37*ING401.TEMP+63
ING402	27*ING402.TEMP+72	34*ING402.TEMP+66
	Squadron3	**Squadron4**
ING301	ING301.TEMP*4.3602+92.5556	ING301.TEMP*10.7934+87.854
ING302	30*ING302.TEMP+66	60*ING302.TEMP+36
ING401	37*ING401.TEMP+63	30*ING401.TEMP+68
ING402	27*ING402.TEMP+71	24*ING402.TEMP+75

Table 97. Linear Equations of Single Cluster Courses

	Squadron1	Squadron2
END413	END413.TEMP*4.9705+88	END413.TEMP*4.9705+88
END414	END414.TEMP*5.8077+83	END414.TEMP*5.8077+83
END424	END424.TEMP*9.1226+68.1429	END424.TEMP*9.1226+68.1429
END425	END425.TEMP*8.6882+80.0769	END425.TEMP*8.6882+80.0769
	Squadron3	**Squadron4**
END413	END413.TEMP*4.9705+88	END413.TEMP*4.9705+88
END414	END414.TEMP*5.8077+81.963	END414.TEMP*5.8077+81.963
END424	END424.TEMP*9.1226+68.1429	END424.TEMP*9.1226+68.142
END425	END425.TEMP*8.6882+80.0769	END425.TEMP*8.6882+80.076

Appendix L: Variables and Attributes used in Simulation Models

Variables

- TNOW: embedded ARENA variable used for semester (temporary attribute).

- *coursecode*_F: counter variable used for statistic (e.g. MAT101_F) used in validation steps.

- *coursecode*_A: counter variable if student get "AA" at course (e.g. MAT101_A) used in validation steps.

Attributes

- *coursesode*temp: course temporary grade random variable obtained by rv generation according to the cluster's distributions given in Appendix J (e.g. MAT101temp).

- *coursecode*: continuous variable of course grade over 100 obtained by inverse transformation using parameters of each squadron given in Appendix K. (e.g. MAT101).

- *coursecode*F: total of failures of the student at course (can take values 0,1,2) (e.g. MAT101F).

- hds: total course hours taken in a week.

- crdactive: each course's credit at the curriculum (temporary attribute).

- hdsactive: hours of the course taken (temporary attribute).

- hdsmax: maximum available course hours per cadet in a week.

- overhds: total course hours overloaded.

- *coursecode*rpt: repetition of the course, also used for make-up examination eligibility (e.g. MAT101rpt).

- *coursecode*donem: semester of the course taken (e.g. MAT101donem).

- *coursecode*yerine: binary variable if course is taken for a replacement of another failed elective course (e.g. END4X1yerine).

- *coursecode*credit: multiplication of grade letter credit equivalent and grdactive (e.g. MAT101credit).

- yko: sGPA.

- gko: cumulative GPA.

- credithedef: maximum of cumulative GPA or sGPA lower limit values.

- totalcredit: total credit earned throughout the education.

- totalderscredit: total of course credits taken throughout the education.

- semcredit: total credit earned at the semester.

- semderscredit: total of course credits taken at the semester.

- yuk: binary variable used for upgrade examination requirement.

- ekbut: binary variable used for senior cadets to get extra make-up examination.

- ekyuk: binary variable used for senior cadets to get extra upgrade examination.

- goztkr: consecutive probation counter attribute.

- goz: total probation counter attribute.

- doubleF: binary attribute for failing twice from a course.

- fl: attribute used to define the squadron membership of cadet (used for grade assignment).

- CT_{ij}: technical group stage i cluster j attribute, S_i: {1,2,3}, S_j: {1,2,3} if i=1,3; S_j:{1,2,3,4} if i=2.

- CC_j: computer courses' clusters attribute, S_j: {1,2,3}.

- CE_{ij}: English courses' clusters attribute, S_i: {1,2}, S_j: {1,2,3}.

- EL_{ij}: English proficiency levels attribute, S_i: {1,2}, S_j:{1 (beginner), 2 (intermediate), 3 (advanced), 4 (super)}.

- Entity.VATime: embedded ARENA variable used for tracking cadets time spent in system.

- mo_i: binary variable for course hour slots of Monday, i: 1,…,8.

- tu_i: binary variable for course hour slots of Tuesday, i: 1,…,8 for seniors and i: 1,…,6 for others (seventh and eight hours were reserved physical training).

- we_i: binary variable for course hour slots of Wednesday, i: 1,…,5.

- th_i: binary variable for course hour slots of Thursday, i: 1,…,8.

- fr_i: binary variable for course hour slots of Friday, i: 1,…,8.

Appendix M: Simulation Model Developed for Validation of Clustering Methodology

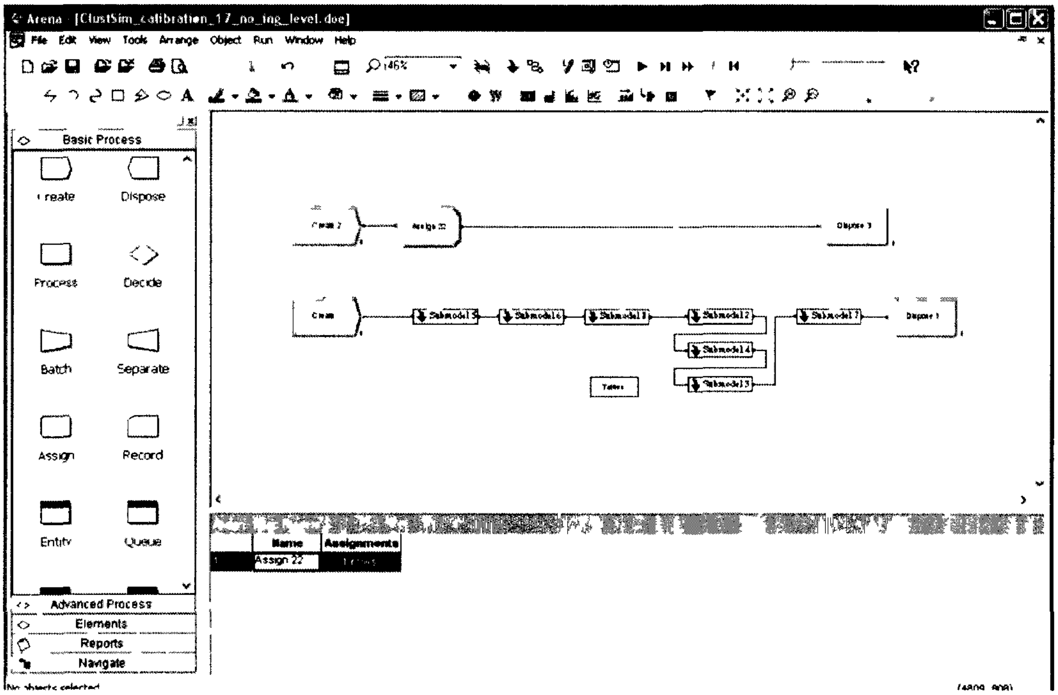


Figure 34. General view of ARENA simulation model used for validation of clustering

