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Analyzing the Fundamental Aspects and Developing a Forecasting Model to Enhance the Student Admission and Enrollment System of MSOM Program

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Analyzing the Fundamental Aspects and Developing a Forecasting Model to Enhance the Student Admission and Enrollment System of MSOM Program

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by

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Abstract

A forecasting model, associated with predictive analysis, is an elementary requirement for academic leaders to plan course requirements. The M.S. in Operations Management (MSOM) program at the University of Arkansas desires to understand future student enrollment more accurately. The available literature shows that there is an absence of forecasting models based on quantitative, qualitative and predictive analysis. This study develops a combined forecasting model focusing on three admission stages. The research uses simple regression, Delphi analysis, Analysis of Variance (ANOVA), and classification tree system to develop the models. It predicts that 272, 173, and 136 new students will apply, matriculate and enroll in the MSOM program during Fall 2017, respectively. In addition, the predictive analysis reveals that 45% of applicants do not enroll in the program. The tuition fee of the program is negatively associated with the student enrollment and significantly influences individuals' decision. Moreover, the students' enrollment in the program is distributed over 6 semesters after matriculation. The classification tree classifies that 61% of applicants with non-military status will join the program. Based on the outcomes, this study proposes a set of recommendations to improve the admission process.

Acknowledgements

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I. INTRODUCTION

The colleges and universities in the United States of America are experiencing an increase in the number of graduate level students every year. A survey by the National Center for Education Statistics (“Fast Facts,” 2017) reveals that the institutions are expecting to award 3.73% more graduate-level degrees during the 2017-18 academic year when compared to the previous academic year. The University of Arkansas follows this trend. The University enrolled 4,275 graduate students in all departments during Fall 2016, a 1.3% increase from the previous year. The University of Arkansas’ academic council is committed to recruiting more graduate students for its 86 master’s degree and 50 doctoral programs to maintain the University’s research mission as a Carnegie Research I institution. (“U of A Enrollment,” 2016).

The Master of Science in Operations Management (MSOM) program at the University of Arkansas has been committed to the University mission of providing quality graduate education since 1974. The program has the largest number of graduate students and provides education through online, live or hybrid modalities. However, the MSOM program faces many challenges. The MSOM program does not receive the state’s funding for higher education. In general, the state’s funding for higher education in the United States has been decreasing for the last 20 years. The recent economic recession further worsened the funding trend. The rising cost of research components, software-licensing fees, healthcare, journal subscriptions and other utilities are posing an immense threat to the budget for education. It is a critical task for the program to distribute the available resources efficiently since there is no new funding available from the state (“Campus Planning Update,” 2016).

The resource allocation largely depends on the estimation of student enrollments in the program. The forecasting system is an essential predictive tool for the department in such a complex environment. As defined, it is a planning instrument for the leaders to cope with future uncertainties based on the analysis of the past and present data trends. The quantitative forecasting is based on numerical analysis that attempts to associate two or more variables, and time series analysis that uses past information to make a prediction. The qualitative analysis depends on experienced employees' knowledge and judgment to provide valuable insights about the future admissions. A combination of quantitative and qualitative forecasting can help the MSOM department effectively predict future student registrations and assist in the revenue and expenditure budget, course offerings, human resources planning and supportive resource allocation. However, the forecast accuracy is interrelated with the availability of precise data, admission process, off-campus facilities, courses offered online and other factors.

This thesis strives to answer the question: can we predict next year's MSOM student enrollment more accurately? This research obtained the appropriate data from a complex records system and analyzed the application, matriculation and enrollment information of the MSOM program. The study focused on identifying existing data patterns and developing a quantitative forecasting model based on the analysis. The process included a qualitative exploration to improve the forecasting accuracy. Additionally, the study performed quantitative predictive analysis on the available information to pinpoint the fundamental aspects associated with the enrollment decision. The research combined the findings with forecasting outcomes and recommended future strategic efforts.

This paper is as follows: in Section 2, the paper reviews the literature on predicting the total new student enrollments using forecasting models. In Section 3, the paper clearly outlines the specific objectives of the research. Section 4 covers the research methodology. Section 5 defines the system components, develops the models and computes the accuracy to validate the research. Section 6 covers the predictive analysis of the data sets. Finally, Section 7 discusses future research opportunities.

II. LITERATURE REVIEW

This research focused on two broad intentions. The first aim was to develop an appropriate forecasting model to estimate the future new student admissions to the MSOM program. Secondly, the study used predictive analytics to model an individual's actions and improve forecasting performance by combining the outcomes. The literature review focuses on both features of the study.

Boes and Pflaumer (2006) used Autoregressive Integrated Moving Average (ARIMA) methods to analyze the structural ratios and develop a forecasting model to estimate university student enrollments in Germany. The study analyzed the structural ratios by relating the number of university students to the population of the same age. The aim of this study was to improve the existing transition model, which does not consider the prediction intervals and lacks the forecast uncertainty measure. The research predicted that the total student enrollment at the university level in Germany would reach 2.35 million students by 2015. However, the forecast interval ranged between 1.72 and 2.98 million at a 95% confidence interval in 2015, a very wide margin. This analysis process considered only population as a factor in describing the structural ratios.

Ward (2007) proposed a forecasting model using a "3-year average" method to estimate new student application, admission, and enrollment information. This model was designed to predict the total number of applications required to achieve the targeted student matriculation figures and improve the enrollment rates. Furthermore, their forecasting model developed a system to distribute the new students basing on their entrance exam scores and grade point averages, and assist the financial aid administrators. This model used 5 years' worth of data to predict future new student registrations. However, the 3-year average method failed to reflect the trend and seasonal impacts in the forecasting model. The 3-year moving average method is not suitable for a sophisticated data pattern and the process is vulnerable to any fluctuation in the time series (Stevenson, 2012). In addition, the model used only yield rate method to justify the performance of the forecast model.

Zan et al. (2013) proposed multiple forecast models to predict the future student enrollments at the State University of New York at Binghamton. Their study analyzed the historical student enrollment information at three different levels – university, school, and division. The analysis compared the performance of different forecasting models and revealed that the 1-year average method produced the lowest Mean Absolute Percentage Error (MAPE) of 40% for the Spring semester using the school level data set. On the other hand, average return ratio method provided the forecasting error of 81% for Fall semester using the university-level data set. It is not feasible to use two different forecasting models for two semesters using two diverse data sets. Also, these models need more rationalization from other accuracy perspectives rather than depending on only forecasting error. In addition, these proposed models do not justify an individual student's motivation to join the institution.

Callahan (2011) mentioned in his white paper that Institutional Planning, Assessment, and Research (IPAR) division developed an enrollment projection model for Winona State University in Minnesota. The data set included the current class-to-class level new student enrollment information, retention rate, advancement rate and non-advancement rate. Also, it used Fall to Spring and Spring to Fall class information and estimated the Summer enrollments directly from the past terms. Finally, a 3-year moving average method projected the new student enrollment in the university for the upcoming semester. The moving average forecasting method has significant drawbacks when trend and seasonality are present in the data set. In addition, it did not consider the environmental factors, such as tuition fees and unemployment rate that influence the student's enrollment decisions. However, the paper did not specify the accuracy of the forecasting model.

Lavilles and Arcilla (2012) developed a student enrollment-forecasting model for the Mindanao State University in the Philippines as a part of the electronic School Management System (e-SMS). The new model aimed to replace the naïve forecasting model previously used by the university. The study developed forecasting models using three different methods – simple moving average, single and double exponential smoothing approaches over a period of 5 years. The results revealed that the simple moving average is not suitable for their data pattern. The single exponential smoothing method, with an alpha of 0.9, exhibited low MAPE. The outcome showed that 80% of the subjects considered the latest observation as a major factor in estimating the number of enrollments. The remaining 20% emphasized on the old records. This model projected 20.5% better accuracy than the existing naïve forecasting model. The double exponential smoothing method, with an alpha of 0.9 and beta of 0.1, displayed MAPE of 16.4%. Furthermore, the researchers used 182 subjects to generate the least error model based on the available data. About 58% subjects resulted in lowest MAPE using double exponential smoothing and remaining 42% subjects used single exponential smoothing. However, the study did not optimize the alpha value using Mean Squared Error (MSE). Also, the study could have used tracking signals and control charts to check the accuracy of the forecasting model.

Trusheim and Rylee (2011) developed a predictive forecasting model to link the enrollment and budgeting process of the University of Delaware. The objective of this study was to develop an enrollment projection model and a tuition model and establish a relationship between them for a better planning strategy. This study accommodated the freshmen, transfer, readmit and continuing student information through the 1999-07 academic years to predict the enrollment for 2008-09. The model further classified the data set into full-time and part-time categories and calculated the 5-year semester-to-semester retention rate. Furthermore, the study collected the estimated student enrollment information from the provost and enrollment management committee and verified the numbers with the admission office. Finally, the estimated value was multiplied by the 5-year retention rate to obtain the enrollment forecast for the 2008-09 academic years. The accuracy check revealed that the model predicted within 1% of the actual enrollment. However, the model did not consider other enrollment criteria or drop rates during the semester. Also, the simple moving average method struggles to reflect the actual retention rate in presence of the trend and seasonality. In addition, there is a major drawback in justifying the performance of the proposed model.

Chen (2008) developed a quantitative forecasting model to predict student enrollment at Oklahoma State University. This integrated forecast model analyzed the student enrollment information over 42 years, during the period Fall 1962 - Fall 2004, and checked the explanatory power with 15 independent variables. In the first phase, the ARIMA (1,1,0) revealed that the number of Oklahoma high school graduates significantly contributes to the Oklahoma State University enrollment. The accuracy of this model was 97.89% and coefficient of determination, R^2, was 0.96. In the second phase, the linear regression model discovered that one year lagged enrollment and Oklahoma high graduates are highly correlated with the university enrollment.

The MAPE of this model was 1.62% and R^2 was 0.97. Also, this study found that the linear regression model outperformed the ARIMA model at three turning points. There is an opportunity to improve the performance of this model by combining it with a qualitative forecasting model. In addition, a control chart can help the university leaders to track the validity of the forecasting model in future.

Rehman and Larik (2015) compared three forecasting models to develop a concrete decision making policy for COMSATS Institute of Information Technology in the Pakistan. The models are a simple linear regression model, a linear trend model, and Holt's linear trend model. The study used 12 years of new student admission information to develop the forecasting models. The study discovered that the simple linear regression model provided better accuracy as measured by the variance of the predicted values from the actual values. But this study did not analyze the historical data pattern and justify the selection of the forecasting models. Also, this study did not clarify the optimization process of the coefficient factors. The simple linear regression model was accepted based on a single accuracy standpoint, which may not be correct considering other accuracy testing methods.

Bowe and Merritt (2013) used SAS® BI platform to develop the short and long-term student enrollment-forecasting model for Kennesaw State University in the Georgia. This study selected a ratio-based forecasting model for short-term purpose and used SAS® Enterprise Guide® to construct the model. The researchers determined that a stable business environment surrounds Kennesaw State University and the ratio-based forecasting model is highly reliable for such a scenario. The analysis calculated the average census-to-registration ratio based on the Fall enrollment data set during 2003-10 and used it for estimating future enrollments. Similarly, the researchers selected a mixed ARIMA model to predict the long-term student enrollment in the university and used SAS® Forecast Studio® to develop the model. However, the study used limited independent variables to develop the ARIMA model. In addition, it did not measure the accuracy levels to justify the performance of the forecasting models. The Kennesaw State University can take the advantage of the SAS software to predict the individual's decision to join the institution.

Robson and Matthews (2011) compared two forecasting models to more accurately predict student enrollments at Utah Valley University. The ARIMA model used 22 years of student enrollment data set and the results both displayed an R^2 value of 0.99. The linear regression results revealed that unemployment rate and number of Utah high school graduates had a significant impact on the university's enrollment. This model showed acceptable accuracy results through the Ljung-Box chi-square and MSE tests. On the other side, the mixed model used 12 years of enrollment data set and divided the students into 6 distinct registration categories. The outcomes revealed that the retention of existing students significantly influenced the enrollment growth. Also, the model indicated that the enrollment from high school might gradually decrease due to supply limitations and demand permeation. The study had the opportunity to combine the quantitative outcomes with qualitative features and improve the overall forecasting performance. Furthermore, the study did not perform the predictive analysis to understand student's motivation to join this particular institution.

Aadland, Godby, and Weichman (2007) classified the student enrollment information into four categories to develop the forecasting models for the University of Wyoming. Firstly, the researchers developed a linear regression model over the time 1957-2005 to predict undergraduate enrollment from the permanent residents of Wyoming. The model revealed that all the 5 variables, such as tuition fees, energy prices, 8^{th} – 12^{th} grade enrollment in Wyoming's education system, Wyoming's community college enrollment, and University of Wyoming athletic success, have an affect on the enrollment. The model came with a R^2 measure of 92.5%. Secondly, the researchers used a semi-log regression model to predict the undergraduate enrollment from regional states. The result showed that their out of state tuition fee policy led to 129 fewer less regional undergraduate student enrollments. On the other hand, an increase in neighboring state Colorado's college admissions was a predictor of enrollment growth for the University of Wyoming. The model presented an R^2 measure of 94.2%. Thirdly, this study used a linear regression model to explain the university's graduate enrollment. The result showed a strong relationship between economic conditions in the United States and graduate enrollment. The resulting R^2 was 91.9%. Finally, this research used a simple linear trend regression model to explain the undergraduate enrollment in the university from "all other" states. The analysis showed that predicted enrollment tracked actual enrollment properly over the short period. The resulted R^2 was 97.4% due to the linear trend. This study checked the accuracy of the models using the out-of-sample method and the results were within -0.5% and -1.5% margin of error. However, it is challenging to maintain three different forecasting models to predict future student enrollments in the university.

Davidson (2005) analyzed 10 independent variables, such as campus visit, high school program, online application, direct correspondence, entrance exam scores etc., using a logistic regression model to predict the level of influence each variable had on individual student's perspective to join Hardin-Simmons University in the Texas. The model considered both matriculated and non-matriculated student information over a period of 5 years, 1999-2003. The study revealed that housing status, the area of study, test scores, school ranking, ethnicity, religious denomination, and region of the state highly influenced student enrollment in the university. The index for the student's projected possibility for entering the university is 92.70%. This study aimed to accurately forecast a student's prospects for enrolling in the university but a standard quantitative and qualitative forecasting model did not support the model. In addition, the study failed to address the impact of the tuition fee on individual's decision-making process.

Ledesma (2009) focused on a Wisconsin-based private liberal arts college and developed a predictive forecasting model to calculate future student enrollments. It is notable that a private liberal arts college has a different organizational mission compared to a public university; the private college here had a religious affiliation and higher tuition rates. This research developed a logistic regression model that considered student enrollment as the target variable and student personal and demographic characteristics including academic performance, marketing and promotion related variables indicating applicant's first interaction with the college, and applicant's college preference and involvement with university sports as the predictor variables. The model used Fall 2001 admission data set to estimate the coefficients and validated the forecasting accuracy using Fall 2002 admission data set. The result indicated that the student's high school GPA is inversely correlated with the enrollment decision. The academically strong applicants had more options to decide on where to attend college and they mostly favor colleges other than this one. The out of sample prediction accuracy was 64%. However, the model's sensitivity was 21% and specificity was 43%. The model used a small 2-year sample size and divided the primary data into the developmental and validation sample sets. The data set is too small to reflect any seasonal, stationary or trend patterns and diminishes the forecasting accuracy.