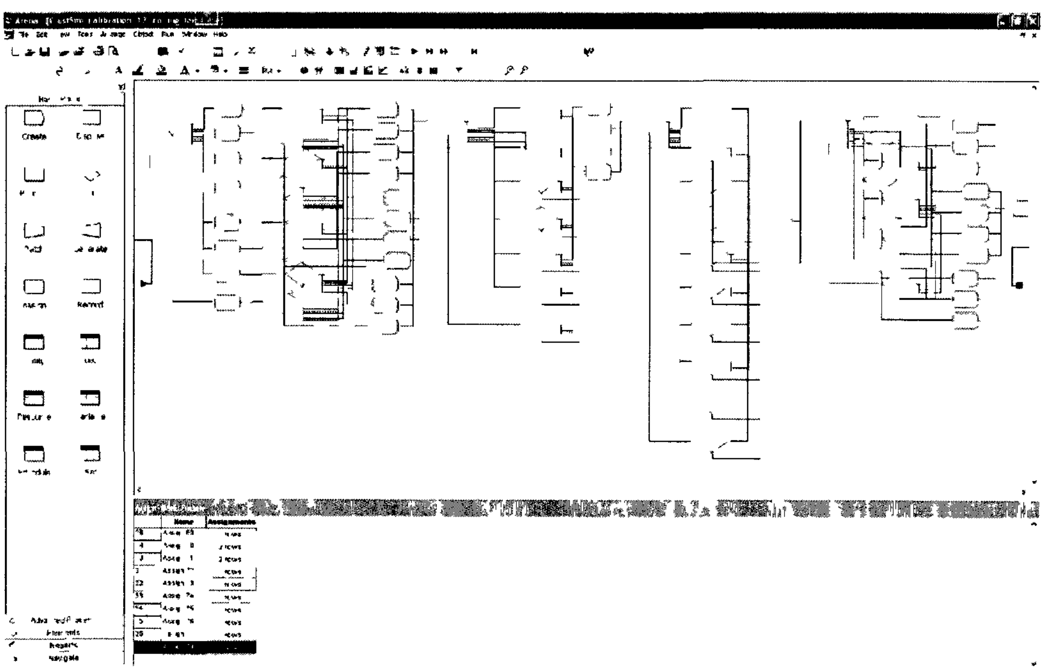


Figure 35. Cluster assignment submodel in the validation model

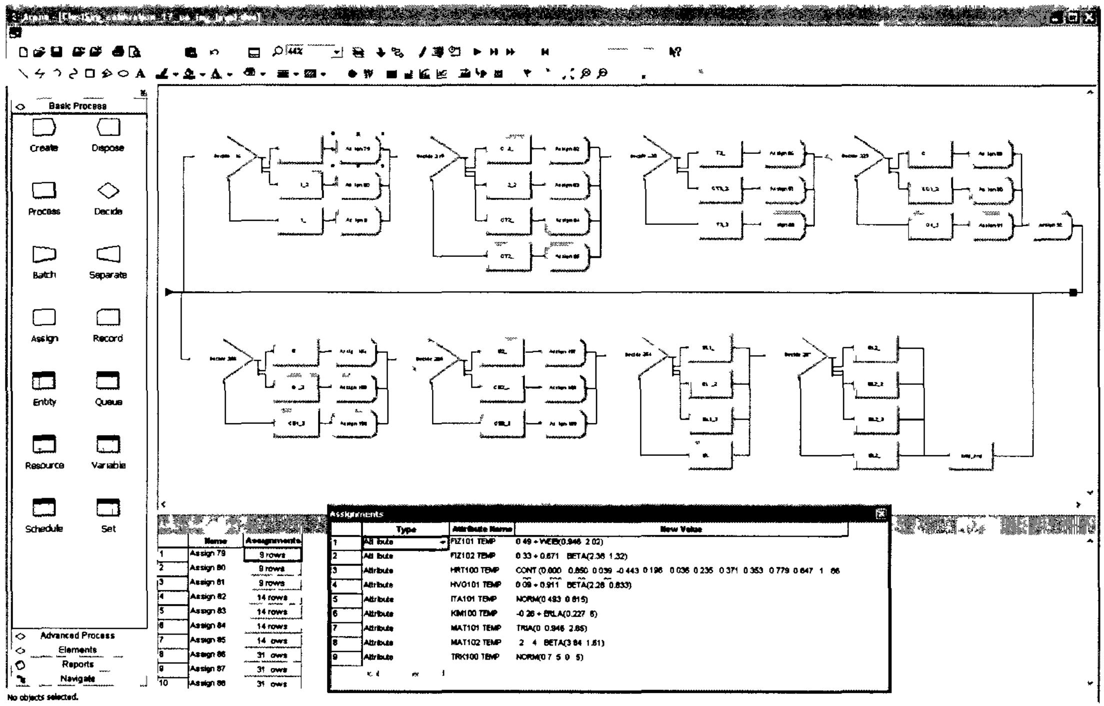


Figure 36. Distribution-grade assignment submodel and counters in the validation model

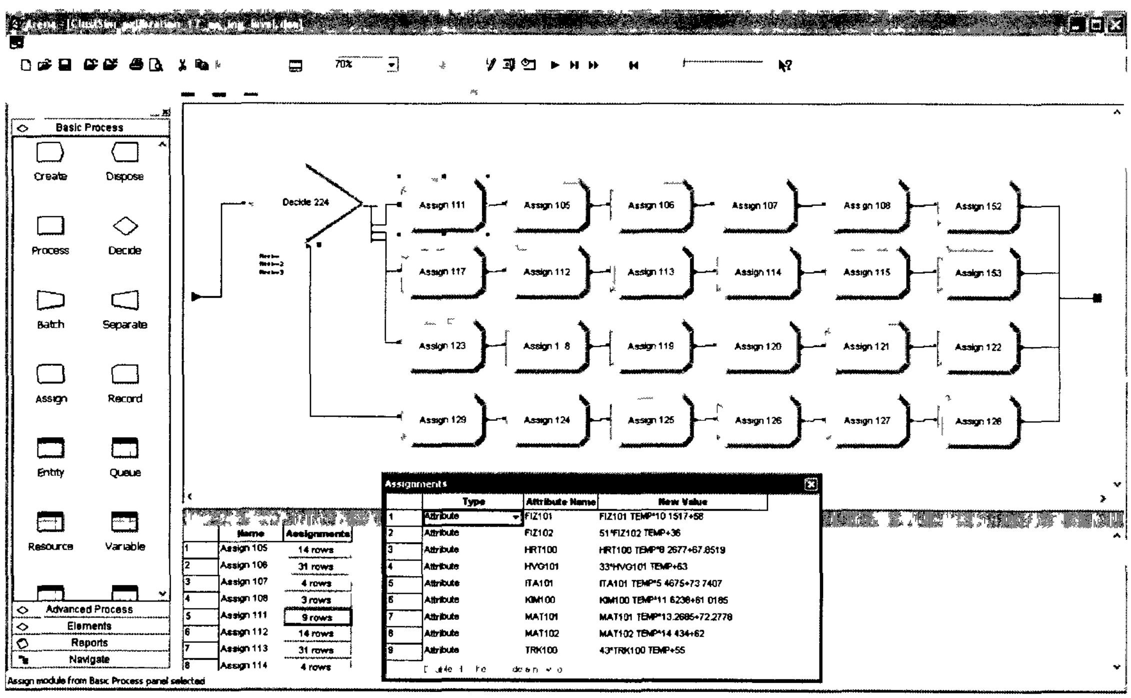


Figure 37. Grade assignment submodel in the validation model

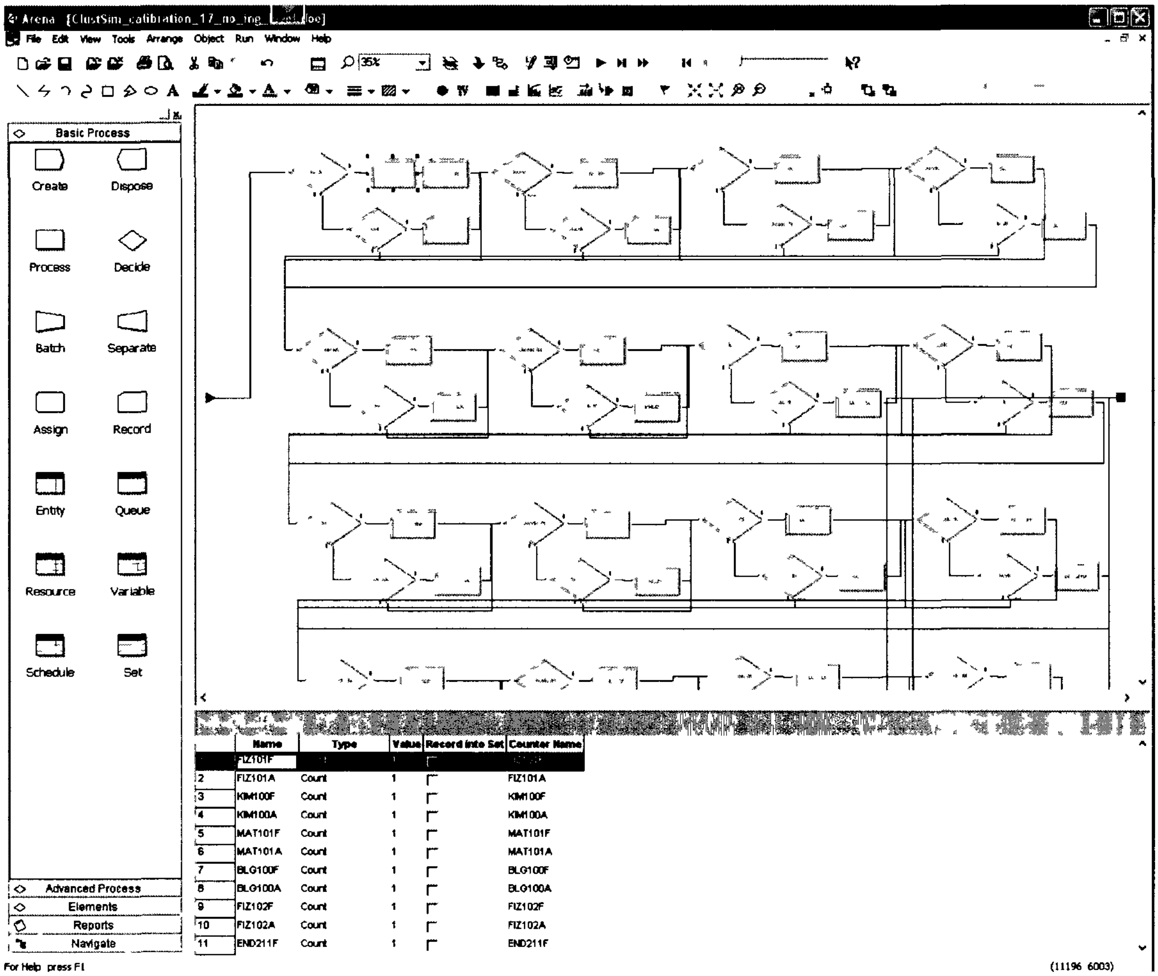


Figure 38. One of three counter submodels used for ratio statics in the validation model

Appendix N: The Simulation Model of New Evaluation System

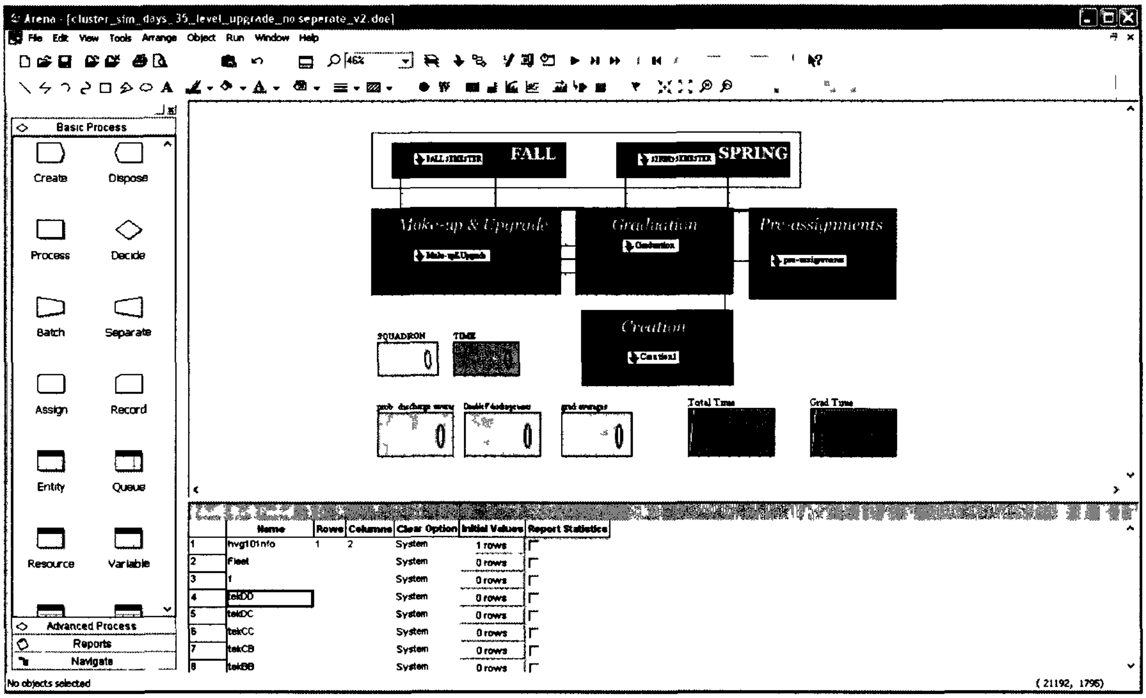


Figure 39. Simulation model main view

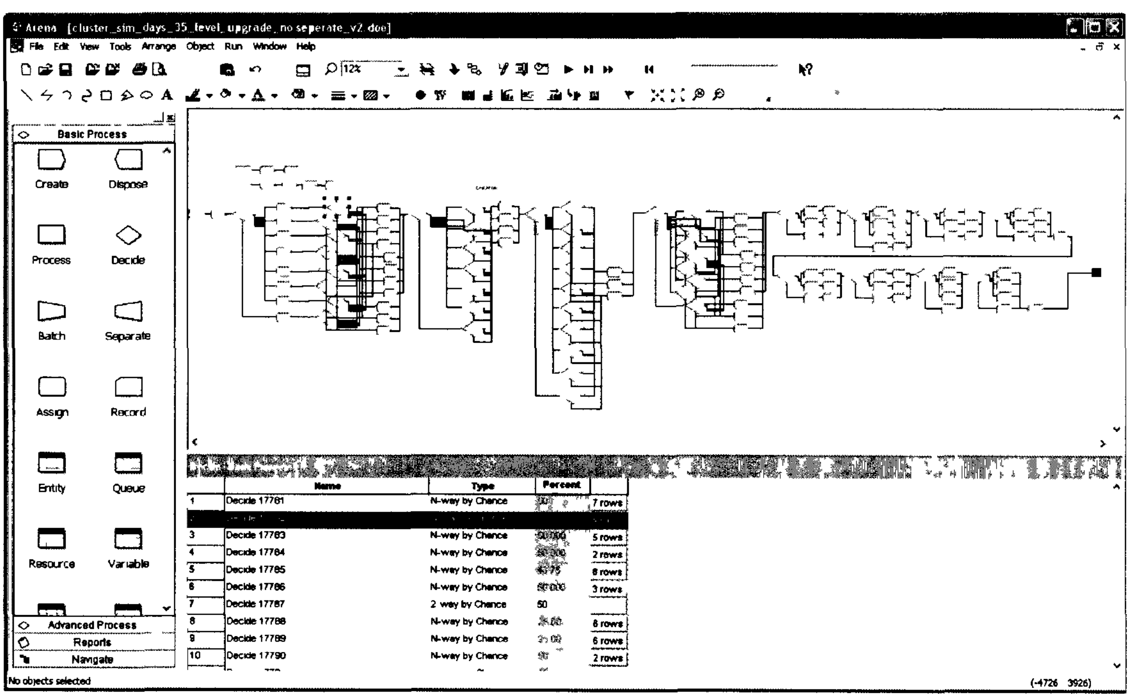


Figure 40. Creation submodel

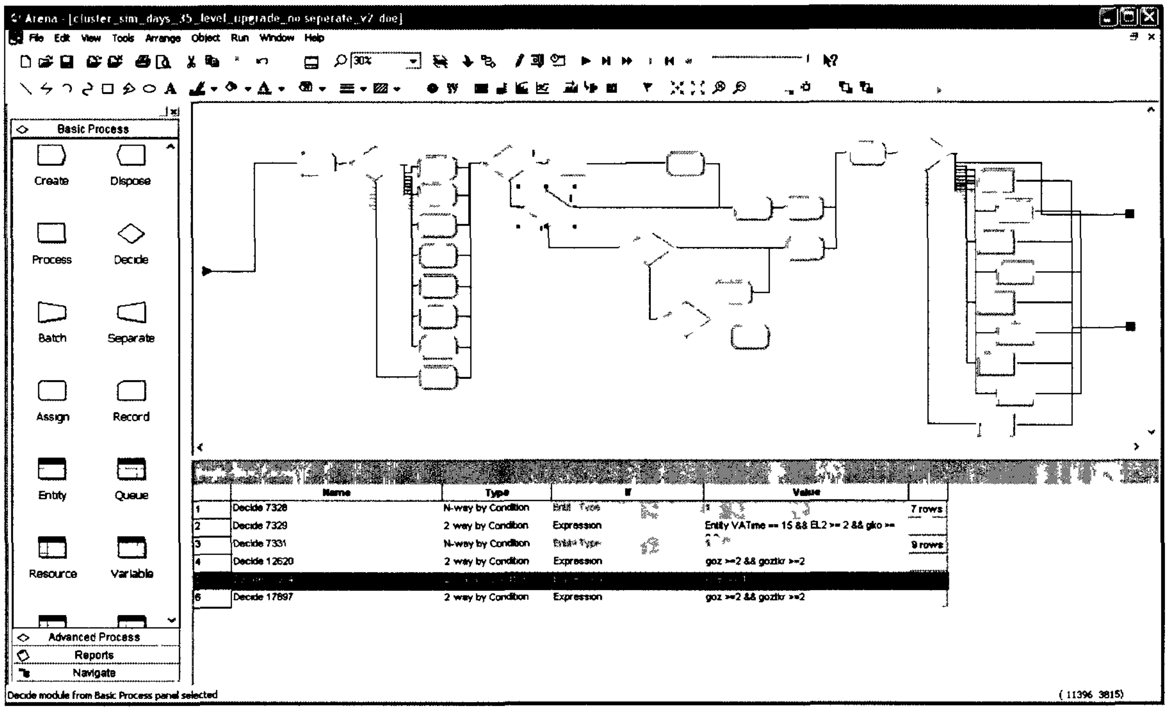


Figure 41. Pre-assignment submodel

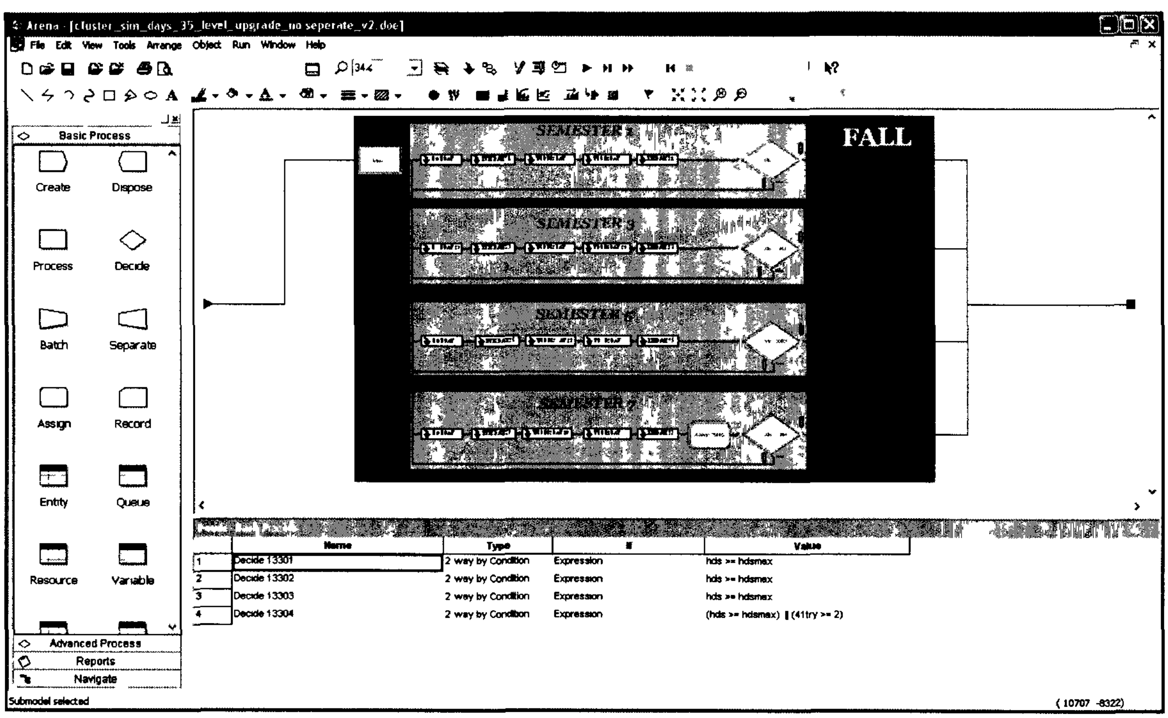


Figure 42. Semester submodel main view