Maltz, Murphy, and Hand (2007) emphasized incorporating the financial aid policy in predicting new student enrollment for Willamette University College of Liberal Arts in the

Oregon. This study implemented a two-phase project for the institution to develop a predictive model and a user-friendly interface. As a part of the project, this study thoroughly analyzed the existing process of estimating enrollment and tuition fee discount rate to identify the flaws in the system. Initially, the new predictive system used a decision tree model that provided an accuracy of 70.30%. But the decision tree model generated only the discrete breakpoints to explain the impact of financial aid on individual's decision to enroll, rather than the impact of small adjustments to financial aid plans. Finally, the system used logistic regression model, which revealed that 70% of the admitted students declined to enroll. The analysis discovered that students from Oregon had a 55% likelihood of enrollment, which increased to 75% with a promise of more than $10,000 in financial aid. Also, non-Oregon residents who visited the campus had a 55% chance of enrolling after admission. This study solely focused on the predictive analysis in developing the forecasting model and did not use the qualitative methods. Also, the correctness of the model was based on the error matrix only.

The last set of reviewed studies, Zeng, Yuan, Li, and Zou (2014), used the decision tree model to forecast the popularity of Chinese colleges and to help potential Chinese students to select the most promising college. The researchers mined popularity change ratio information from an 8-year data set gathered from 6 provinces of China. Then they used the gain ratio based algorithm to construct the decision tree model. The study set the parameter value at 10 to achieve an accurate forecasting result. The decision tree revealed that the science colleges outnumbered the arts colleges. The confusion matrix revealed that the accuracy of the model is 65.42%. In addition, the area under ROC curve showed 0.685 relativeness between false positive rate and true positive rate. This study reflected only the applications received by the individual colleges and did not consider other important factors in constructing the decision tree model. Also, the data set was limited to the science and arts colleges.

Table 1 shows the summary of the literature review:

Table 1. Summary of literature review

Sl No.	Aspects Bibliography	Quantitative Model	Qualitative Model	Accuracy Measure	Predictive Model	Factors	Observations
1	Boes and Pflaumer (2006)	ARIMA	No	Measure of uncertainty	No	Number of university students to the population of the same age.	High uncertainty level, only population factor, large area of concentration
2	Ward (2007)	3-year average	No	Yield rate	No	Application, matriculation and enrollment	Trend and seasonal impacts are not reflected, no standard accuracy measurement
3	Zan et al. (2013)	1-year average, average return ratio	No	Error matrix	No	University, school and division	2 different models for 2 different semesters using 2 different data set, poor accuracy level
4	Callahan (2011)	3-year average	No	No	No	Class-to-class level new student enrollment information, retention rate, advancement rate and non-advancement rate	No accuracy measurement, did not consider the changes over summer semester
5	Lavilles and Arcilla (2012)	Simple moving average, single and double exponential smoothing	No	MAPE	No	Enrollment	Did not calculate MAD and MSE, the alpha value is not optimized
6	Trusheim and Rylee (2011)	5-year moving average	Yes	Forecast error	No	Freshmen, transfer, readmit and continuing student information	Did not consider other enrollment criteria and drop rates, trend and seasonal impacts are not reflected, major drawback in conducting the accuracy test
7	Chen (2008)	ARIMA (1,1,0), linear regression model	No	MAPE, RMSE, MAE	No	15 independent variables - demographics (Oklahoma high school graduates and competitor OU enrollment), state tax fund, appropriations for Oklahoma higher education, and economic climate indicators (Oklahoma unemployment rate, Oklahoma per capita income, the United States GNP, and the United States Consumer Price Index	Did not combine with qualitative model, control chart can check the validity of the model in future
8	Rehman and Larik (2015)	Simple linear regression model, linear trend model, and Holt's linear trend model.	No	MAPE	No	Admission	Did not analyze the data pattern, didn't justify model selection process, accuracy is based on only one method
9	Bowe and Merritt (2013)	Ratio-based forecasting model, mixed ARIMA model	No	No	No	Registration, census	Did not check the accuracy of the models, didn't justify individual's decision to join the university
10	Robson and Matthews (2011)	ARIMA model, mixed forecasting model	No	Ljung-Box chi-square, MSE tests	No	Enrollment	Did not combine with qualitative model and predictive analysis
11	Aadland, Godby and Weichman (2007)	Linear regression model, semi-log regression model, simple linear trend regression model	No	Out-of-sample	No	State resident, regional, all other state and graduate enrollment	It is challenging to maintain three different forecasting model
12	Davidson (2005)	No	No	Index	Logistic regression model	Housing status, area of study, test score, school ranking, ethnicity, denominational preference, start term, gender, origin of application and region of the state	Not supported by quantitative and qualitative forecasting model, didn't consider tuition fees
13	Ledesma (2009)	No	No	Sensitivity and specificity	Logistic regression model	Personal and demographic characteristics, marketing and promotion related variables and applicant's college preference and concern in university sports	Low accuracy rate, small data size
14	Maltz, Murphy and Hand (2007)	No	No	Error matrix	Decision tree model, Logistic regression model	Financial aid, geography	Did not associate qualitative input, accuracy is based on only one method.
15	Zeng, Yuan, Li and Zou (2014)	No	No	Error matrix	Decision tree model, Logistic regression model	Application based on popularity	Only considered science and arts colleges, didn't consider other factors in constructing the decision tree mode

III. RESEARCH OBJECTIVE

The Industrial Engineering Department in the School of Engineering at the University of Arkansas offers the MSOM program. The department offers the live program to students through four program sites. They are the Northwest Arkansas campus at Fayetteville, AR, Northwest Florida campus at Hurlburt Field, FL, Central Arkansas campus at Air Force Base, Little Rock, AR, and Greater Memphis campus at Naval Activity, Mid-South Millington, TN. The facility locations are presented in Figure 1:

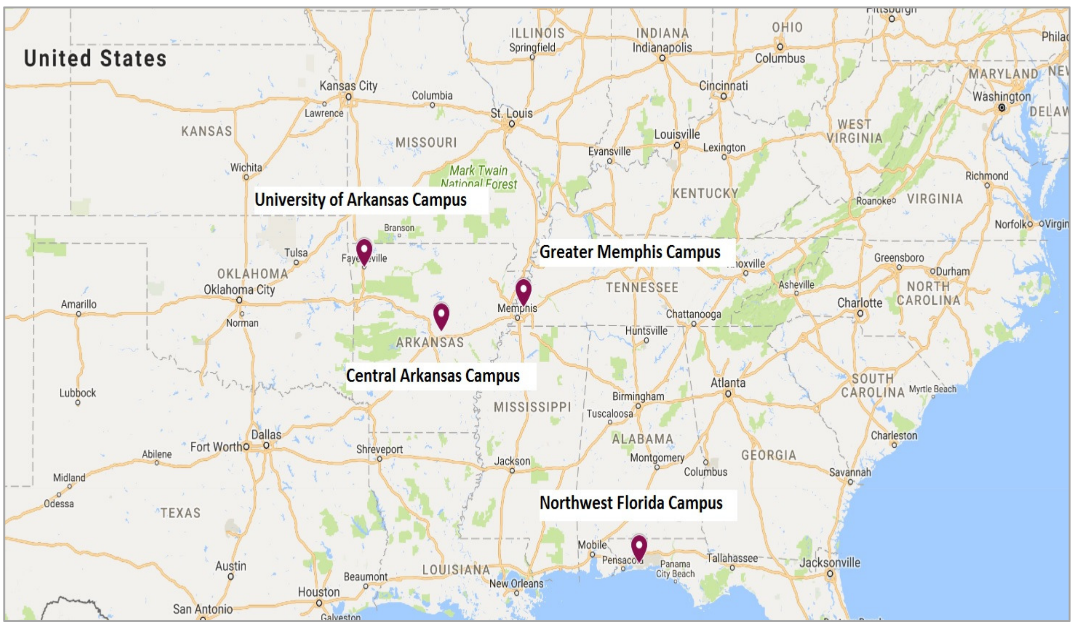


Figure 1. MSOM program facility locations

In addition, the program offers online courses for students, allowing them to complete the degree remotely. The new student registration process goes through three principal stages. They are the application, matriculation and enrollment stages. To date, the department has no standard forecasting mechanism to predict new student admission and enrollment for every semester. As an alternative, the department uses a qualitative approach to forecast the number of new students. Considering the facts, the research aims to analyze the application and enrollment process to develop a forecasting model for the MSOM program. The research covers the following specific objectives:

1. To develop a quantitative forecasting model for application, matriculation and enrollment numbers.

2. To develop a qualitative forecasting model for application, matriculation and enrollment numbers, and compare the results with the quantitative model.

3. To check the accuracy of the forecasting model.

4. To perform predictive analysis to determine the individual’s likelihood of attending the program.

5. To identify the leading factors for these three areas and their relationship with the increase of the new student enrollment.

IV. METHODOLOGY

A quality data set is the base point to maintain research integrity. The researchers must systematically collect the data from consistent sources, formulate hypotheses that address the research questions, and evaluate the results. However, it is a challenging task to filter the necessary information from a large data set and ensure the data accuracy. Specifically, information from secondary sources requires extensive investigation to avoid misleading figures and maintain the quality of the research (“Responsible Conduct in Data Management,” 2005). This study received a large set of student admission and enrollment information and performed wide-ranging analysis to gather new student application, matriculation and enrollment data for each semester. The analysis process focused on the newly applied, matriculated and enrolled students and excluded the students who are not in the MSOM program. Furthermore, this study accommodated relevant information in the data set to assess an individual student's decision to join the MSOM program.

According to Stevenson (2012), there are two common approaches to forecasting – the qualitative approach and the quantitative approach. Qualitative methods consist of subjective inputs, which often defy specific numerical models. On the other hand, quantitative forecasting techniques are more intensively objective than their qualitative counterparts. Quantitative methods use historical data to make a forecast. They usually avoid individual biases that sometimes infect qualitative methods. The data pattern is also a significant factor in understanding how the time series behaved in the past. If such behavior continues in the future, the past pattern works as a guide in selecting a suitable forecasting method. Furthermore, the quantitative approach can be combined with the qualitative method to improve the overall forecasting performance. The management's opinion and judgment about the critical political and economic factors can significantly advance the forecasting performance better than a quantitative model alone, which may lag behind real world data. Based on the data analysis outcomes, this study selected an exponential smoothing method to develop the quantitative forecasting model and the Delphi method to construct the qualitative forecasting model. This study then combined the outcomes of both models to predict the new student application, matriculation and enrollment more precisely. In addition, the ARIMA model was used to verify the relationship between the variables and the three data sets.

Accuracy and control of the forecast is a vital aspect of developing the forecast model. It is essential to include an indication of the extent to which the forecast may deviate from the value of the variable that actually occurs. Stevenson also mentioned that it is vital to monitor forecast errors, during periodic forecasts, to determine if the errors are within reasonable bounds. If they are not, it is necessary to take corrective action. Stevenson prescribes Mean Absolute Deviation (MAD), MSE and MAPE to calculate the accuracy of the forecast. However, Delurgio (1999) emphasizes introducing a tracking signal and developing a control chart to further measure the forecast accuracy. This study took a unique step to optimize the forecasting model using three accuracy techniques – MAD, MSE and MAPE calculations, tracking signal, and control chart.

The summary of the process (Russell & Taylor, 2011) is as follows:

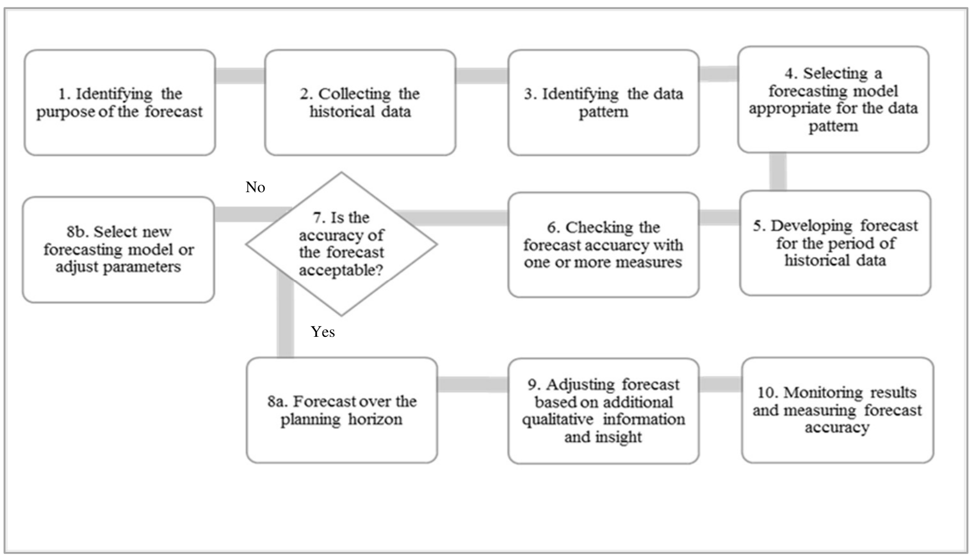


Figure 2. Forecasting process, by Russell & Taylor (2011)

The prescribed forecasting process relies on the historical or lagging data set that indicates the past admission and enrollment patterns. Nevertheless, it is essential to determine the future opportunities and define the strategies for a range of possibilities. Considering the data, this study developed a decision tree using the repulsive function. This analysis is based on a recursive partition (rpart), which divided the data set into training (70%) and test (30%) categories. The tree is helpful for exploratory analysis, as the binary structure of the tree is simple to visualize and provides easily interpretable results. The decision tree usually provides higher prediction accuracy. However, the model performance varies when a new and unexpected situation appears. This is because the decision tree is created by learning simple rules based on training data (Laurinec, 2017). Furthermore, this study constructed a confusion matrix to measure the performance of the decision tree model.

V. FORECASTING MODEL DEVELOPMENT

System Definition

The University of Arkansas has a central database system that contains new student application, matriculation, and enrollment information for every semester. However, every program has individual admission and enrollment requirements for new students. The admission and enrollment system in the MSOM program consists of three principal stages with multiple sub-stages. The new student information is embedded in multiple layers and correlated with different admission and enrollment criteria. This study focused on the following principal stages to extract the new student information:

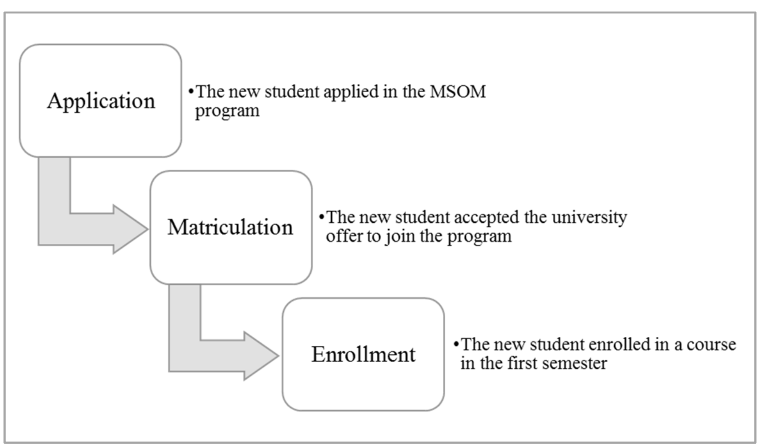


Figure 3. New student information mining stages

The study gathered new student data for the last 10 years from a secondary source: the university database. The data set contains student information for the Spring, Summer and Fall semesters under a unique terminology. The first of the four-digit code represents a symbolic number (which is only a placeholder), the second and third digits represents the calendar year and the last digit specifies the semester. The explanation of the terms are as follows:

Table 2. Term explanation

Term	Number	Year	Semester
1**3	1	**	Spring
1**6	1	**	Summer
1**9	1	**	Fall

Data Analysis

The study extracted application, matriculation and enrollment information from the research data set. However, the data mining was extremely challenging due to the complexity of the facts query process and overlapping of multi-layer information. This study spent significant time and efforts to filter the data set and gather new student information for the three stages. Figure 4 shows the total number of new students who applied, matriculated and enrolled in the MSOM program during the last 10 years to display the underlying behavior of the data:

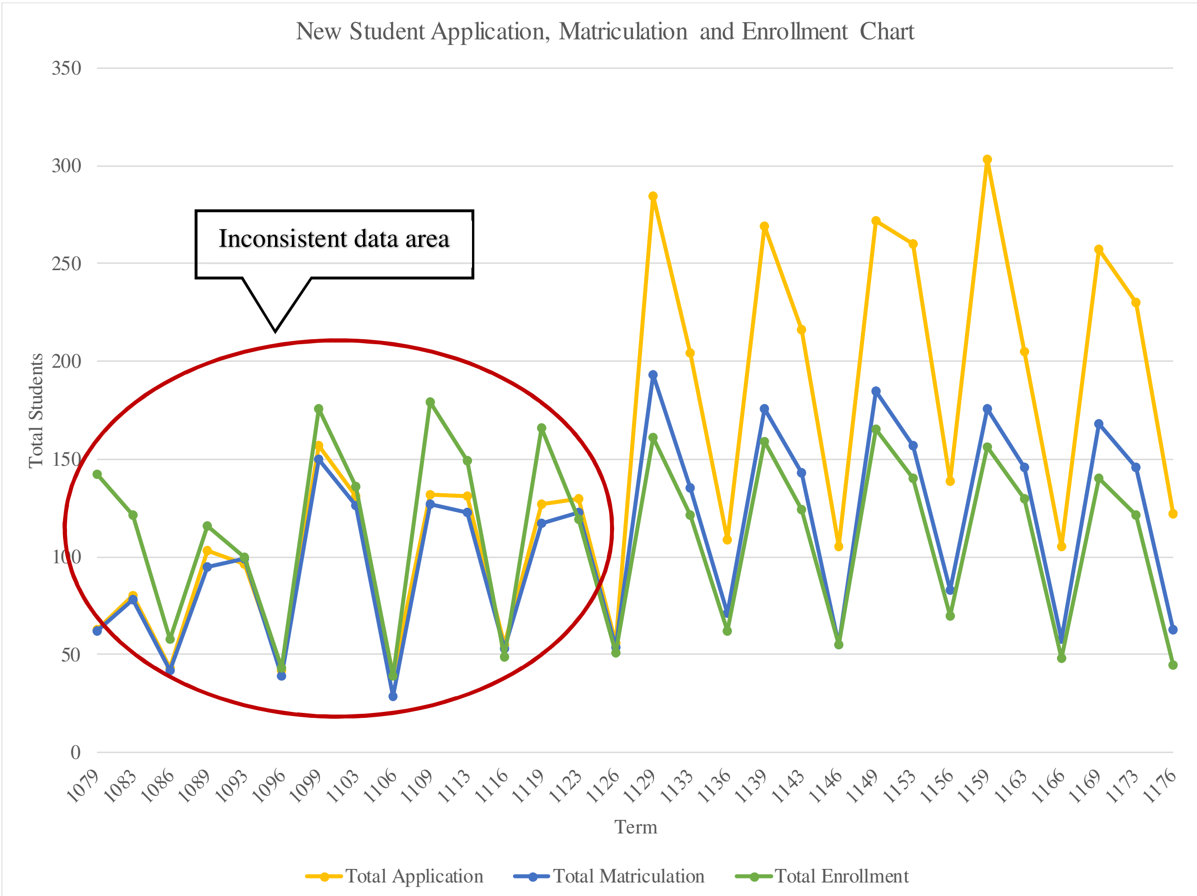


Figure 4. New student application, matriculation and enrollment chart

The chart revealed that the total number of students enrolled in the program is higher than the total number of students applied and matriculated during the 1079 - 1126 terms. The outcome reflected an inconsistency in the extracted data set and therefore it was not suitable for forecasting purposes. On the right-hand side of the chart, it displays that the total number of students applied is higher than the matriculated students and that the total number of students matriculated is higher than enrolled students for the most recent 15 terms, from 1129 to 1176. The result reflected the consistent data from new student applications, matriculation, and enrollment. The researcher decided to use the last 15 terms' data set to meet the research objectives. Table 2 shows the final data set used for this research purpose.

Table 3. Final application, matriculation and enrollment data set

Term	Application	Matriculation	Enrollment
1129	284	193	161
1133	204	135	121
1136	109	71	62
1139	269	176	159
1143	216	143	124
1146	105	55	55
1149	272	185	165
1153	260	157	140
1156	139	83	70
1159	303	176	156
1163	205	146	130
1166	105	58	48
1169	257	168	140
1173	230	146	121
1176	122	63	45

Moreover, the analysis process evaluated the data set to detect the presence of trend and seasonal patterns. There are obvious, strong seasonal effects, with Fall being the highest season and Summer being the lowest season. After the seasonal effects were accounted for, there was a minor downward trend over the last 5 years in application, matriculation, and enrollment numbers. The coefficient of determination, R^2, was significantly low for all the phases, which concluded that there is no statistically significant trend pattern associated with the data sets. The Analysis of Variance (ANOVA) identified a strong presence of seasonal patterns in the data sets. Lind, Marchal and Wathen (2010) mentioned that the p-value is the probability of obtaining a test statistic result at least as extreme as the one that is actually observed, assuming that the null hypothesis is true under statistical significance testing. The p-value not only results in a decision regarding the null hypothesis but also it gives additional insight into the strength of the decision.

According to the test results, the application, matriculation, and enrollment stages have p-values of 0 for Summer semester and 0.001, 0.0002 and 0.0004 for Fall semester respectively. The p-values were significant at the 95% significance level. The adjusted R^2 were 0.92, 0.96 and 0.96 for application, matriculation and enrollment stages respectively. The results concluded that the data sets have strong seasonal patterns. The APPENDIX section contains the detailed calculation of the ANOVA test. The summary of the analysis follows in Table 4:

Table 4. ANOVA analysis to identify seasonal patterns

Aspects	Application		Matriculation		Enrollment	
Regression Statistics						
R Square	0.942		0.969		0.970	
Adjusted R Square	0.926		0.961		0.962	
ANOVA	***Coefficients***	***P-value***	***Coefficients***	***P-value***	***Coefficients***	***P-value***
Intercept	218.8222	0.0000	148.7778	0.0000	134.3111	0.0000
Summer	-107.5222	0.0000	-78.9778	0.0000	-70.3111	0.0000
Fall	54.5222	0.0010	33.7778	0.0002	28.1111	0.0004
Period	0.5222	0.6671	-0.4222	0.4980	-0.8889	0.1217

Based on these results, this study decided to remove the seasonal impacts from the data sets. The seasonal factors are widely used to de-season the data sets. According to Stevenson (2012), the seasonal factors are the seasonal percentages in the multiplicative model. He mentioned that the number of periods needed in a centered moving average has to be equal to the number of seasons involved in the index calculation process. In case of semester-based data, the de-season process used a three period moving average. Further calculation averaged the seasonal components to eliminate the error and isolate the seasonal relatives. The seasonal factors were standardized to three in order to match the number of semesters per academic year (Delurgio, 1999). The APPENDIX section contains the detailed calculation of the seasonal indexes. The summary of the seasonal indices are as follows:

Table 5. Seasonal indices for application, matriculation and enrollment data sets

Season	Application		Matriculation		Enrollment	
	Average Index	Standard Index	Average Index	Standard Index	Average Index	Standard Index
Fall	1.337	1.345	1.353	1.360	1.358	1.360
Spring	1.084	1.091	1.117	1.123	1.126	1.127
Summer	0.561	0.564	0.514	0.517	0.513	0.513

Table 6 shows the de-seasonalized application, matriculation and enrollment information after dividing the original data by the respective seasonal standard indices:

Table 6. De-seasonalized application, matriculation and enrollment data set

Term	De-seasonalized Application	De-seasonalized Matriculation	De-seasonalized Enrollment
1129	211	142	118
1133	187	120	107
1136	193	137	121
1139	200	129	117
1143	198	127	110
1146	186	106	107
1149	202	136	121
1153	238	140	124
1156	246	161	136
1159	225	129	115
1163	188	130	115
1166	186	112	94
1169	191	124	103
1173	211	130	107
1176	216	122	88

Quantitative Forecasting Model Development and Accuracy Testing

This study simulated multiple forecasting models on the stationary data sets to achieve better accuracy results through three different testing methodologies. The simple exponential smoothing method performed the best of all, satisfying all the base line requirements. Delurgio (1999) supported the result as he prescribes simple exponential smoothing as the most suitable forecasting method for this data pattern.

The smoothing constant (α) represents the sensitivity of the forecast to new data points. The α value ranges between 0 and 1. A lower α value helps to smooth the forecasting curve but makes it less sensitive to the forecasting error. A higher α value reduces the smoothness of the curve but makes it more sensitive to forecasting error. Normally, the α value is optimized by minimizing the MSE value. However, this study attempted to adjust the α value by satisfying the MSE, tracking signal and control chart procedures. The tracking signal works as an indicator to check the bias of the nominated forecasting model. It is the ratio of the cumulative sum of forecast errors to the MAD. A tracking point within the standard range ±4 indicates that the forecasting method is performing suitably. In addition, a control chart is a useful tool to monitor the forecast errors. The chart contains an Upper Control Limit (UCL), Lower Control Limit (LCL) and a centerline that represents an error of zero. The forecast errors are plotted on the control chart in the order they occur. Each error is judged separately and should be distributed according to a normal distribution around a mean of zero. 99.74% of the values are expected to stay within ±3s range of the center line (Stevenson, 2012). In view of the facts, this study decided to optimize the α value satisfying all the testing methods and achieve the best possible forecasting results.

Table 7 shows the simple exponential smoothing model for application data set with accuracy controls.

Table 7. Forecasting model and accuracy controls for application data set

Term	De-seasonalized Application	Forecast	Tracking Signal (±4)
1129	211		
1133	187	211	-1.47
1136	193	198	-1.76
1139	200	195	-1.49
1143	198	198	-1.48
1146	186	198	-2.20
1149	202	192	-1.55
1153	238	197	0.93
1156	246	219	2.57
1159	225	234	2.04
1163	188	229	-0.47
1166	186	207	-1.74
1169	191	196	-2.02
1173	211	193	-0.95
1176	216	203	-0.13
1179		**210**	

α	**0.54**
MAD	**16**
MSE	**430**
MAPE	**8%**

S	**20.75**
UCL	**62.24**
LCL	**-62.24**

The MAD measures the difference between actual and average forecast values providing equal weight to all errors. For the application data set, the MAD was 16 students; that means the average absolute deviation from the mean was 16 students.

The MSE measures the average of the squares of the errors. The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. The forecasting model showed MSE score of 430.

The MAPE provides the measurement of forecast error relative to the actual value. The forecasting model expressed a MAPE score of 8% for the application data set; that means the average absolute percentage of error was 8%.

The tracking signal calculated the ratio of the cumulative sum of forecast errors to the MAD. The results displayed that all the values are within the ±4 limits, which indicates that the forecast model is free of bias.

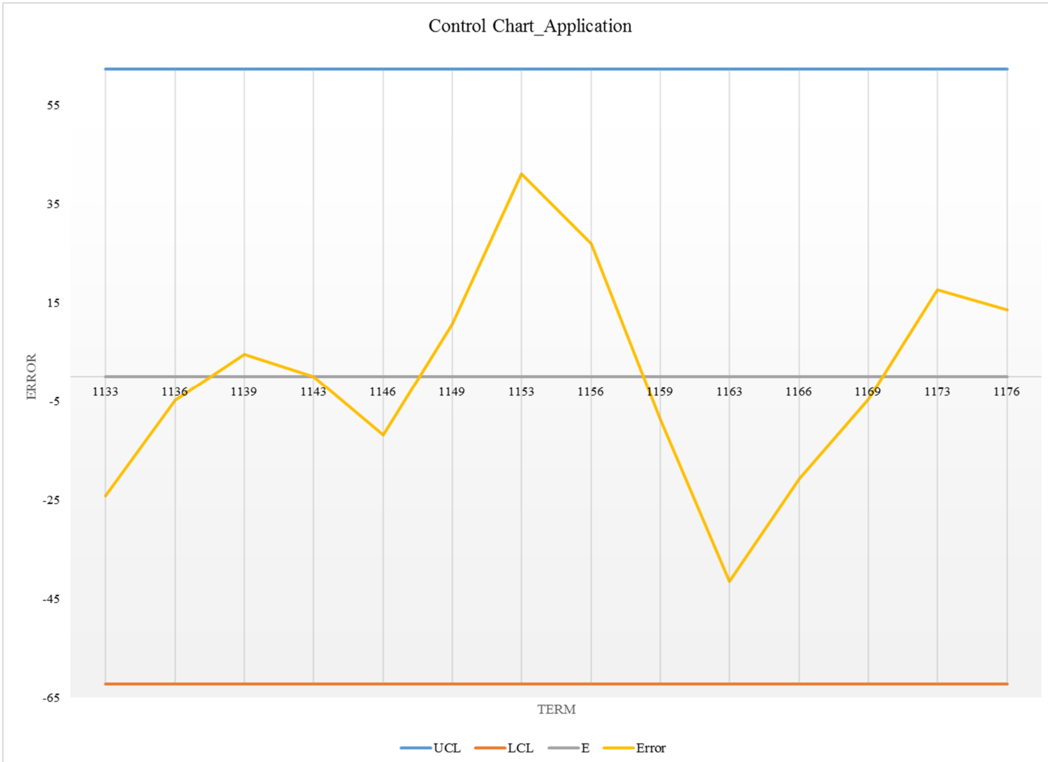


Figure 5. Control chart for application data set

The control chart for the application data (Figure 5) shows that all the errors are within the specified limits. Moreover, the errors are randomly distributed on both sides of the centerline, which indicates that the forecast model is working properly for the data set. In summary, the quantitative forecast model for the application data set satisfied all the testing methods and projected that 210 new students would apply to the MSOM program during the 1179 term.

Table 8 shows the simple exponential smoothing model for the matriculation data set with accuracy controls.

Table 8. Forecasting model and accuracy controls for matriculation data set

Term	De-seasonalized_Matriculation	Forecast	Tracking Signal (±4)
1129	142		
1133	120	142	-1.73
1136	137	132	-1.30
1139	129	135	-1.71
1143	127	132	-2.10
1146	106	130	-3.97
1149	136	119	-2.65
1153	140	127	-1.63
1156	161	133	0.60
1159	129	145	-0.66
1163	130	138	-1.31
1166	112	134	-3.08
1169	124	124	-3.16
1173	130	124	-2.68
1176	122	127	-3.06
1179		**125**	

α	**0.45**
MAD	**13**
MSE	**228**
MAPE	**10%**

S	**15.11**
UCL	**45.34**
LCL	**-45.34**

For the matriculation data set, the MAD was 13 students. The forecasting model scored 228 in MSE measure. The calculation revealed a MAPE score of 10% for the matriculation data set; that means the average absolute percentage of error was 10%. Moreover, the tracking signal system shows that all the values are within the ±4 limits, which indicates that there is no bias in the forecast model.

The control chart for matriculation data set in Figure 6 shows that all the errors are within the specified limits. However, the errors are not randomly distributed on both sides of the centerline, which indicates that the model may not perform satisfactorily in the future. In summary, the quantitative forecast model for the matriculation data set satisfied all the testing methods and projected that 125 new students would matriculate in the MSOM program during the 1179 term.