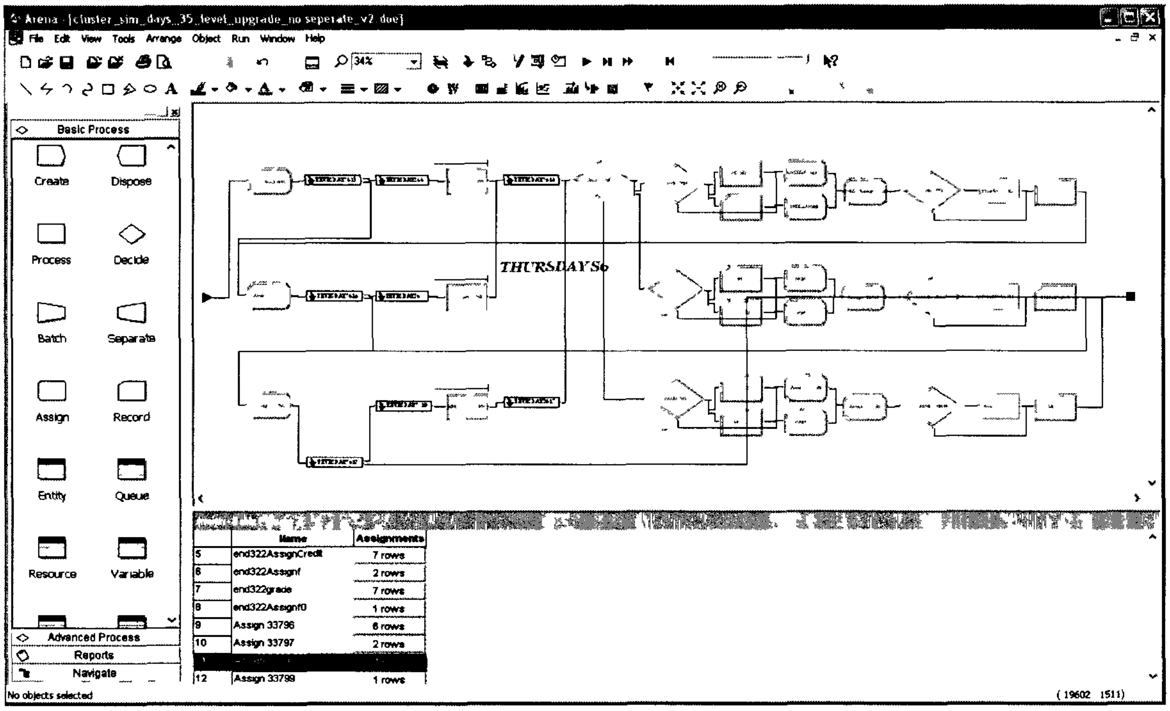


Figure 43. An example of day submodels in semester submodel

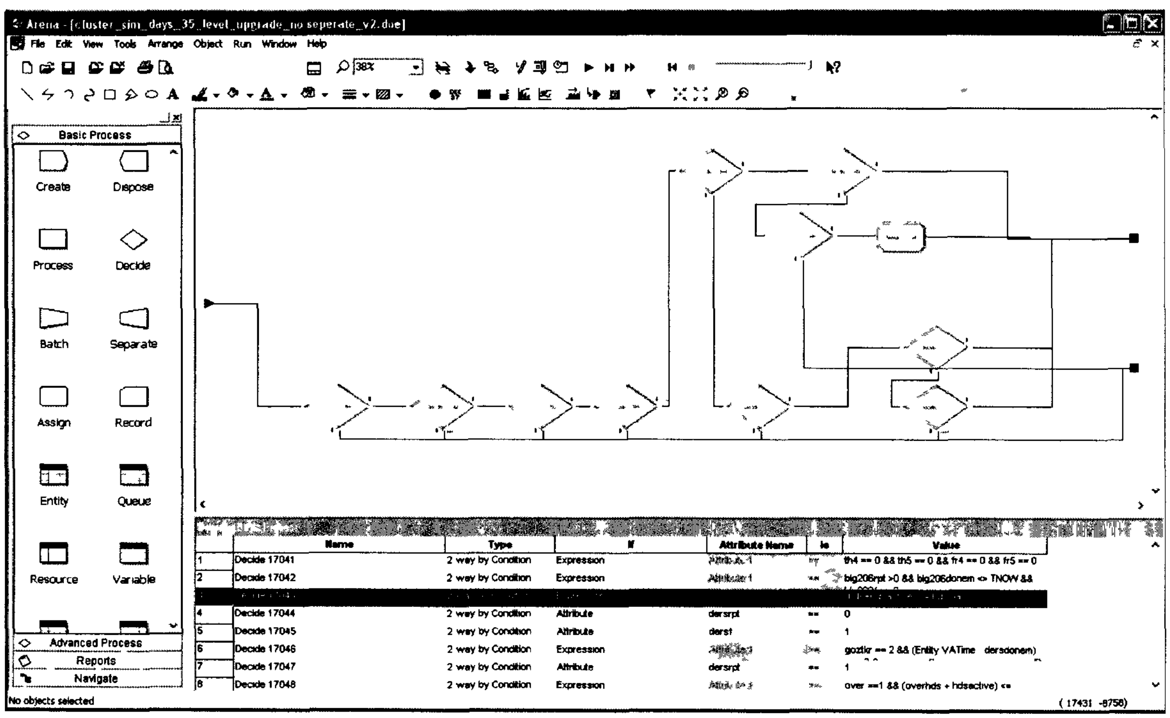


Figure 44. An example of prerequisite check for a course submodels in day submodel

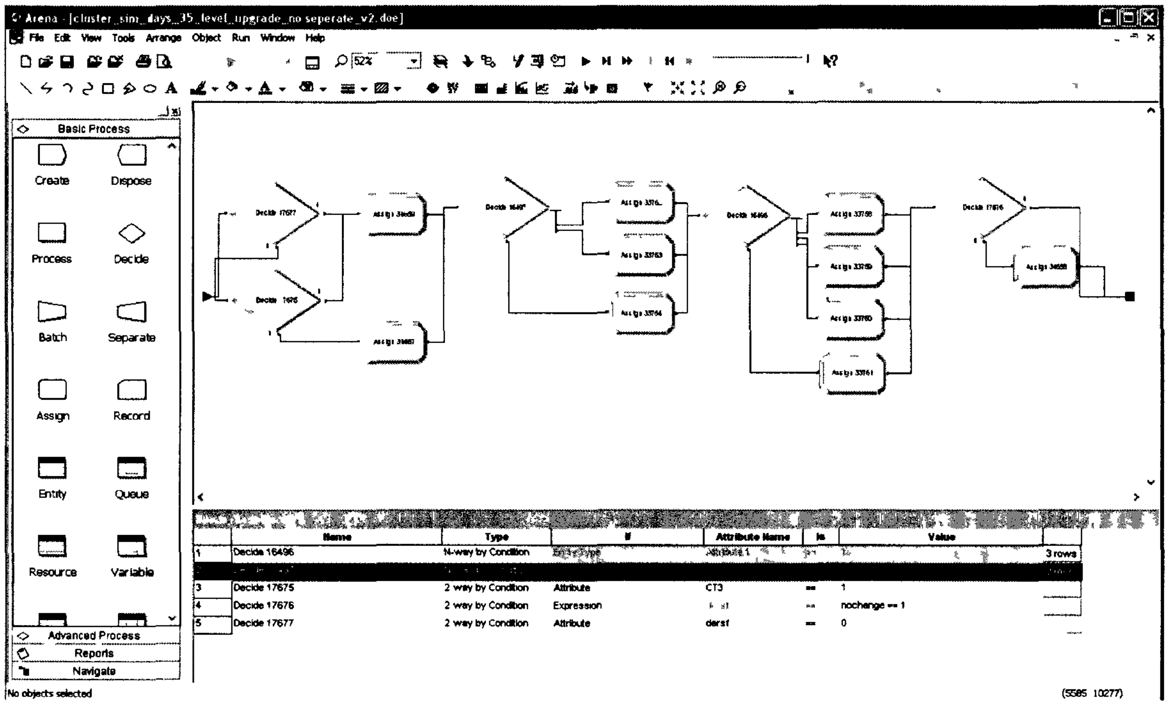


Figure 45. An example of distribution and grade assignment for a course submodels in day submodel

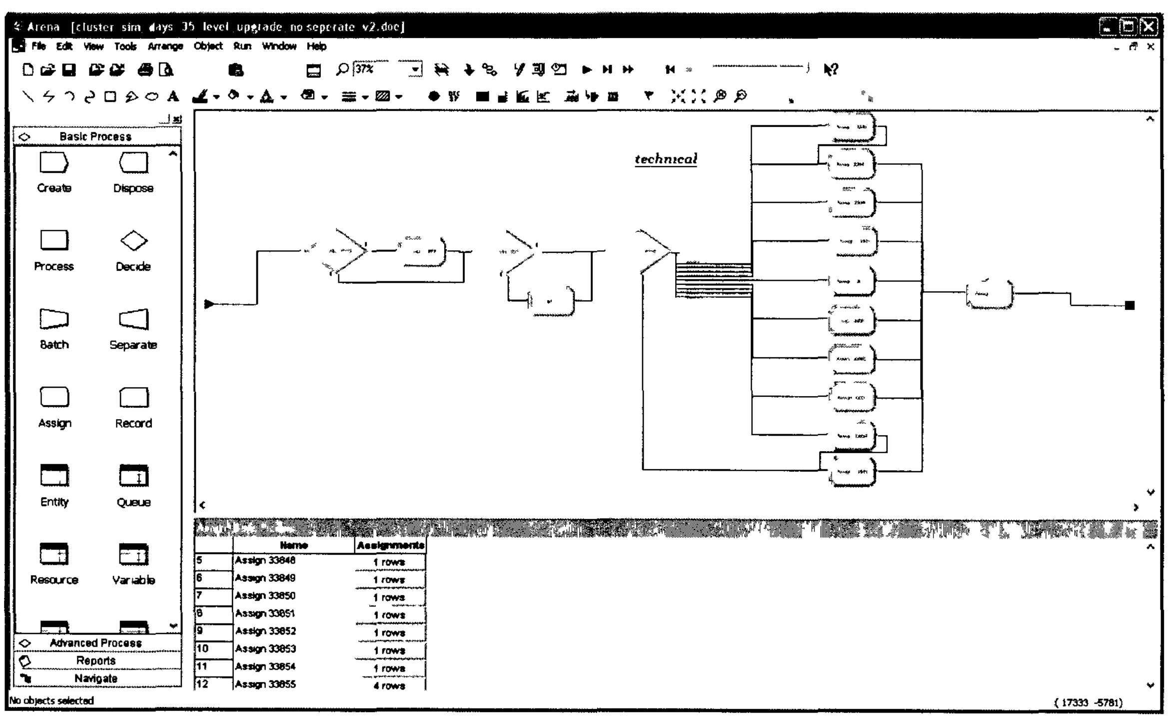


Figure 46. An example of credit assignment for a course submodels in day submodel