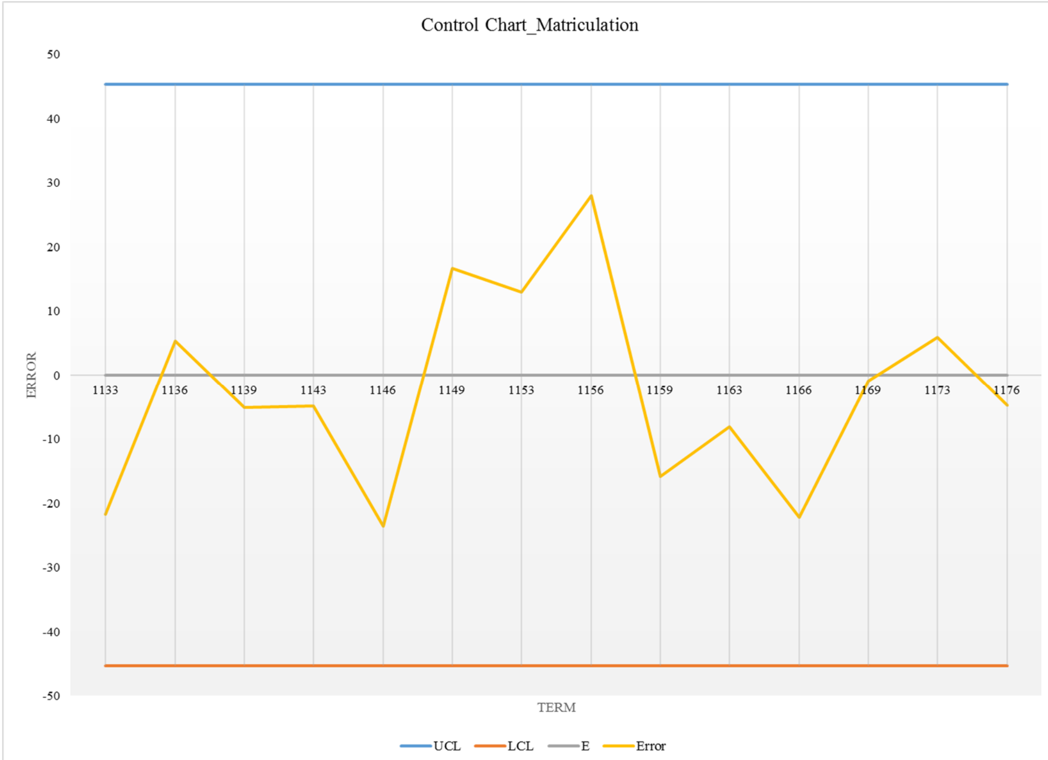


Figure 6. Control chart for matriculation data set

Table 9 shows the simple exponential smoothing model for the enrollment data set with accuracy controls.

Table 9. Forecasting model and accuracy controls for enrollment data set

Term	De-seasonalized_Enrollment	Forecast	Tracking Signal (±4)
1129	118		
1133	107	118	-1.13
1136	121	111	-0.13
1139	117	118	-0.19
1143	110	117	-0.92
1146	107	112	-1.45
1149	121	109	-0.18
1153	124	117	0.53
1156	136	122	2.00
1159	115	132	0.29
1163	115	120	-0.22
1166	94	117	-2.60
1169	103	101	-2.43
1173	107	102	-1.93
1176	88	106	-3.76
1179		**94**	

α	**0.67**
MAD	**10**
MSE	**137**
MAPE	**9%**

S	**11.72**
UCL	**35.16**
LCL	**-35.16**

The MAD was 10 students for the enrollment data set; that means the average absolute deviation from the mean was 10 students. Also, the forecasting model scored 137 in MSE measure. The calculation revealed a MAPE score of 9% for the enrollment data set; that means the average absolute percentage of error was 9%. Moreover, the tracking signal system presented that all the values are within the ±4 limits, which indicates that the model is not biased.

The control chart for enrollment data set in Figure 7 displayed that all the errors are within the specified limits. Furthermore, the errors are randomly distributed on both sides of the centerline but the curve is slowly sloping downward. It indicates that the forecast model is working properly for the data set but may not perform adequately in the future. In summary, the quantitative forecast model for enrollment data set pleased all the testing methods and projected that 94 new students would enroll in the MSOM program during the 1179 term and afterward.

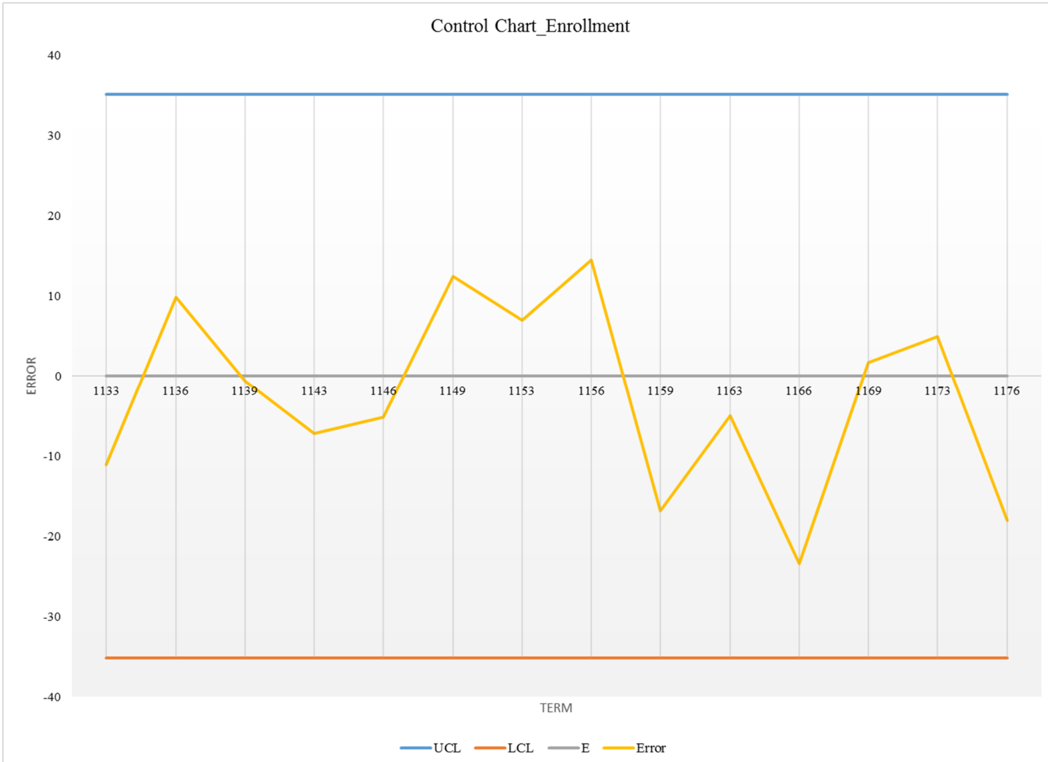


Figure 7. Control chart for enrollment data set

In the final stage of developing the quantitative forecasting model, it was required to incorporate the seasonality in the forecast. This study used the seasonal relatives for incorporating the seasonality in the forecasting model of every stage. Table 10 shows the seasonalized forecast for Fall, and a similar analysis can be conducted for the Spring and Summer seasons.

Table 10. Seasonalized forecast

Stages	De-seasonalized Forecast	Seasonal Relative (Fall)	Seasonalized Forecast
Application	210	1.345	**282**
Matriculation	125	1.360	**170**
Enrollment	94	1.360	**128**

Qualitative Forecasting Model Development

The qualitative forecasting models are mostly subjective, which depends on the opinion and judgment of the experienced employees. The Delphi method is one of the most popular and widely used qualitative forecasting models. It is a systematic and collaborative forecasting model that relies on the response of a panel of experts with specific reasoning. This study decided to perform Delphi analysis on a panel of administrators to gather their opinion on new student application, matriculation and enrollment number in the MSOM program. The panel consisted of two members who work closely with the program admission, marketing, and promotional activities. This research developed a two round Delphi questionnaire focusing on the three stages. The questionnaires are available in the APPENDIX section. The summary of the first round Delphi analysis is as follows:

Table 11. Summary of the first round Delphi analysis

Question	1st Panelist's Response	2nd Panelist's Response	Average
Application			
How many new students will you forecast for Fall 2017?	250	275	263
How many new students AT LEAST will you forecast for Fall 2017?	200	257	229
How many new students AT MOST will you forecast for Fall 2017?	275	300	288
Matriculation			
How many new students will you forecast for Fall 2017?	170	185	178
How many new students AT LEAST will you forecast for Fall 2017?	150	170	160
How many new students AT MOST will you forecast for Fall 2017?	190	190	190
Enrollment			
How many new students will you forecast for Fall 2017?	125	165	145
How many new students AT LEAST will you forecast for Fall 2017?	110	140	125
How many new students AT MOST will you forecast for Fall 2017?	150	175	163

The panelists suggested that on average 263 new students would apply to the program during Fall 2017 semester. The number of new applicants may vary between 229 and 288. Among them, the panelists expected 178 new students to matriculate in the program, ranging between 160 and 190 students. Finally, the panelists predicted that on average 145 new students would enroll in the program and the enrollment may vary between 125 and 163 students. This study compiled the information in the second round Delphi analysis and requested the panelists to reconsider their predictions. The summary of the second round Delphi analysis is as follows –

Table 12. Summary of the second round Delphi analysis

Question	1st Panelist's Response	2nd Panelist's Response	Average
Application			
How many new students will you forecast for Fall 2017?	250	270	260
How many new students AT LEAST will you forecast for Fall 2017?	200	250	225
How many new students AT MOST will you forecast for Fall 2017?	275	300	288
Matriculation			
How many new students will you forecast for Fall 2017?	170	180	175
How many new students AT LEAST will you forecast for Fall 2017?	150	170	160
How many new students AT MOST will you forecast for Fall 2017?	190	190	190
Enrollment			
How many new students will you forecast for Fall 2017?	125	160	143
How many new students AT LEAST will you forecast for Fall 2017?	110	140	125
How many new students AT MOST will you forecast for Fall 2017?	150	175	163

The panelists suggested that on average 260 new students would apply to the program during Fall 2017 semester after reviewing the first round Delphi analysis outcomes. The number of applicants may vary between 225 and 288. Moreover, the panelists estimated 175 new students to matriculate in the program, ranging between 160 and 190. Lastly, the panelists anticipated that on average 143 new students would enroll in the program and the enrollment may vary between 125 and 163 students.

This analysis calculated the second-degree mean of the outcomes of the two round Delphi analysis to concrete the qualitative forecasting model results. Table 13 summarized that on average 261 new students would apply to the program during the upcoming semester. A total of 144 new students would enroll in the program followed by the matriculation of 176 new students during Fall 2017. The summary of the analysis is as follows in Table 13.

Table 13. Summary of the Delphi analysis

Question	1st Round Average	2nd Round Average	Second Degree Average
Application			
How many new students will you forecast for Fall 2017?	263	260	**261**
How many new students AT LEAST will you forecast for Fall 2017?	229	225	227
How many new students AT MOST will you forecast for Fall 2017?	288	288	288
Matriculation			
How many new students will you forecast for Fall 2017?	178	175	**176**
How many new students AT LEAST will you forecast for Fall 2017?	160	160	160
How many new students AT MOST will you forecast for Fall 2017?	190	190	190
Enrollment			
How many new students will you forecast for Fall 2017?	145	143	**144**
How many new students AT LEAST will you forecast for Fall 2017?	125	125	125
How many new students AT MOST will you forecast for Fall 2017?	163	163	163

Combined Forecasting Model

The analysis found that the quantitative and qualitative forecasting model predictions are close to each other at every stage. In this regard, this study decided to average the results to conclude the prediction for application, matriculation and enrollment stages. The model predicts that 272, 173 and 136 new students would apply, matriculate and enroll in the MSOM program respectively during Fall 2017 semester. The combined forecasting model is as follows:

Table 14. Combined forecasting model

Stages	Quantitative Forecast	Qualitative Forecast	Combined Forecast
Application	282	261	**272**
Matriculation	170	176	**173**
Enrollment	128	144	**136**

VI. PREDICTIVE ANALYSIS

Classification Tree Model

This study developed a classification tree model to justify an individual student's decision to join the MSOM program. The classification tree attempted to pinpoint the factors influencing a student's judgment by using rpart analysis. In the analysis, the target attribute was student “Enrolled” and the independent attributes were “Gender”, “Military_Status”, “Birth_Year”, “Ethnic_Group”, “State”, “Country” and The Standard & Poor's 500 index, abbreviated as the “SP_500_Prices”. The model considered a seed of 55 and minbucket of 7, which is a standard in R programming. In addition, the entire data set was divided into training (70%) and test (30%) categories (Viswanathan, 2015). Initially, the model generated a classification tree with more than 100 leaf nodes and the study decided to prune the tree. The cp chart revealed that a cp value of 0.0031 could provide a better classification tree with a smaller number of leaf nodes. The pruned classification tree is shown in Figure 8.

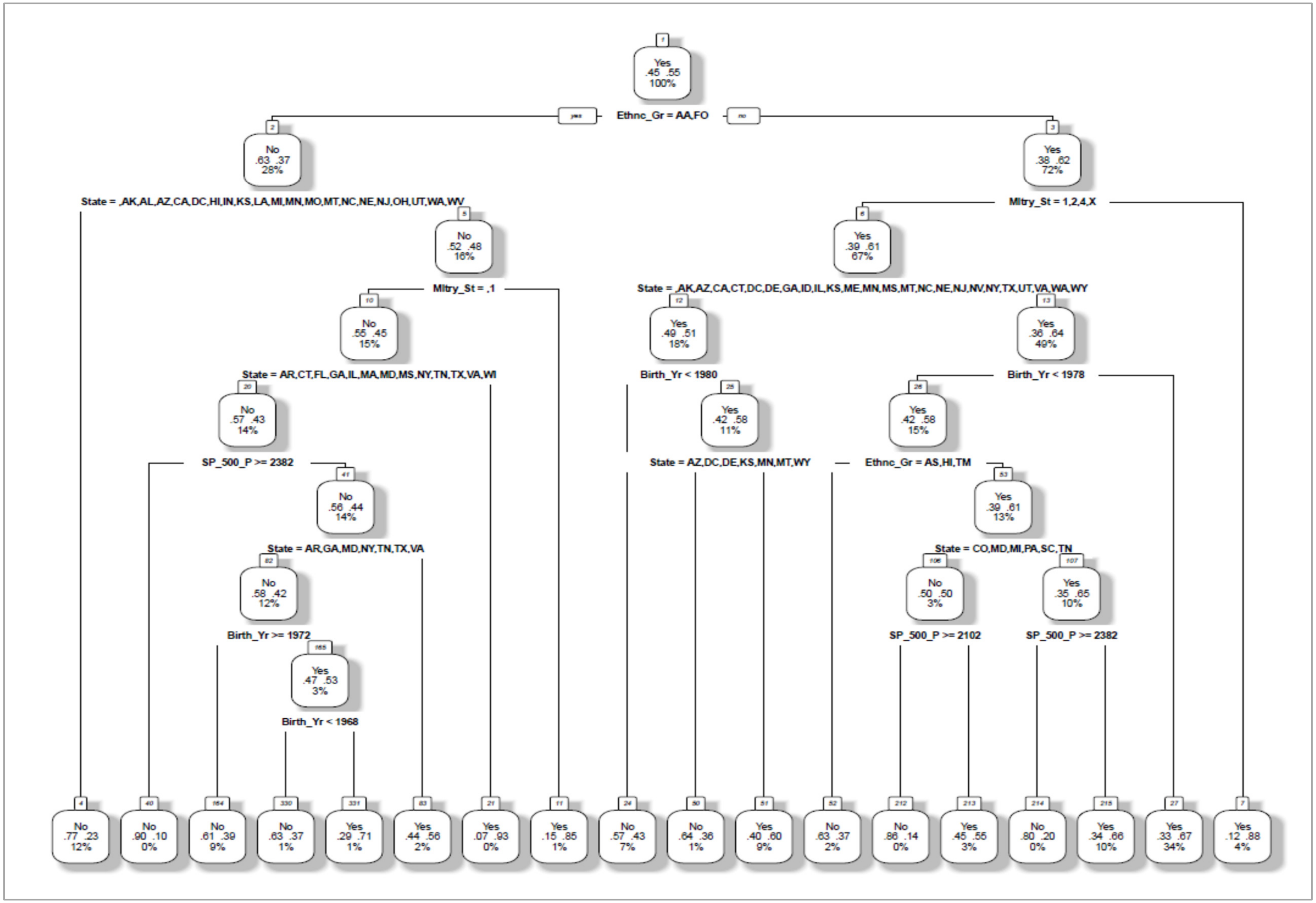


Figure 8. Pruned classification tree

The summary of the analysis displays that 55% of the applicants enrolled in the program and the remaining 45% did not enroll. Therefore, if this study randomly selects an applicant from the data set, there is a 0.55 probability of getting a positive result and a 0.45 probability of getting a negative consequence. If this analysis follows the naïve rule then it is correct 55% of the time.