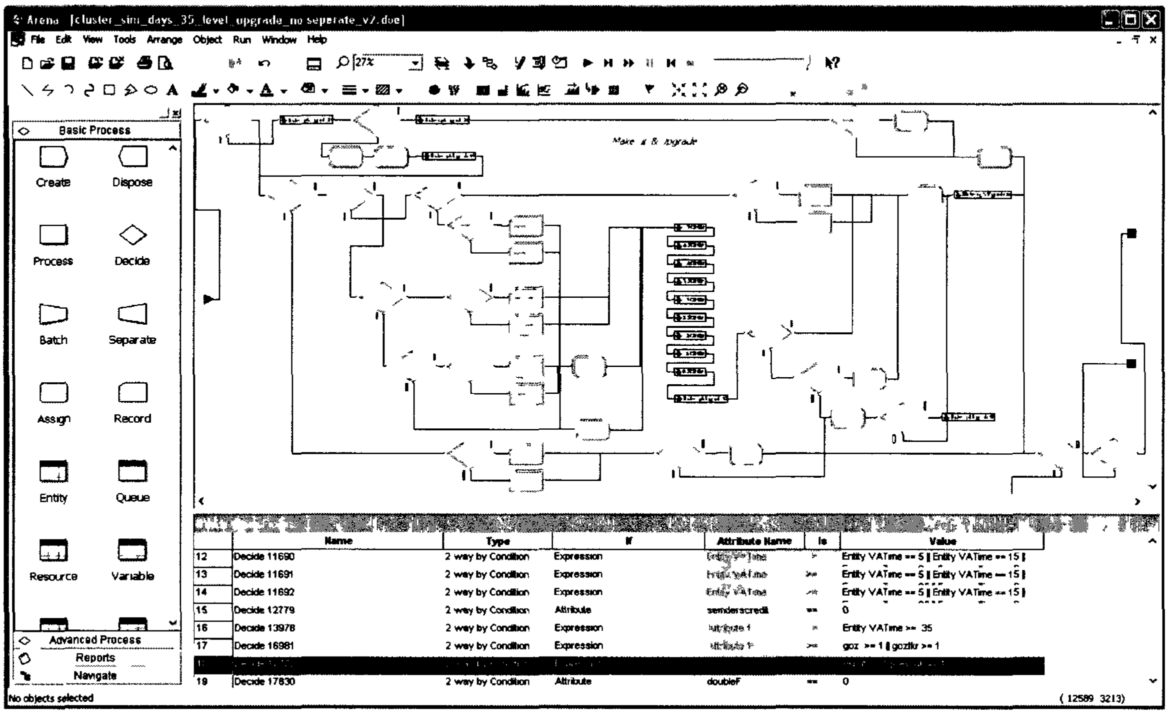


Figure 47. Make-up and upgrade submodel main view

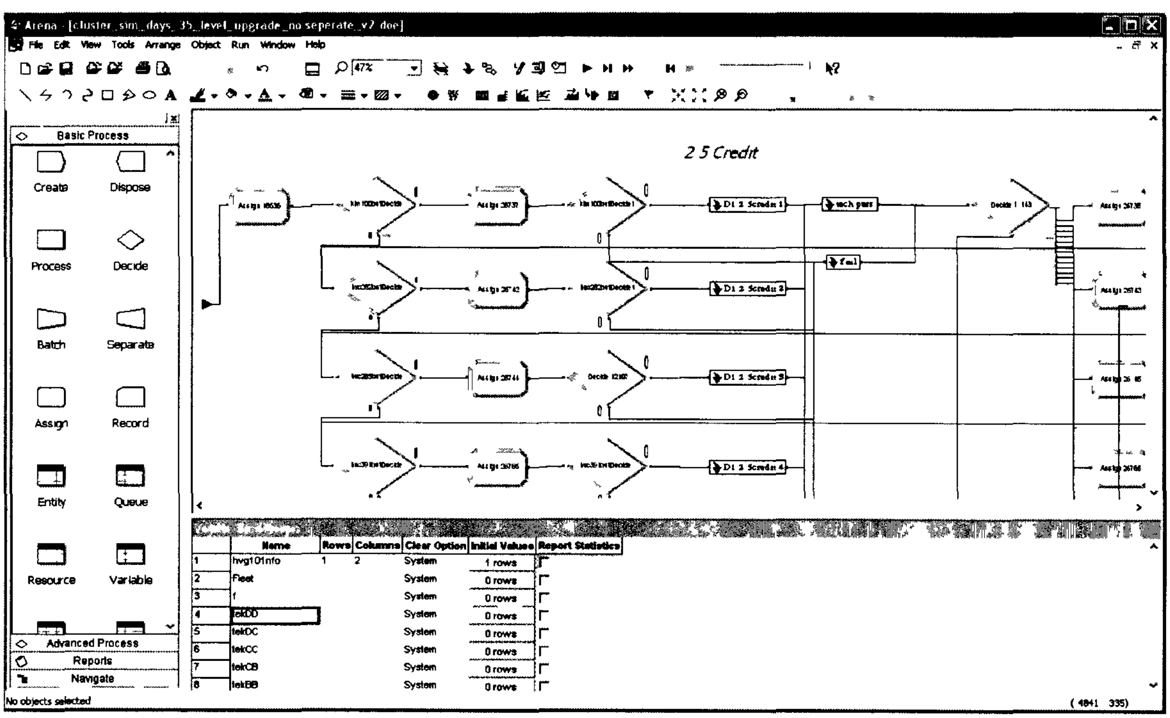


Figure 48. An example of credit group submodels in make-up and upgrade submodel

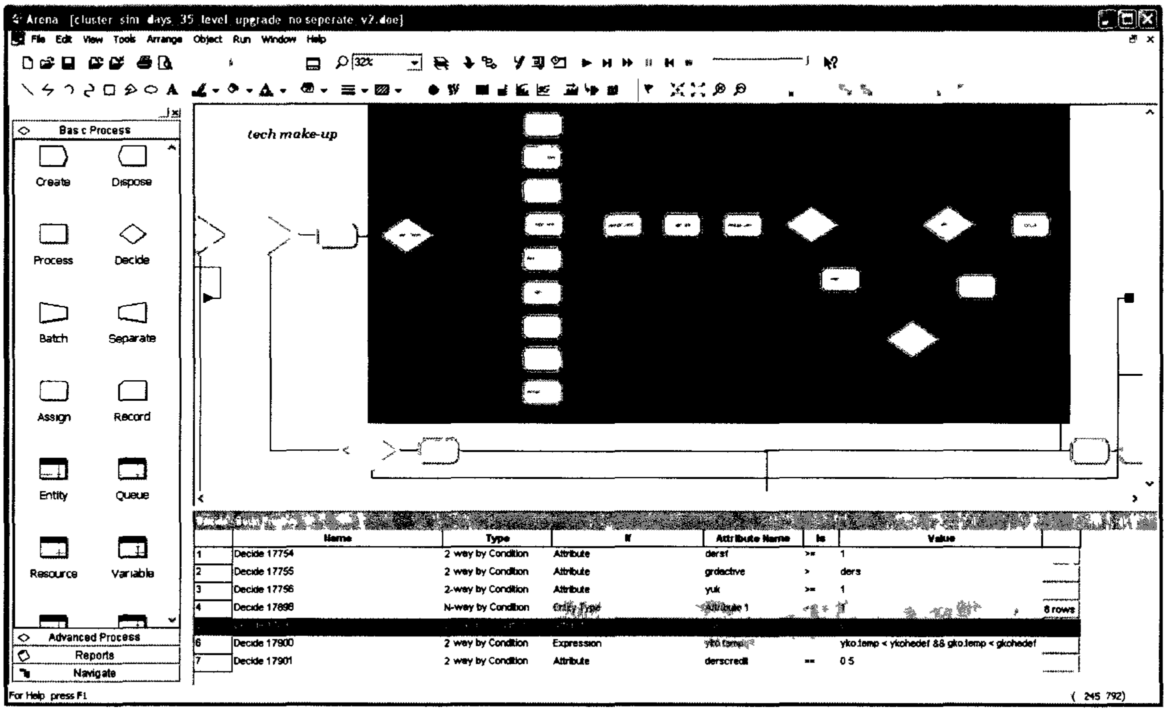


Figure 49. An example of grade and credit assignment submodels in make-up and upgrade submodel

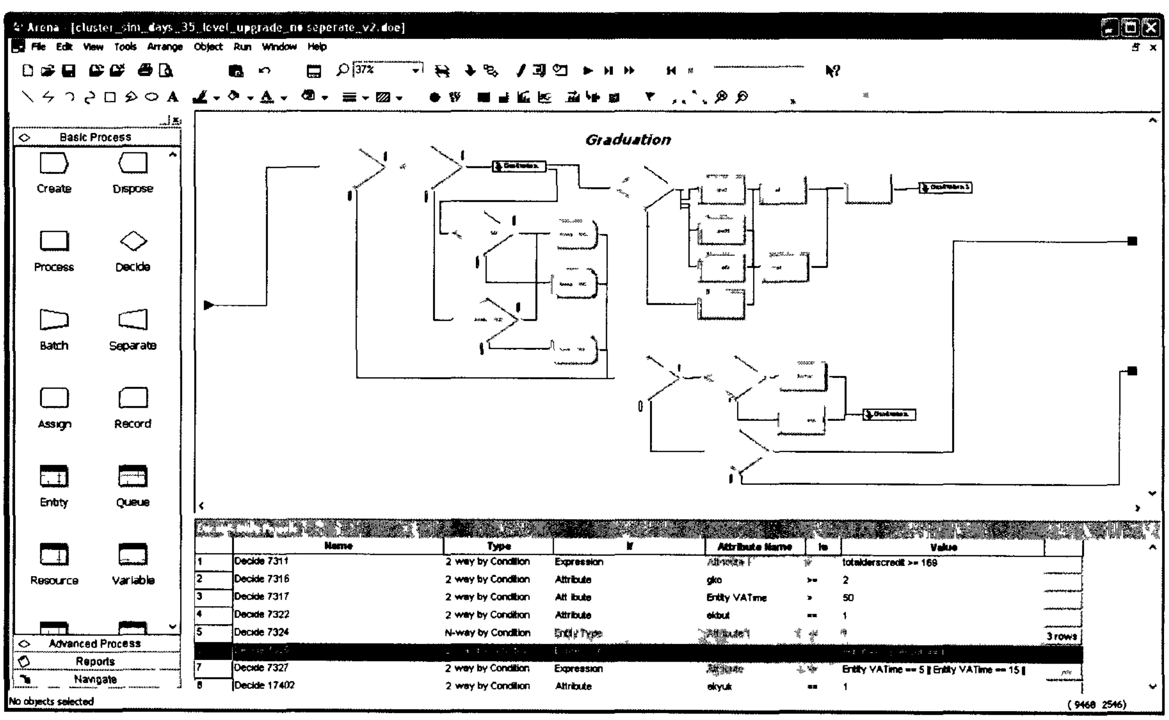


Figure 50. Graduation submodel

Appendix O: Calibration results

Table 98. Calibration results

Course Code	π_0	half with		half with +0.02		Course Code	π_0	half with		half with +0.02	
		up	down	up	down			up	down	up	down
AYZ400A	0.513	0.524	0.472	0.544	0.452	HSA300F	0.020	0.028	0.022	0.048	0.002
AYZ400F	0.000	0.000	0.000	0.020	0.000	HTR400A	0.063	0.099	0.072	0.119	0.052
BGL100A	0.313	0.333	0.290	0.353	0.270	HTR400F	0.000	0.000	0.000	0.020	0.000
BGL100F	0.000	0.000	0.000	0.020	0.000	HUK301A	0.012	0.015	0.012	0.035	0.000
BGL200A	0.292	0.281	0.258	0.301	0.238	HUK301F	0.016	0.021	0.018	0.041	0.000
BGL200F	0.000	0.000	0.000	0.020	0.000	HUK302A	0.043	0.060	0.044	0.080	0.024
BLG100A	0.131	0.152	0.147	0.172	0.127	HUK302F	0.004	0.000	0.000	0.020	0.000
BLG100F	0.029	0.048	0.035	0.068	0.015	HVC282A	0.178	0.220	0.164	0.240	0.144
BLG101A	0.160	0.160	0.138	0.180	0.118	HVC282F	0.190	0.209	0.172	0.229	0.152
BLG101F	0.093	0.134	0.104	0.154	0.084	HVC285A	0.385	0.370	0.344	0.390	0.324
BLG206A	0.232	0.221	0.195	0.241	0.175	HVC285F	0.016	0.021	0.015	0.041	0.000
BLG206F	0.040	0.049	0.036	0.069	0.016	HVC287A	0.118	0.109	0.095	0.129	0.075
EKO201A	0.107	0.112	0.090	0.132	0.070	HVC287F	0.200	0.223	0.217	0.243	0.197
EKO201F	0.123	0.145	0.124	0.165	0.104	HVC381A	0.231	0.226	0.179	0.246	0.159
EKO202A	0.141	0.159	0.154	0.179	0.134	HVC381F	0.031	0.037	0.028	0.057	0.008
EKO202F	0.032	0.027	0.022	0.047	0.002	HVC382A	0.151	0.142	0.124	0.162	0.104
END211A	0.179	0.201	0.175	0.221	0.155	HVC382F	0.069	0.096	0.069	0.116	0.049
END211F	0.004	0.018	0.016	0.038	0.000	HVC391A	0.013	0.011	0.010	0.031	0.000
END251A	0.246	0.295	0.236	0.315	0.216	HVC391F	0.262	0.281	0.255	0.301	0.235
END251F	0.119	0.152	0.121	0.172	0.101	HVG101A	0.431	0.422	0.396	0.442	0.376
END252A	0.257	0.295	0.240	0.315	0.220	HVG101F	0.000	0.000	0.000	0.020	0.000
END252F	0.036	0.068	0.056	0.088	0.036	ING101A	0.228	0.215	0.197	0.235	0.177
END303A	0.074	0.071	0.061	0.091	0.041	ING101F	0.020	0.046	0.039	0.066	0.019
END303F	0.164	0.202	0.175	0.222	0.155	ING102A	0.182	0.197	0.180	0.217	0.160
END304A	0.042	0.073	0.059	0.093	0.039	ING102F	0.084	0.068	0.061	0.088	0.041
END304F	0.178	0.202	0.188	0.222	0.168	ING201A	0.212	0.234	0.223	0.254	0.203
END322A	0.123	0.157	0.137	0.177	0.117	ING201F	0.000	0.015	0.013	0.035	0.000
END322F	0.030	0.057	0.048	0.077	0.028	ING202A	0.408	0.410	0.400	0.430	0.380
END332A	0.525	0.520	0.490	0.540	0.470	ING202F	0.015	0.014	0.008	0.034	0.000
END332F	0.000	0.000	0.000	0.020	0.000	ING301A	0.480	0.502	0.485	0.522	0.465
END341A	0.336	0.340	0.327	0.360	0.307	ING301F	0.024	0.016	0.012	0.036	0.000
END341F	0.012	0.021	0.019	0.041	0.000	ING302A	0.361	0.416	0.381	0.423	0.373
END342A	0.225	0.250	0.216	0.270	0.196	ING302F	0.008	0.014	0.008	0.034	0.000
END342F	0.004	0.024	0.015	0.044	0.000	ING401A	0.396	0.418	0.406	0.438	0.386
END361A	0.066	0.087	0.078	0.107	0.058	ING401F	0.000	0.007	0.005	0.027	0.000
END361F	0.135	0.155	0.147	0.175	0.127	ING402A	0.453	0.452	0.445	0.472	0.425
END382A	0.345	0.329	0.306	0.349	0.286	ING402F	0.000	0.000	0.000	0.020	0.000
END382F	0.017	0.026	0.019	0.046	0.000	ISL402A	0.176	0.182	0.156	0.202	0.136