The classification tree contains 18 leaf nodes, which are developed from 3,080 cases. Node 1 of the classification tree reveals that 55% of the applicants successfully enrolled in the MSOM program whereas 45% students did not enroll. The cases that meet the condition of ethnic group African American (AA) and Foreign (FO) proceeds to the left and others transfer to the right. Node 2 reaches from the parent node and represents 28% of the total number of cases. Node 2 describes that 63% of the African American and Foreign students did not enroll in the program. This section is further branched based on the AK, AL, AZ, CA, DC, HI, IN, KS, LA, MI, MN, MO, MT, NC, NE, NJ, OH, UT, WA and WV states. Node 4 represents 12% cases and labels that 77% applicants from these 20 states did not enroll in the program. Node 5 shows that 52% applicants from other states did not enroll in the program, considering 16% cases.

Furthermore, Node 3 characterizes 72% of the total cases and describes that students from Asian (AS), Caucasian (CA), Hispanic (HI), Hawaiian (HW), Native American (IN), Two or More (TM) and Not Reported (NR) ethnic groups enrolled in the program in 62% cases. Node 3 is branched further based on the military status. Node 6 represents 67% of the total cases and labels that applicants with Not Indicated (1), No Military Service (2) and Not a Veteran (X) military status have 61% chances to enroll in the program. Node 7 represents the students with

Veteran of US Armed Forces (5, Y) and shows that 88% of them enrolled in the program. However, Node 7 contains only 4% of the total cases.

In addition, Node 6 is classified based on the applicants from AK, AZ, CA, CT, DC, DE, GA, ID, IL, KS, ME, MN, MS, MT, NC, NE, NJ, NV, NY, TX, UT, VA, WA and WY states. Node 13 reveals that 64% applicants from other states enrolled in the courses considering 49% of the total cases. Another interesting fact is that the applicant from other states, whose birth year is after 1978, has 67% chance to enroll in the program. A confusion matrix shows the number of correct and incorrect predictions made by the classification model compared to the actual outcomes (target value) in the data. The confusion matrix for test data set is as follows:

Table 15. Confusion matrix for test data set

	Predicted	
Actual	No	Yes
No	216	198
Yes	121	388

Total Cases	**923**
Error rate	**35%**
Correctness rate	**65%**
Lift	**1.19**

The confusion matrix for test data set shows an error rate of 35%. The correctness rate on the test data set is 65% and the lift is 1.19. The lift is a measure of the effectiveness of a classification model calculated as the ratio between the results obtained with and without the model (“Model Evaluation,” 2016). In a perfect scenario, the confusion matrix should win the naïve classification and produce a lift more than 1.00. In this analysis, the correctness rate of the confusion matrix is better than that of the naïve model and the lift is showing 19% improvement over the base performance.

Dropout at Matriculation and Enrollment Stages

The analysis of the 10 years' application, matriculation and enrollment data set directed that a significant number of applicants were dropping out at the matriculation and enrollment levels. This study further analyzed the semester wise dropout rates in matriculation stage considering the total number of applications as the reference line and generated an area chart in Figure 9:

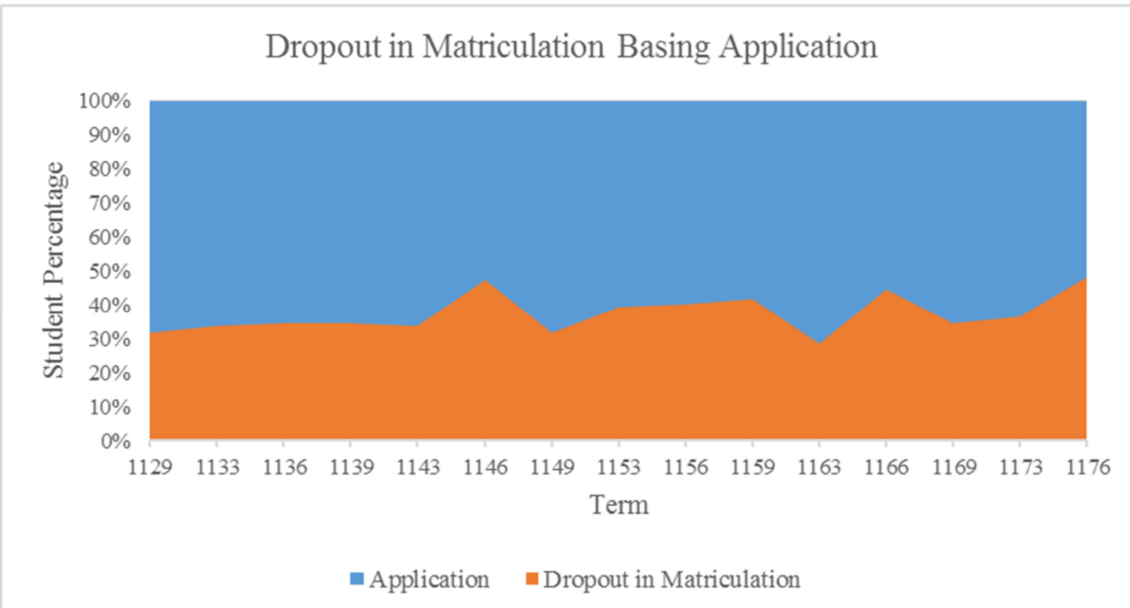


Figure 9. Dropout in matriculation stage

The entire area of the chart represents the total applicants during the 1129 – 1176 periods. The overlapping zone, where the orange zone overlaid the blue area, signifies the dropout rates at matriculation stage. On average, 38% of the total applicants failed to matriculate in the program. In addition, this study examined the semester wise dropout rates in enrollment stage considering the total number of matriculated students as the point of reference and prepared an area chart in Figure 10:

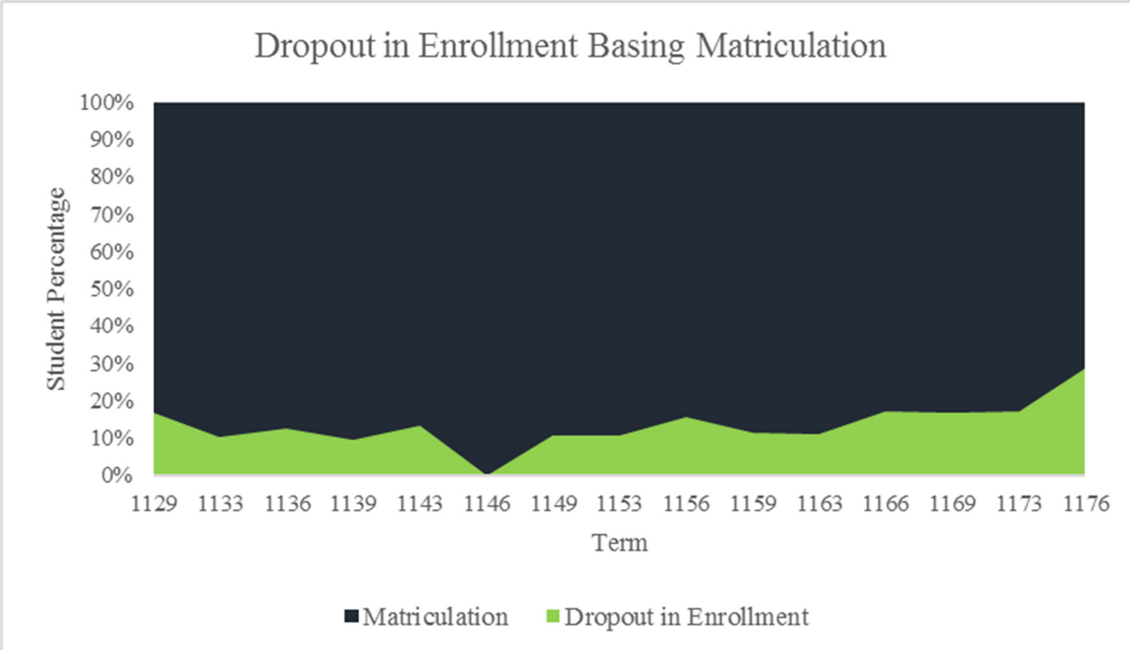


Figure 10. Dropout in enrollment stage

The entire area of the chart represents the total matriculated students during the 1129 – 1176 periods. The overlapping zone, where the green zone overlapped the deep blue area, denotes the dropout rates at enrollment stage. On average, 13% of the total matriculated students did not enroll in the program at all. However, the 1176 term information requires an additional update, as the students tend to enroll in following semesters.

Correlation between Admission Stages and Tuition Fees

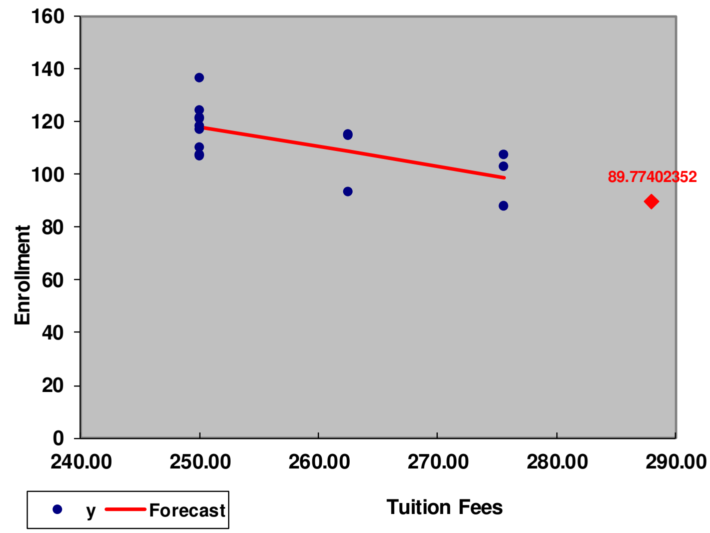
During the data analysis, this study exposed that the tuition of the program is considerably correlated with the admission stages. Based on the data, this research decided to explore the relationship between the tuition fees and admission stages by using simple linear regression model. The first model based on the application data set directed that the tuition fees are not the deciding factor for the applicants in joining the program. The coefficient of determination (R^2) for this model was 0.002, which indicates that only 0.2% of the change in the application is predicted by the change in tuition fees. Similarly, the second model based on the matriculation data set revealed that only 9% change in matriculation is anticipated by the change in tuition fees. However, the third model, based on the enrollment data set, the outcome was different from the others:

Table 16. Correlation between tuition fees and enrollment

Simple Linear Regression
Enrollment

Slope =	-0.74	R =	-0.64
Intercept =	303.22	R^2 =	0.41

Tuition Fees	Enrollment	Forecast	Error
$ 250.00	118	118	0
$ 250.00	107	118	-11
$ 250.00	121	118	3
$ 250.00	117	118	-1
$ 250.00	110	118	-8
$ 250.00	107	118	-11
$ 250.00	121	118	3
$ 250.00	124	118	6
$ 250.00	136	118	18
$ 262.50	115	109	6
$ 262.50	115	109	7
$ 262.50	94	109	-15
$ 275.63	103	99	4
$ 275.63	107	99	8
$ 275.63	88	99	-11



x = 288
Dx = 1
Forecast: 90

The regression model in Table 16 discovered that the new student enrollment in the MSOM program is negatively correlated with the tuition fees. The final equation of the model is as follows:

Enrollment = 303.22 – (0.74 * Tuition Fees)

According to the equation, a $100 increase in the tuition fees will decrease the new student enrollment by 74 students. The coefficient of determination (R^2) for this model is 0.41, which indicates that tuition fees influence 41% of the change in student enrollment. If the administrative leaders intend to increase the tuition fee to $288 by Fall 2017 semester, the enrollment in the program will decrease to 122 students after seasonalizing the outcome with standard index. This analysis concluded that tuition fees are not a major concern for the new students when they are applying and matriculating in the program. However, changes in the tuition fees strongly influenced their decision to enroll in the program.

Enrollment Distribution

An in-depth analysis found that many students did not enroll in the same semester they gave their consent to join the MSOM program. In some cases, the enrollment of students overextended up to 13 semesters after the matriculation. Figure 11 shows the distribution of semester wise new students' first enrollment including the matriculating term:

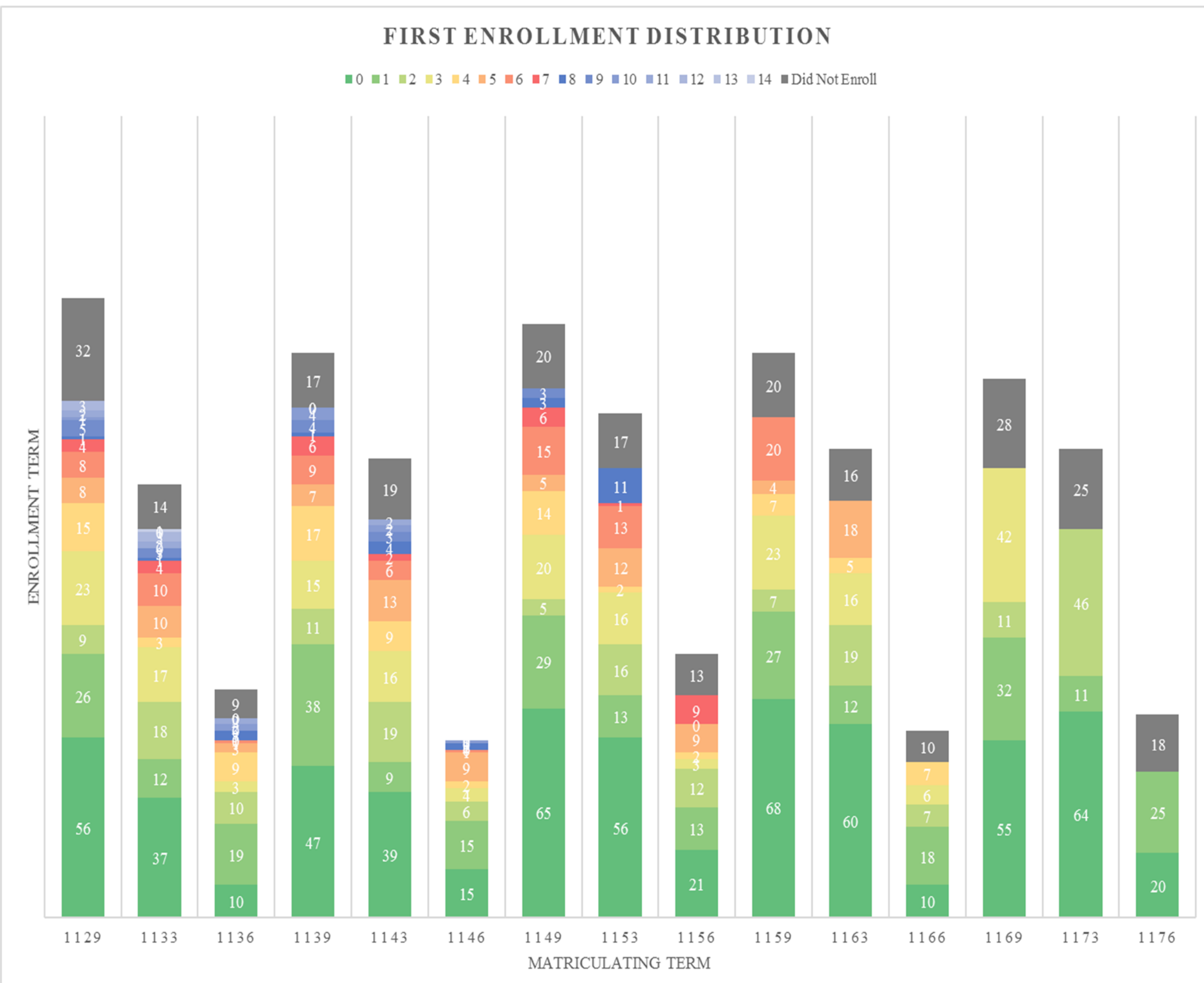


Figure 11. Enrollment distribution

The chart displays the enrollment distribution of each term, which is extended up to the last enrolling semester. The chart reveals that on average 35% of students enrolled in the same term they matriculated to join the program. Another 21% students enrolled in the following semester of matriculation. Furthermore, 12% and 11% students enrolled in the program during the 2nd and 3rd semester of matriculation respectively. The enrollment further extended to the 4th and 5th semester by 6%. The remaining 10% of students prolonged their enrollment in the later semesters. The top layer of the stack diagram shows the number of the students who matriculated but did not enroll in the program so far.