Table 98. Calibration results **(continued)**

Course Code	π_0	half with		half with +0.02		Course Code	π_0	half with		half with +0.02	
		up	down	up	down			up	down	up	down
END402A	0.346	0.335	0.313	0.355	0.293	ISL402F	0.006	0.006	0.004	0.026	0.000
END402F	0.006	0.019	0.012	0.039	0.000	IST100A	0.072	0.067	0.054	0.087	0.034
END413A	0.889	0.888	0.886	0.908	0.866	IST100F	0.008	0.016	0.011	0.036	0.000
END413F	0.000	0.000	0.000	0.020	0.000	ITA101A	0.007	0.009	0.007	0.029	0.000
END414A	0.704	0.700	0.693	0.720	0.673	ITA101F	0.007	0.035	0.027	0.055	0.007
END414F	0.000	0.000	0.000	0.020	0.000	ITA102A	0.151	0.158	0.118	0.178	0.098
END422A	0.106	0.133	0.113	0.153	0.093	ITA102F	0.040	0.048	0.036	0.068	0.016
END422F	0.083	0.107	0.094	0.127	0.074	KIM100A	0.149	0.171	0.144	0.191	0.124
END423A	0.388	0.410	0.366	0.430	0.346	KIM100F	0.109	0.115	0.098	0.135	0.078
END423F	0.019	0.021	0.016	0.041	0.000	LID402A	0.390	0.372	0.363	0.392	0.343
END424A	0.095	0.105	0.103	0.125	0.083	LID402F	0.000	0.000	0.000	0.020	0.000
END424F	0.016	0.021	0.019	0.041	0.000	LOJ201A	0.236	0.236	0.208	0.256	0.188
END425A	0.538	0.542	0.539	0.562	0.519	LOJ201F	0.000	0.000	0.000	0.020	0.000
END425F	0.000	0.000	0.000	0.020	0.000	MAT101A	0.199	0.244	0.216	0.264	0.196
END429A	0.131	0.126	0.103	0.146	0.083	MAT101F	0.127	0.166	0.145	0.186	0.125
END429F	0.050	0.041	0.029	0.061	0.009	MAT102A	0.123	0.153	0.126	0.173	0.106
END452A	0.588	0.576	0.539	0.596	0.519	MAT102F	0.112	0.126	0.106	0.146	0.086
END452F	0.006	0.019	0.015	0.039	0.000	MAT201A	0.464	0.506	0.452	0.526	0.432
END472A	0.428	0.444	0.346	0.464	0.326	MAT201F	0.020	0.034	0.026	0.054	0.006
END472F	0.012	0.028	0.018	0.048	0.000	MAT202A	0.240	0.241	0.218	0.261	0.198
END492A	0.767	0.775	0.744	0.795	0.724	MAT202F	0.080	0.092	0.082	0.112	0.062
END492F	0.006	0.003	0.002	0.023	0.000	PSK301A	0.443	0.463	0.433	0.483	0.413
FIZ101A	0.058	0.070	0.055	0.090	0.035	PSK301F	0.000	0.001	0.000	0.021	0.000
FIZ101F	0.170	0.207	0.178	0.227	0.158	SYT400A	0.140	0.163	0.103	0.183	0.083
FIZ102A	0.058	0.082	0.077	0.102	0.057	SYT400F	0.009	0.027	0.019	0.047	0.000
FIZ102F	0.086	0.102	0.094	0.122	0.074	THU301A	0.307	0.292	0.259	0.312	0.239
HRK401A	0.325	0.319	0.277	0.339	0.257	THU301F	0.004	0.006	0.004	0.026	0.000
HRK401F	0.000	0.000	0.000	0.020	0.000	TRK100A	0.234	0.266	0.211	0.286	0.191
HRT100A	0.083	0.103	0.088	0.123	0.068	TRK100F	0.030	0.023	0.016	0.043	0.000
HRT100F	0.047	0.075	0.061	0.095	0.041	YON304A	0.206	0.209	0.172	0.229	0.152
HSA300A	0.229	0.222	0.145	0.242	0.125	YON304F	0.084	0.112	0.069	0.132	0.049

Appendix P: Independent sample T-test Results of Departmental Differences

Table 99. Computer Engineering and Industrial Engineering

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Upper	Lower
asGPA	Equal variances assumed	.975	**.326**	-2.559	112	**.012**	-.201	.0788	-.357	-.0455
	Equal variances not assumed			-2.534	101.06	.013	-.201	.079	-.359	-.0437
averageF	Equal variances assumed	.833	**.363**	1.296	112	**.197**	.085	.0654	-.0448	.2143
	Equal variances not assumed			1.282	100.56	.203	.085	.0661	-.0464	.2159

Table 100. Electronics Engineering and Industrial Engineering

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Upper	Lower
asGPA	Equal variances assumed	.108	**.743**	-.063	134	**.950**	-.004	.069	-.1401	.1315
	Equal variances not assumed			-.063	131.83	.950	-.004	.069	-.1402	.1316
averageF	Equal variances assumed	3.321	**.071**	.113	134	**.910**	.0059	.052	-.0969	.1086
	Equal variances not assumed			.111	122.22	.911	.0059	.053	-.0982	.1099

Table 101. Aeronautics Engineering and Industrial Engineering

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Upper	Lower
asGPA	Equal variances assumed	1.742	**.190**	-.212	105	**.832**	-.018	.0849	-.1864	.1503
	Equal variances not assumed			-.206	80.37	.837	-.018	.088	-.1923	.1563
averageF	Equal variances assumed	.041	**.839**	.275	105	**.784**	.017 9	.065	-.1106	.1464
	Equal variances not assumed			.277	91.97	.782	.017 9	.065	-.1102	.1459

Appendix Q: Simulation Results

Table 102. Results, averages and variances of 10 replications for the graduation time

	Design Points							
Replications	**0**	**1**	**2**	**3**	**4**	**12**	**13**	**23**
1	40.6	40.7	40.8	40.8	40.6	40.6	40.5	40.6
2	40.6	40.5	40.5	40.5	40.9	40.9	40.6	40.7
3	40.6	40.4	40.5	40.7	40.6	40.6	40.5	40.8
4	40.5	40.3	40.5	40.7	40.9	40.8	40.6	40.8
5	40.6	40.8	40.8	40.5	40.8	40.8	40.8	40.8
6	40.5	40.7	40.7	40.8	40.9	40.8	40.7	40.7
7	40.5	40.7	40.8	40.6	41	40.7	40.7	40.5
8	40.4	40.5	40.6	40.6	40.5	40.5	40.3	40.6
9	40.5	40.6	40.4	40.5	40.8	40.6	40.4	40.7
10	40.6	40.5	40.7	40.5	40.8	40.6	40.7	40.5
Average	40.54	40.57	40.63	40.62	40.78	40.69	40.58	40.67
Variance	0.005	0.025	0.022	0.015	0.026	0.017	0.024	0.013
	Design Points							
Replications	**14**	**24**	**34**	**123**	**124**	**134**	**234**	**1234**
1	40.6	40.7	40.8	40.8	40.6	40.6	40.6	40.6
2	40.6	40.5	40.5	40.5	40.9	40.9	40.9	40.9
3	40.6	40.4	40.5	40.7	40.6	40.6	40.6	40.6
4	40.6	40.3	40.5	40.7	41	40.8	40.8	40.8
5	40.6	40.8	40.8	40.5	40.8	40.7	40.8	40.8
6	40.4	40.7	40.7	40.5	40.9	40.5	40.9	40.5
7	40.5	40.7	40.8	40.8	41	40.7	41	40.7
8	40.4	40.5	40.6	40.6	40.5	40.5	40.5	40.5
9	40.5	40.6	40.5	40.6	40.8	40.6	40.9	40.6
10	40.8	40.5	40.7	40.5	40.8	40.8	40.9	40.9
Average	40.56	40.57	40.64	40.62	40.79	40.67	40.79	40.69
Variance	0.014	0.025	0.018	0.015	0.030	0.018	0.028	0.023