Recommendations

This study has the following recommendations based on the research findings:

- The forecasting models revealed that new student application, matriculation, and enrollment are decreasing. The coefficient of determination is slowing increasing in each step of the admission process. It may become a major issue in the future and management should increase marketing efforts. Corporate-focused online advertisements, latest ranking information, retaining students from undergraduate programs and scholarship offers can play important role in promotional efforts.

- The classification tree revealed that applicants with Not Indicated (1), No Military Service (2) and Not a Veteran (X) military status have a 61% chance to enroll in the program and the outcome is supported by 67% of total cases. The result suggests that the department has immense opportunity to optimize the capacities of off-campus locations. Furthermore, the University leaders may consider signing a Memorandum of Understanding (MoU) with the military divisions by providing them a special offer.

- The predictive analysis found that 45% of applicants are not enrolling in the program. The outcome is supported by both classification tree model (45%) and dropout analysis (46%). The administrative staffs are working hard to process the students' application documents but their hard work is not paying off due to the dropouts. The University leaders may introduce an application fee to reduce the dropout rates.

- The predictive analysis revealed that tuition fee effects students' decision to enroll in the program. Tuition fees influence 41% of the change in student enrollment and a $100 increase in the tuition fees will decrease new student enrollment by 74 students. If the administrative leaders intend to increase the tuition fee to $288, the enrollment in the program will decrease to 122 students. Ultimately, the new student enrollment will decrease by six students from the quantitative model prediction due to increase in the tuition fees.

- The applicants are not enrolling in the same semester in which they give their consent to join the MSOM program. On average, only 35% of students enrolled during the matriculating term and the main portion of students' enrollment is distributed in the following 5 semesters. The enrollment distribution period is creating a complex situation for administrative processes. The University leaders may evaluate and revise the enrollment policies.

VII. CONCLUSION

The university enrollment environment is progressively competitive and less predictable than any time before. The administrators are constantly monitoring the student enrollment patterns and developing forecasting models to predict the new student numbers. However, every university has a unique admission pattern and requires in-depth analysis of next level metrics to make resource allocation decisions. This research combines quantitative and qualitative forecasting model and predicts the new student admission in the MSOM program. Three accuracy measures justified the performance of the forecasting models. In addition, the combined forecasting model is supported by a series of predictive analysis to improve the enrollment processes. The forecasting models revealed that new student application, matriculation, and enrollment in the MSOM program are experiencing a downward trend and require significant marketing efforts. On average, 45% of the applicants are dropping out in enrollment level that is causing complexity in offering the courses. The predictive analysis discovered that the dropout is negatively correlated with the tuition fees of the program. These findings will assist the leaders to make acute decisions in adopting the admission patterns of the MSOM program.

This research focused on a specific program of the university and the discoveries open the door for expanding the research objectives. Future models can incorporate engagement and behavioral data into their predictive models to identify the changes in the factors influencing students' decision and develop an early alert system. Furthermore, this research will work as a platform for the future experimentation on deploying a complete predictive analysis based forecasting system for the University of Arkansas.

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APPENDIX

Table 17. Statistical significance of regression for application data set in Table 4

Application

Regression Statistics	
Multiple R	0.971
R Square	0.942
Adjusted R Square	0.926
Standard Error	19.420
Observations	15.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3.000	67216.967	22405.656	59.412	0.000
Residual	11.000	4148.367	377.124		
Total	14.000	71365.333			

	Coefficient.	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	218.822	12.838	17.045	0.000	190.566	247.079	190.566	247.079
Summer	-107.522	12.339	-8.714	0.000	-134.680	-80.365	-134.680	-80.365
Fall	54.522	12.339	4.419	0.001	27.365	81.680	27.365	81.680
Period	0.522	1.182	0.442	0.667	-2.079	3.123	-2.079	3.123

Table 18. Statistical significance of regression for matriculation data set in Table 4

Matriculation

Regression Statistics	
Multiple R	0.985
R Square	0.969
Adjusted R Square	0.961
Standard Error	9.901
Observations	15.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3.000	34013.067	11337.689	115.662	0.000
Residual	11.000	1078.267	98.024		
Total	14.000	35091.333			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	148.778	6.545	22.731	0.000	134.372	163.184	134.372	163.184
Summer	-78.978	6.291	-12.555	0.000	-92.823	-65.132	-92.823	-65.132
Fall	33.778	6.291	5.369	0.000	19.932	47.623	19.932	47.623
Period	-0.422	0.603	-0.701	0.498	-1.748	0.904	-1.748	0.904

Table 19. Statistical significance of regression for enrollment data set in Table 4

Enrollment

Regression Statistics	
Multiple R	0.985
R Square	0.970
Adjusted R Square	0.962
Standard Error	8.709
Observations	15.000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3.000	26797.467	8932.489	117.777	0.000
Residual	11.000	834.267	75.842		
Total	14.000	27631.733			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	134.311	5.757	23.329	0.000	121.639	146.983	121.639	146.983
Summer	-70.311	5.533	-12.707	0.000	-82.490	-58.132	-82.490	-58.132
Fall	28.111	5.533	5.080	0.000	15.932	40.290	15.932	40.290
Period	-0.889	0.530	-1.677	0.122	-2.055	0.278	-2.055	0.278

Table 20. Seasonal indices for application data set in Table 5

Application

Number of "seasons" = 3

Season	**Average Index**	**Standard Index**
Fall	**1.337**	**1.345**
Spring	**1.084**	**1.091**
Summer	**0.561**	**0.564**

Clear

Period	**Season**	**Actual**	**MA**	**Center**	**Index**
1	Fall	284			
2	Spring	204		199	1.0251256
3	Summer	109	199	194	0.5618557
4	Fall	269	194	198	1.3585859
5	Spring	216	198	196.66667	1.0983051
6	Summer	105	196.66667	197.66667	0.5311973
7	Fall	272	197.66667	212.33333	1.2810047
8	Spring	260	212.33333	223.66667	1.1624441
9	Summer	139	223.66667	234	0.5940171
10	Fall	303	234	215.66667	1.4049459
11	Spring	205	215.66667	204.33333	1.0032626
12	Summer	105	204.33333	189	0.5555556
13	Fall	257	189	197.33333	1.3023649
14	Spring	230	197.33333	203	1.1330049
15	Summer	122	203		

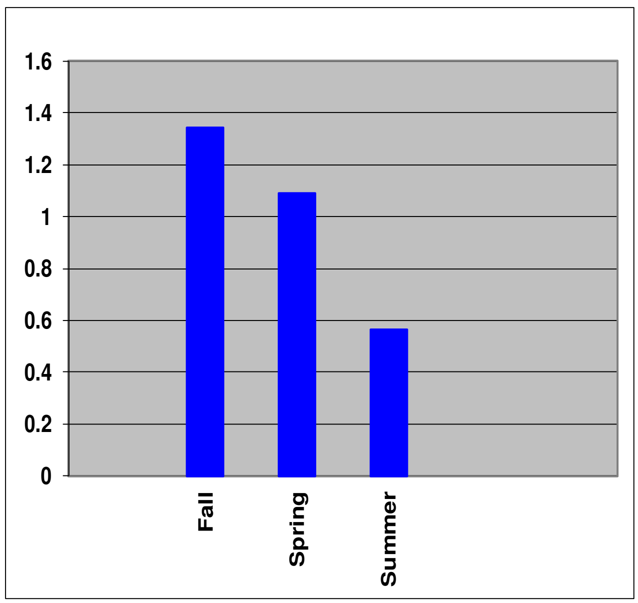

Table 21. Seasonal indices for matriculation data set in Table 5

Matriculation

Number of "seasons" = 3

Season	Average Index	Standard Index
Fall	1.353	1.360
Spring	1.117	1.123
Summer	0.514	0.517

Clear

Period	Season	Actual	MA	Center	Index
1	Fall	193			
2	Spring	135		133	1.0150376
3	Summer	71	133	127.33333	0.5575916
4	Fall	176	127.33333	130	1.3538462
5	Spring	143	130	124.66667	1.1470588
6	Summer	55	124.66667	127.66667	0.4308094
7	Fall	185	127.66667	132.33333	1.3979849
8	Spring	157	132.33333	141.66667	1.1082353
9	Summer	83	141.66667	138.66667	0.5985577
10	Fall	176	138.66667	135	1.3037037
11	Spring	146	135	126.66667	1.1526316
12	Summer	58	126.66667	124	0.4677419
13	Fall	168	124	124	1.3548387
14	Spring	146	124	125.66667	1.1618037
15	Summer	63	125.66667		

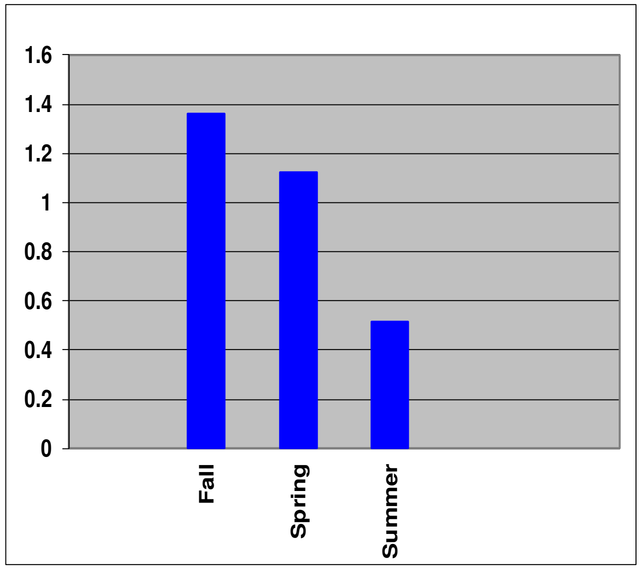

Table 22. Seasonal indices for enrollment data set in Table 5

Enrollment

Number of "seasons" = 3

Season	Average Index	Standard Index
Fall	1.358	1.360
Spring	1.126	1.127
Summer	0.513	0.513

Clear

Period	Season	Actual	MA	Center	Index
1	Fall	161			
2	Spring	121		114.66667	1.0552326
3	Summer	62	114.66667	114	0.5438596
4	Fall	159	114	115	1.3826087
5	Spring	124	115	112.66667	1.1005917
6	Summer	55	112.66667	114.66667	0.4796512
7	Fall	165	114.66667	120	1.375
8	Spring	140	120	125	1.12
9	Summer	70	125	122	0.5737705
10	Fall	156	122	118.66667	1.3146067
11	Spring	130	118.66667	111.33333	1.1676647
12	Summer	48	111.33333	106	0.4528302
13	Fall	140	106	103	1.3592233
14	Spring	121	103	102	1.1862745
15	Summer	45	102		

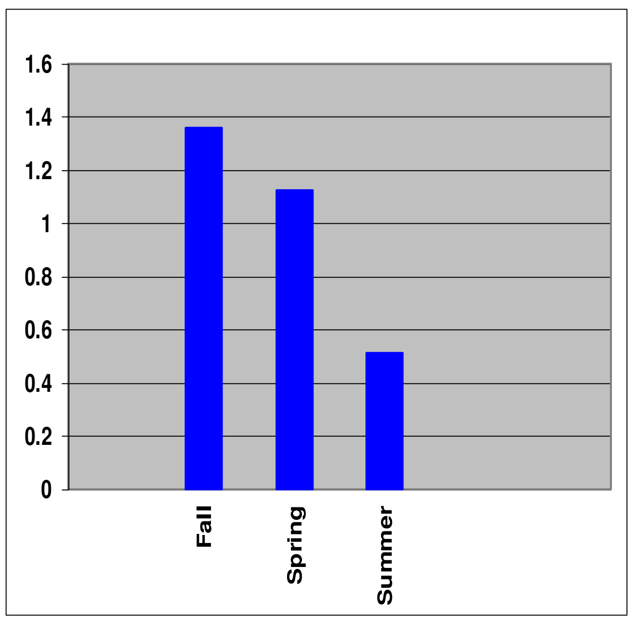

Table 23. Forecasting model and accuracy controls for application data set Table 7

Term	De-season Application	Forecast	(A - F)	│A - F│	(A - F)²	(│A - F│)/A	Cumulative Sum of Error	Tracking Signal (±4)
1129	211							
1133	187	211	-24.19	24.19	585.37	12.94%	-24.19	-1.47
1136	193	198	-4.87	4.87	23.72	2.52%	-29.06	-1.76
1139	200	195	4.54	4.54	20.62	2.27%	-24.52	-1.49
1143	198	198	0.05	0.05	0.00	0.02%	-24.48	-1.48
1146	186	198	-11.81	11.81	139.46	6.34%	-36.29	-2.20
1149	202	192	10.67	10.67	113.88	5.28%	-25.61	-1.55
1153	238	197	40.96	40.96	1678.07	17.19%	15.35	0.93
1156	246	219	26.96	26.96	726.85	10.94%	42.31	2.57
1159	225	234	-8.72	8.72	76.04	3.87%	33.59	2.04
1163	188	229	-41.42	41.42	1715.34	22.04%	-7.83	-0.47
1166	186	207	-20.80	20.80	432.65	11.17%	-28.63	-1.74
1169	191	196	-4.62	4.62	21.32	2.42%	-33.24	-2.02
1173	211	193	17.59	17.59	309.34	8.34%	-15.66	-0.95
1176	216	203	13.57	13.57	184.03	6.27%	-2.09	-0.13
1179		**210**		**230.77**	**6026.67**	**111.62%**		

α	**0.54**
MAD	**16**
MSE	**430**
MAPE	**8%**

S	**20.75**
UCL	**62.24**
LCL	**-62.24**

Table 24. Forecasting model and accuracy controls for matriculation data set Table 8

Term	De-season_Matriculation	Forecast	(A - F)	│A - F│	(A - F)²	(│A - F│)/A	Cumulative Sum of Error	Tracking Signal (±4)
1129	142							
1133	120	142	-21.70	21.70	470.99	18.06%	-21.70	-1.73
1136	137	132	5.32	5.32	28.32	3.87%	-16.38	-1.30
1139	129	135	-5.13	5.13	26.29	3.96%	-21.51	-1.71
1143	127	132	-4.90	4.90	24.03	3.85%	-26.41	-2.10
1146	106	130	-23.53	23.53	553.85	22.10%	-49.94	-3.97
1149	136	119	16.59	16.59	275.32	12.20%	-33.35	-2.65
1153	140	127	12.89	12.89	166.19	9.22%	-20.46	-1.63
1156	161	133	27.99	27.99	783.59	17.42%	7.53	0.60
1159	129	145	-15.89	15.89	252.44	12.28%	-8.35	-0.66
1163	130	138	-8.15	8.15	66.42	6.27%	-16.50	-1.31
1166	112	134	-22.18	22.18	492.11	19.76%	-38.69	-3.08
1169	124	124	-0.97	0.97	0.94	0.79%	-39.66	-3.16
1173	130	124	5.94	5.94	35.25	4.57%	-33.72	-2.68
1176	122	127	-4.76	4.76	22.63	3.90%	-38.48	-3.06
1179		**125**		**175.95**	**3198.36**	**138.25%**		

α	**0.45**
MAD	**13**
MSE	**228**
MAPE	**10%**

S	**15.11**
UCL	**45.34**
LCL	**-45.34**

Table 25. Forecasting model and accuracy controls for enrollment data set Table 9

Term	De-season_Enrollment	Forecast	(A - F)	│A - F│	(A - F)²	(│A - F│)/A	Cumulative Sum of Error	Tracking Signal (±4)
1129	118							
1133	107	118	-11.09	11.09	123.01	10.33%	-11.09	-1.13
1136	121	111	9.83	9.83	96.59	8.13%	-1.26	-0.13
1139	117	118	-0.63	0.63	0.39	0.53%	-1.89	-0.19
1143	110	117	-7.16	7.16	51.33	6.51%	-9.05	-0.92
1146	107	112	-5.18	5.18	26.82	4.83%	-14.23	-1.45
1149	121	109	12.48	12.48	155.68	10.28%	-1.75	-0.18
1153	124	117	6.94	6.94	48.14	5.59%	5.18	0.53
1156	136	122	14.51	14.51	210.64	10.64%	19.70	2.00
1159	115	132	-16.88	16.88	284.78	14.71%	2.82	0.29
1163	115	120	-5.00	5.00	24.98	4.33%	-2.18	-0.22
1166	94	117	-23.43	23.43	548.84	25.05%	-25.60	-2.60
1169	103	101	1.71	1.71	2.92	1.66%	-23.90	-2.43
1173	107	102	4.92	4.92	24.20	4.58%	-18.98	-1.93
1176	88	106	-18.02	18.02	324.62	20.55%	-36.99	-3.76
1179		**94**		**137.76**	**1922.93**	**127.73%**		

α	**0.67**
MAD	**10**
MSE	**137**
MAPE	**9%**

S	**11.72**
UCL	**35.16**
LCL	**-35.16**

Delphi Questionnaire 1

A Delphi Analysis to Enhance the Student Admission and Enrollment System of MSOM Program

Dear Panelist,

This study is a part of the research project to analyze the fundamental aspects and develop a forecasting model to improve the student admission and enrollment system of MSOM program. This two-round Delphi study aims to develop a qualitative forecasting model for application, matriculation and enrollment stages. A quantitative analysis analyzed the data pattern of last 15 periods and developed a forecasting model using Exponential Smoothing method. The analysis verified the accuracy of the model using three techniques – MAD, MSE and MAPE calculation, Tracking Signal, and Control Chart. The outcomes of the Delphi analysis will be associated with the quantitative model. This study provides you the detailed information in each section for your reference. I cordially request you to provide your best judgment to predict the new student admission in the program and specify the relevant factors influencing an individual student's decision to join the program.

<u>Instructions</u>:

1. This analysis contains three sections – Application, Matriculation, and Enrollment.
2. Each section contains new student information for last 15 terms.
3. Please answer each question and make comments on relevant issues.
4. For further information please contact:

   Sultanul Nahian Hasnat; Email – snhasnat@email.uark.edu

   MSOM Program, Department of Industrial Engineering.

Personal Information:

Name	
Designation	
Program	
Department	
College	
Email	

<u>Application</u>:

The application data set is as follows –

Table 1

Termwise Application Data Set

Term	1129	1133	1136	1139	1143	1146	1149	1153	1156	1159	1163	1166	1169	1173	1176
Application	284	204	109	269	216	105	272	260	139	303	205	105	257	230	122

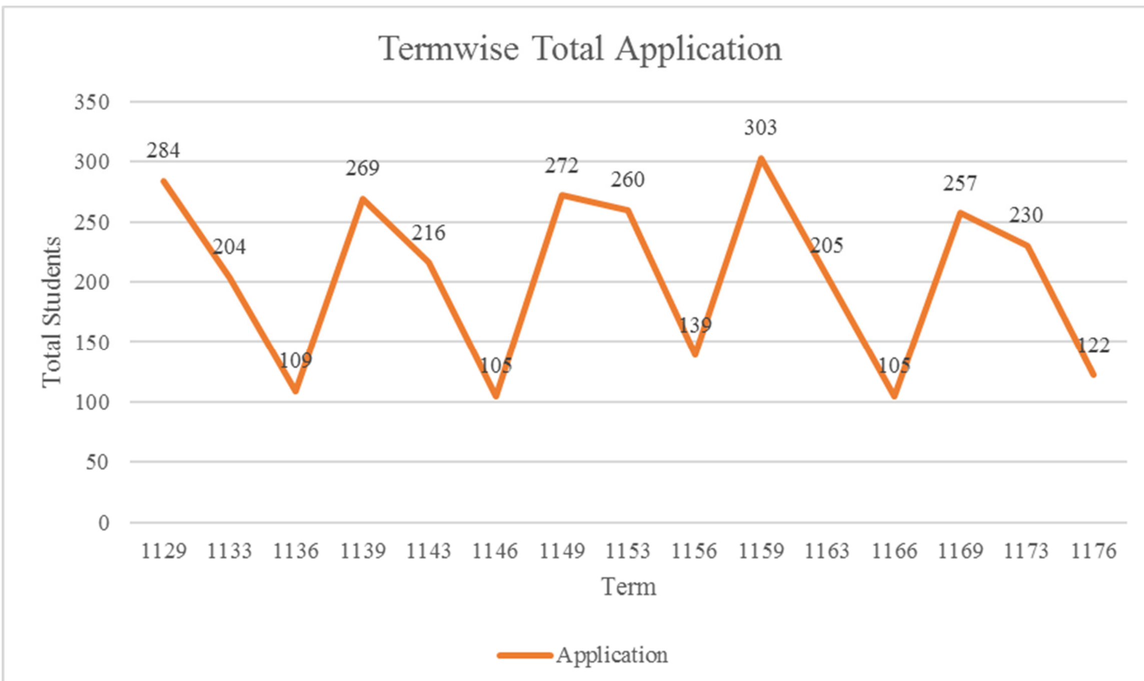

Figure 1. Application Data Set

The Table 1 shows the termwise new application information for the last 15 terms. In addition, Figure 1 provides you a graphical representation of the application data set to understand the underlying behavior of the data pattern.

Question 1:

257 new students applied for admission in MSOM program during Fall 2016 (Term - 1169).

How many new students will you forecast for Fall 2017?	
How many new students AT LEAST will you forecast for Fall 2017?	
How many new students AT MOST will you forecast for Fall 2017?	

Please explain your answers

Question 2:

What factors do you think influence the application numbers?

Matriculation:

The matriculation data set is as follows –

Table 2

Termwise Matriculation Data Set

Term	1129	1133	1136	1139	1143	1146	1149	1153	1156	1159	1163	1166	1169	1173	1176
Matriculation	193	135	71	176	143	55	185	157	83	176	146	58	168	146	63

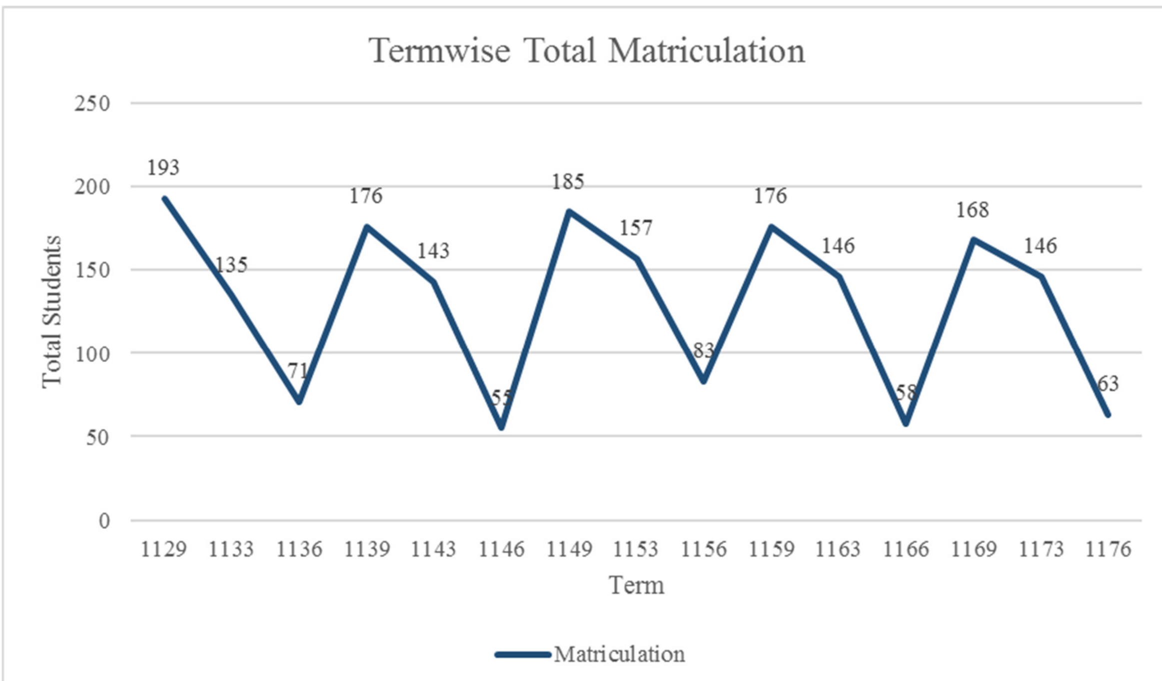

Figure 2. Matriculation Data Set

The Table 2 shows the termwise new matriculation information for the last 15 terms. In addition, Figure 2 provides you a graphical representation of the matriculation data set to understand the underlying behavior of the data pattern.

Question 3:

168 new students matriculated in MSOM program during Fall 2016 (Term - 1169).

How many new students will you forecast for Fall 2017?	
How many new students AT LEAST will you forecast for Fall 2017?	
How many new students AT MOST will you forecast for Fall 2017?	

Please explain your answers

Question 4:

What factors do you think influence the matriculation numbers?

<u>Enrollment</u>:

The enrollment data set is as follows –

Table 3

Termwise Enrollment Data Set

Term	1129	1133	1136	1139	1143	1146	1149	1153	1156	1159	1163	1166	1169	1173	1176
Enrollment	161	121	62	159	124	55	165	140	70	156	130	48	140	121	45

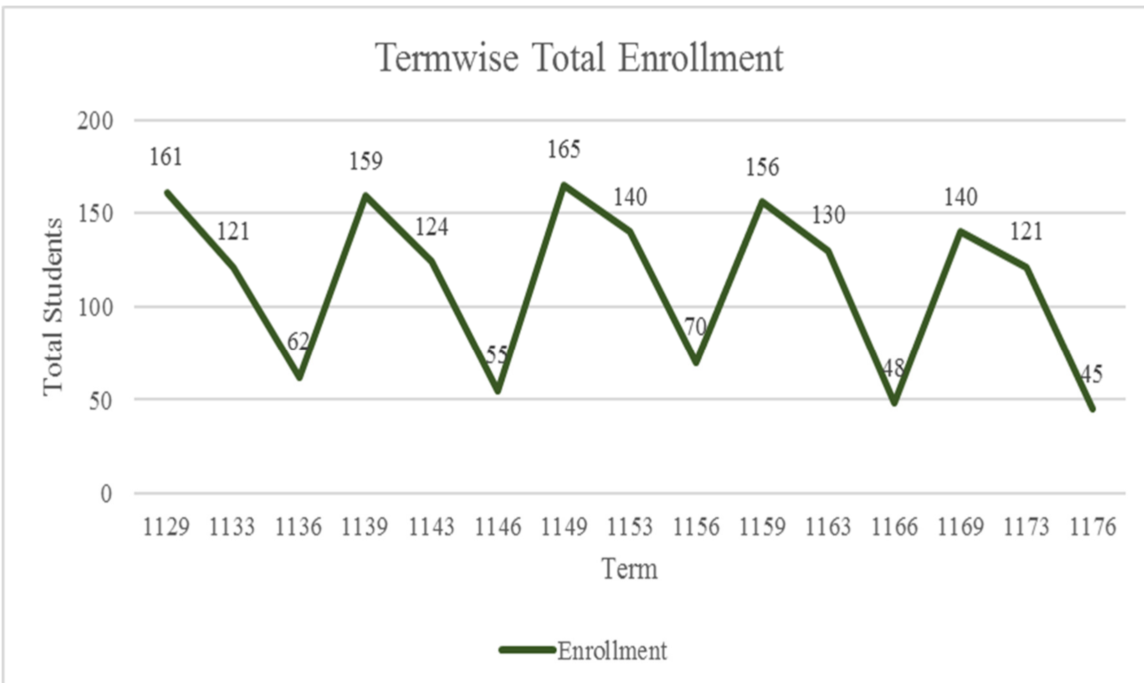

Figure 3. Enrollment Data Set

The Table 3 shows the termwise new enrollment information for the last 15 terms. In addition, Figure 3 provides you a graphical representation of the enrollment data set to understand the underlying behavior of the data pattern.

<u>Question 5</u>:

140 new students enrolled in MSOM program during Fall 2016 (Term - 1169).

How many new students will you forecast for Fall 2017?	
How many new students AT LEAST will you forecast for Fall 2017?	
How many new students AT MOST will you forecast for Fall 2017?	

Please explain your answers

<u>Question 6</u>:

What factors do you think influence the enrollment numbers?

Delphi Questionnaire 2

A Delphi Analysis to Enhance the Student Admission and Enrollment System of MSOM Program

Dear Panelist,

Thank you for participating in the Delphi Questionnaire 1 survey. I am inviting you to join the second round of the study. This study is a part of the research project to analyze the fundamental aspects and develop a forecasting model to improve the student admission and enrollment system of MSOM program. This two-round Delphi study aims to develop a qualitative forecasting model for application, matriculation and enrollment stages. A quantitative analysis analyzed the data pattern of last 15 periods and developed a forecasting model using Exponential Smoothing method. The analysis verified the accuracy of the model using three techniques – MAD, MSE and MAPE calculation, Tracking Signal, and Control Chart. The outcomes of the Delphi analysis will be associated with the quantitative model. This study provides you the detailed information in each section for your reference. I cordially request you to provide your best judgment to predict the new student admission in the program and specify the relevant factors influencing an individual student's decision to join the program.

Instructions:

5. This analysis contains three sections – Application, Matriculation, and Enrollment.
6. Each section contains new student information for last 15 terms. In addition, each segment comprises the outcome of the Delphi Questionnaire 1 survey.
7. Please answer each question and make comments on relevant issues.
8. For further information please contact:

Sultanul Nahian Hasnat; Email – snhasnat@email.uark.edu

MSOM Program, Department of Industrial Engineering.