Table 103. Results, averages and variances of 10 replications for the total number of graduations

Replications	Design Points							
	0	1	2	3	4	12	13	14
1	1920	1880	1920	1890	1920	1910	1920	1890
2	1920	1890	1920	1920	1910	1890	1930	1900
3	1930	1920	1920	1930	1930	1920	1930	1900
4	1940	1920	1940	1910	1870	1890	1930	1890
5	1940	1900	1910	1910	1920	1870	1930	1890
6	1930	1890	1930	1890	1930	1910	1910	1890
7	1920	1900	1920	1870	1900	1900	1900	1910
8	1930	1890	1910	1920	1920	1900	1950	1900
9	1930	1900	1920	1890	1920	1900	1930	1910
10	1900	1900	1920	1900	1890	1870	1920	1910
Average	1926	1899	1921	1903	1911	1896	1925	1899
Variance	137.78	165.56	76.67	334.44	365.56	271.11	183.33	76.67
Replications	Design Points							
	23	24	34	123	124	134	234	1234
1	1920	1880	1920	1890	1920	1910	1920	1910
2	1920	1880	1920	1920	1910	1890	1910	1890
3	1930	1920	1920	1930	1930	1920	1930	1920
4	1940	1920	1940	1910	1900	1890	1930	1890
5	1940	1900	1910	1910	1920	1880	1920	1870
6	1950	1930	1930	1890	1930	1920	1930	1920
7	1920	1900	1910	1870	1900	1900	1900	1900
8	1930	1880	1910	1920	1920	1900	1920	1900
9	1930	1910	1930	1890	1920	1900	1900	1900
10	1920	1900	1920	1900	1890	1870	1900	1890
Average	1930	1902	1921	1903	1914	1898	1916	1899
Variance	111.11	328.89	98.89	334.44	182.22	262.22	160.00	232.22

Table 104. Results, averages and variances of 10 replications for the graduation at seventh semester

Replications	Design Points							
	0	**1**	**2**	**3**	**4**	**12**	**13**	**23**
1	517	496	485	471	518	545	537	524
2	500	541	502	532	474	470	536	493
3	510	514	529	499	505	533	556	481
4	556	565	559	503	505	473	535	482
5	478	489	478	566	474	474	473	465
6	545	480	503	516	498	504	514	523
7	541	486	462	464	444	485	501	530
8	560	509	498	499	552	558	583	517
9	536	500	545	511	508	531	559	524
10	503	510	524	533	494	530	497	559
Average	524.6	509	508.5	509.4	497.2	510.3	529.1	509.8
Variance	729.82	689.56	930.06	901.16	843.51	1091.6	1095.9	816.62
Replications	**Design Points**							
	14	**24**	**34**	**123**	**124**	**134**	**234**	**1234**
1	517	496	485	471	518	545	518	545
2	500	541	502	532	474	470	474	470
3	510	514	529	499	505	533	505	533
4	543	565	559	503	442	473	530	473
5	478	489	478	566	474	487	474	474
6	561	496	503	516	498	548	498	549
7	541	486	482	464	411	492	444	492
8	560	526	498	499	552	558	552	558
9	536	516	545	511	508	531	462	531
10	479	510	524	533	494	509	487	503
Average	522.5	513.9	510.5	509.4	487.6	514.6	494.4	512.8
Variance	933.17	616.77	763.39	901.16	1584.0	1061.6	1082.7	1175.5

Table 105. Results, averages and variances of 10 replications for the discharges due to probation rules

Replications	Design Points							
	0	**1**	**2**	**3**	**4**	**12**	**13**	**23**
1	38	66	45	54	29	44	20	57
2	24	62	26	38	35	64	25	52
3	25	39	30	29	20	47	26	52
4	17	41	25	58	34	56	35	49
5	30	61	23	54	20	69	21	61
6	19	71	37	66	23	36	41	51
7	40	52	41	65	33	53	31	38
8	29	61	42	46	32	40	14	45
9	28	50	30	56	37	50	32	48
10	33	58	30	55	41	75	30	39
Average	28.3	56.1	32.9	52.1	30.4	53.4	27.5	49.2
Variance	55.57	108.99	60.54	132.77	52.49	161.38	62.94	51.96
Replications	**Design Points**							
	14	**24**	**34**	**123**	**124**	**134**	**234**	**1234**
1	38	66	45	54	29	44	29	45
2	24	62	26	38	35	64	35	65
3	25	39	30	29	20	47	20	48
4	16	41	25	58	40	56	27	59
5	30	61	23	54	20	70	27	70
6	16	39	37	66	23	39	23	37
7	40	52	30	65	33	49	33	50
8	29	66	42	46	32	40	32	42
9	28	53	32	56	27	50	36	52
10	30	58	30	55	41	68	37	51
Average	27.6	53.7	32	52.1	30	52.7	29.9	51.9
Variance	62.71	115.57	52.44	132.77	57.56	127.79	32.32	104.10

Table 106. Results, averages and variances of 10 replications for the discharge time due to probation rules

	Design Points							
Replications	**0**	**1**	**2**	**3**	**4**	**12**	**13**	**23**
1	25.8	20.2	26.6	21.5	29.2	23	26.5	23.9
2	26.7	22.3	26.2	20	22.5	22.2	23.8	23.4
3	24.4	22.6	24.5	23.7	29	22.8	26.3	21.5
4	27.9	23.5	28.4	22.9	24.6	19.7	26	20.4
5	25.7	24	27.6	23.9	22.1	22.4	27.1	22.6
6	24.5	23.4	25.7	22.5	25.8	22.7	25.7	23.5
7	27.6	23.2	27.1	23.8	22.3	24.6	26.1	24.1
8	27.4	21.7	26.3	22.4	28.5	21.7	27.9	21.7
9	25.7	22.8	27.3	23.9	26.4	22.7	26.9	22.4
10	25.2	21.9	28.7	23.8	28.1	22.6	24.5	24.8
Average	26.09	22.56	26.84	22.84	25.85	22.44	26.08	22.83
Variance	1.579	1.216	1.587	1.667	8.109	1.487	1.455	1.845
	Design Points							
Replications	**14**	**24**	**34**	**123**	**124**	**134**	**234**	**1234**
1	25.8	20.2	26.6	21.5	29.2	23	29.2	23
2	26.7	22.2	26.2	20	22.5	22.2	22.5	22.2
3	24.4	22.6	24.5	23.7	29	22.8	29	22.8
4	22.2	23.5	28.4	22.9	22.4	19.7	26.4	19.7
5	25.7	24	27.6	23.9	22.1	22.3	22	22.4
6	25.3	21.6	25.7	22.5	25.8	22	25.8	21.9
7	27.6	23.2	25.8	23.8	23.6	22.5	22.3	22.5
8	27.4	20.9	26.3	22.4	28.5	21.7	28.5	21.7
9	25.7	23.3	26.6	23.9	26.4	22.7	25.9	22.7
10	25	21.9	28.7	23.8	28.1	22.7	26.8	22
Average	25.58	22.34	26.64	22.84	25.76	22.16	25.84	22.09
Variance	2.440	1.472	1.638	1.667	8.412	0.903	7.558	0.877

Table 107. Results, averages and variances of 10 replications for the discharge time due to time constraint

	Design Points							
Replications	**0**	**1**	**2**	**3**	**4**	**12**	**13**	**23**
1	8	10	5	13	10	13	18	14
2	13	8	5	7	11	20	11	14
3	7	3	6	4	7	8	10	10
4	5	5	7	7	25	16	7	9
5	8	4	13	5	14	7	13	14
6	7	8	5	13	14	18	11	14
7	5	8	8	8	22	11	19	10
8	4	7	13	8	10	9	12	5
9	6	7	8	9	8	15	10	9
10	4	10	9	7	11	12	8	12
Average	6.7	8.5	7.9	8.1	13.2	12.9	11.9	11.1
Variance	7.122	3.000	9.211	8.767	34.844	18.767	15.211	9.211

	Design Points							
Replications	**14**	**24**	**34**	**123**	**124**	**134**	**234**	**1234**
1	10	10	5	13	10	13	10	13
2	13	12	5	7	11	20	11	20
3	7	3	6	4	7	8	7	8
4	8	5	7	7	9	16	5	16
5	9	4	13	5	14	8	14	7
6	7	3	5	13	14	8	14	12
7	5	8	13	8	18	17	22	17
8	4	8	13	8	10	9	10	9
9	7	9	11	9	8	15	16	15
10	7	10	9	7	11	14	7	12
Average	7.7	7.2	8.7	8.1	11.2	12.8	11.6	12.9
Variance	6.456	10.400	12.456	8.767	10.844	18.844	25.600	17.433

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Volkan Cakir, Adrian Gheorghe, “Undergraduate Education Performance Analysis Using Clustering With EM Algorithm” International Educational Technology Conference, Bogazici University, Istanbul, Turkey, 2010