Personal Information:

Name	
Designation	
Program	
Department	
College	
Email	

Application:

The application data set is as follows –

Table 1

Termwise Application Data Set

Term	1129	1133	1136	1139	1143	1146	1149	1153	1156	1159	1163	1166	1169	1173	1176
Application	284	204	109	269	216	105	272	260	139	303	205	105	257	230	122

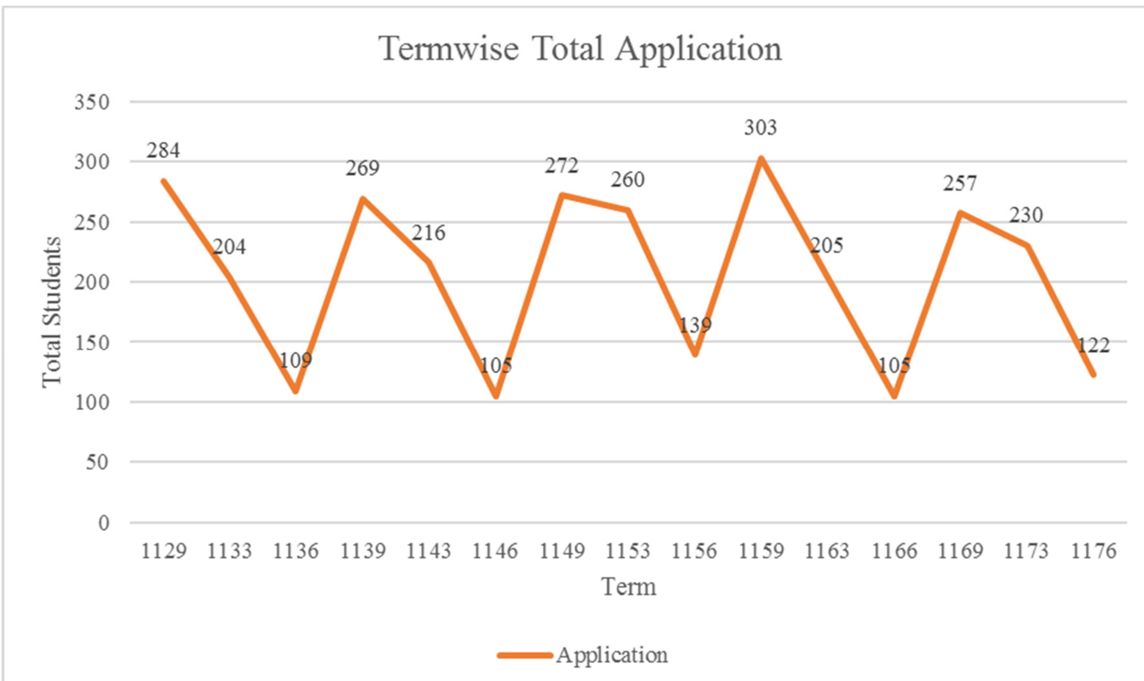

Figure 1. Application Data Set

Table 1 shows the termwise new application information for the last 15 terms. In addition, Figure 1 provides you a graphical representation of the application data set to understand the underlying behavior of the data pattern.

<u>Question 1</u>:

257 new students applied for admission in MSOM program during Fall 2016 (Term - 1169).

	Your Early Feedback	Second Panelist's Feedback	Your Final Prediction
How many new students will you forecast for Fall 2017?	250	275	
How many new students AT LEAST will you forecast for Fall 2017?	200	257	
How many new students AT MOST will you forecast for Fall 2017?	275	300	
Please explain your answers			

<u>Question 2</u>:

What factors do you think influence the application numbers?

Your Early Feedback	Second Panelist's Feedback	Your Final Prediction
• USAF is masking the promotion board results. • Increase in tuition fees. • Military deployment.	• Military funding for tuition fees. • Marketing and recruiting efforts.	

<u>Matriculation</u>:

The matriculation data set is as follows –

Table 2

Termwise Matriculation Data Set

Term	1129	1133	1136	1139	1143	1146	1149	1153	1156	1159	1163	1166	1169	1173	1176
Matriculation	193	135	71	176	143	55	185	157	83	176	146	58	168	146	63

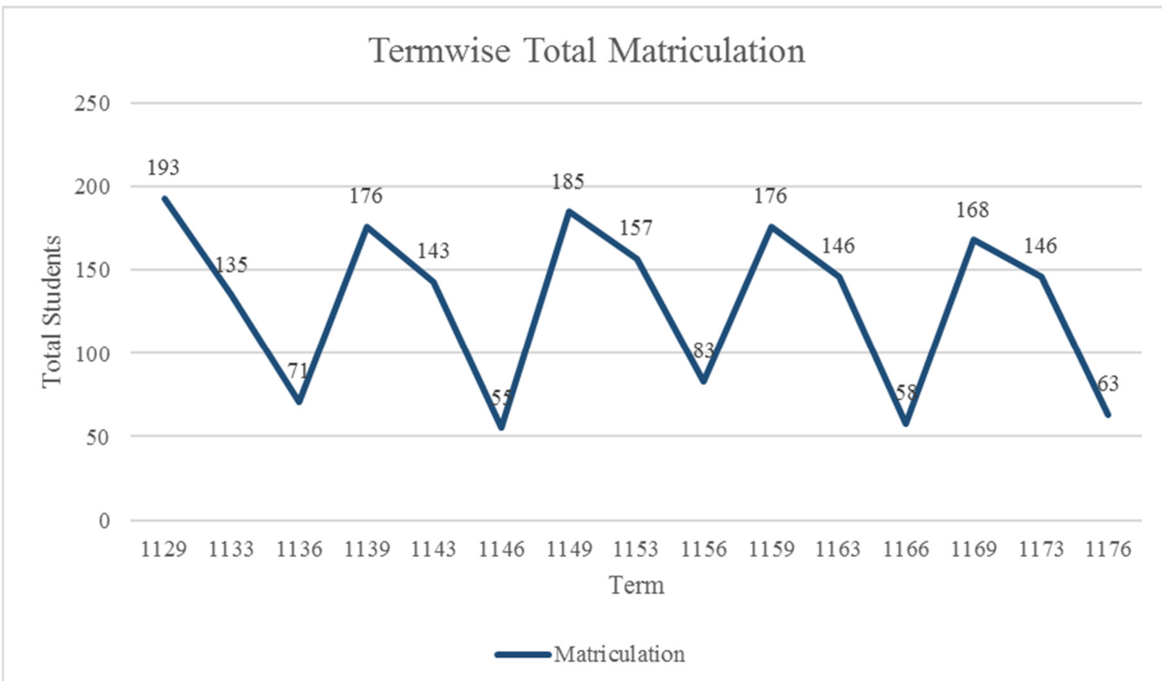

Figure 2. Matriculation Data Set

Table 2 shows the termwise new matriculation information for the last 15 terms. In addition, Figure 2 provides you a graphical representation of the matriculation data set to understand the underlying behavior of the data pattern.

<u>Question 3</u>:

168 new students matriculated in MSOM program during Fall 2016 (Term - 1169).

	Your Early Feedback	Second Panelist's Feedback	Your Final Prediction
How many new students will you forecast for Fall 2017?	170	185	
How many new students AT LEAST will you forecast for Fall 2017?	150	170	
How many new students AT MOST will you forecast for Fall 2017?	190	190	
Please explain your answers			

<u>Question 4</u>:

What factors do you think influence the matriculation numbers?

Your Early Feedback	Second Panelist's Feedback	Your Final Prediction
• Acceptance in other programs. • Increase in tuition fees.	• Student's intention and seriousness to attend the program. • Communication with the staffs/instructors.	

Enrollment:

The enrollment data set is as follows –

Table 3

Termwise Enrollment Data Set

Term	1129	1133	1136	1139	1143	1146	1149	1153	1156	1159	1163	1166	1169	1173	1176
Enrollment	161	121	62	159	124	55	165	140	70	156	130	48	140	121	45

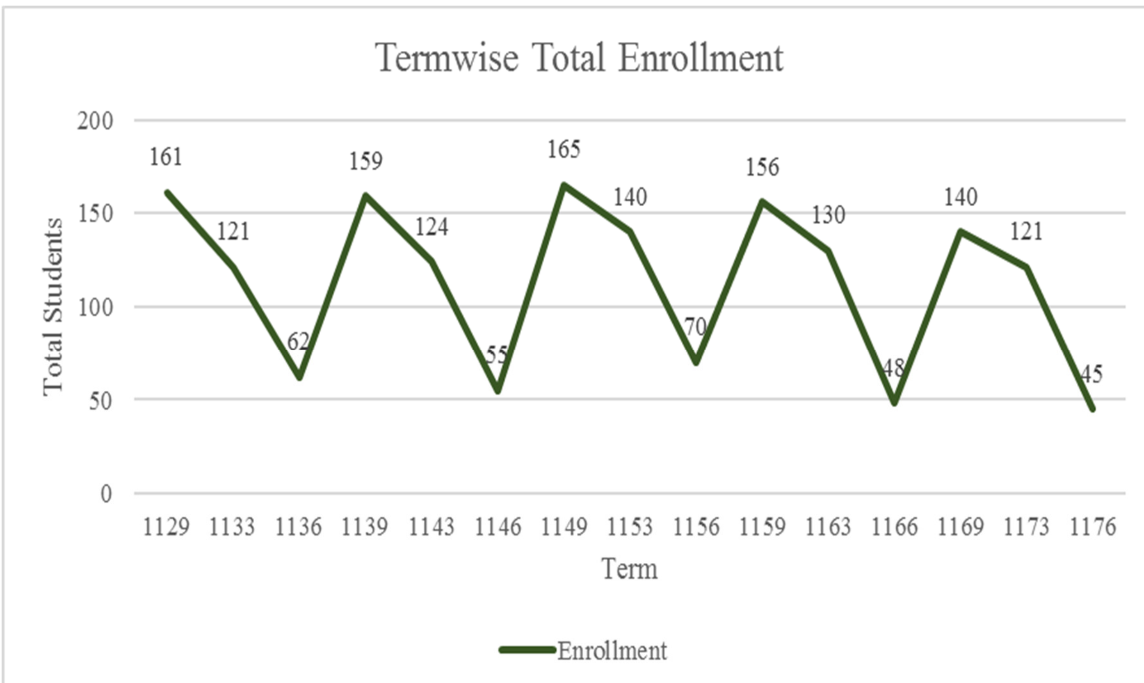

Figure 3. Enrollment Data Set

Table 3 shows the termwise new enrollment information for the last 15 terms. In addition, Figure 3 provides you a graphical representation of the enrollment data set to understand the underlying behavior of the data pattern.

<u>Question 5</u>:

140 new students enrolled in MSOM program during Fall 2016 (Term - 1169).

	Your Early Feedback	Second Panelist's Feedback	Your Final Prediction
How many new students will you forecast for Fall 2017?	125	165	
How many new students AT LEAST will you forecast for Fall 2017?	110	140	
How many new students AT MOST will you forecast for Fall 2017?	150	175	
Please explain your answers			

<u>Question 6</u>:

What factors do you think influence the enrollment numbers?

Your Early Feedback	Second Panelist's Feedback	Your Final Prediction
• Increase in tuition fees. • Economic development. • Issues with the 8-week term. • USAF is masking the degree data.	• Access to tuition funding (tuition assistance from the employer, financial aid).	

Figure 12. R code for pruned classification tree Figure 8

```
# Research Project
# Sultanul Nahian Hasnat
# MSOM Program
# University of Arkansas

setwd("C:/Users/Sultanul/Documents/MSOM Semesters/Summer 8 Week 1_2017/Introduction to Data
Analytics/R Statistical Package/R Data File")
getwd()

oly <- read.csv("Decision Tree Analysis.csv")

# Naive Classification

summary(oly$Enrolled)
table(oly$Enrolled)

# Classification Tree

library(caret)
set.seed(55)
sam <- createDataPartition(oly$Enrolled, p = 0.7, list = FALSE)
train <- oly[sam, ]
test <- oly[-sam, ]

library(rpart)
oly.tree <- rpart(Enrolled ~ Gender + Military_Status + Birth_Year + Ethnic_Group + State + Country +
SP_500_Prices,
              data = oly, control = rpart.control(minbucket = 7, cp = 0))

library(rpart.plot)
prp(oly.tree, type = 2, extra = 104,
   nn = TRUE, fallen.leaves = TRUE,
   faclen = 4, varlen = 8,
   shadow.col = "gray")

oly.tree

# Error Matrix

pred.train <- predict(oly.tree, train, type="class")
table(train$Enrolled, pred.train, dnn = c("Actual", "Predicted"))

pred.test <- predict(oly.tree, test, type="class")
table(test$Enrolled, pred.test, dnn = c("Actual", "Predicted"))

plotcp(oly.tree)

# Pruned Tree

oly.pruned <- prune(oly.tree, 0.0031)
prp(oly.pruned, type = 2, extra = 104,
   nn = TRUE, fallen.leaves = TRUE,
   faclen = 4, varlen = 8,
   shadow.col = "gray")

oly.pruned
```

Figure 13. cp chart for pruned classification tree Figure 8

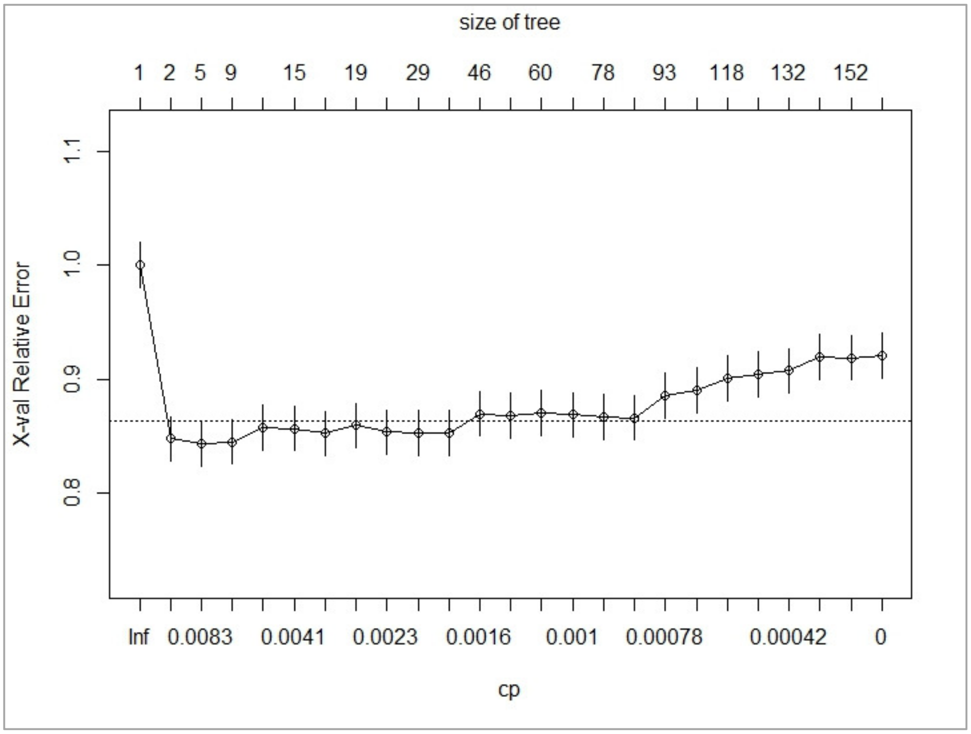

Table 26. New student dropout in Matriculation stage Figure 9

Term	Application	Matriculation	Application	Dropout in Matriculation
1129	284	193	100%	32.04%
1133	204	135	100%	33.82%
1136	109	71	100%	34.86%
1139	269	176	100%	34.57%
1143	216	143	100%	33.80%
1146	105	55	100%	47.62%
1149	272	185	100%	31.99%
1153	260	157	100%	39.62%
1156	139	83	100%	40.29%
1159	303	176	100%	41.91%
1163	205	146	100%	28.78%
1166	105	58	100%	44.76%
1169	257	168	100%	34.63%
1173	230	146	100%	36.52%
1176	122	63	100%	48.36%
Average				**38%**

Table 27. New student dropout in enrollment stage Figure 10

Term	Matriculation	Enrollment	Matriculation	Dropout in Enrollment
1129	193	161	100%	17%
1133	135	121	100%	10%
1136	71	62	100%	13%
1139	176	159	100%	10%
1143	143	124	100%	13%
1146	55	55	100%	0%
1149	185	165	100%	11%
1153	157	140	100%	11%
1156	83	70	100%	16%
1159	176	156	100%	11%
1163	146	130	100%	11%
1166	58	48	100%	17%
1169	168	140	100%	17%
1173	146	121	100%	17%
1176	63	45	100%	29%
Average				**13%**

Table 28. Enrollment distribution Figure 11

Matriculating Term	Matriculation	Enrollment	Didn't Enroll	Enrollment Term															
				1129	1133	1136	1139	1143	1146	1149	1153	1156	1159	1163	1166	1169	1173	1176	1179
1129	193	161	32	56	26	9	23	15	8	8	4	1	5	1	2	3			
1133	135	121	14		37	12	18	17	3	10	10	4	1	3	0	2	3	0	1
1136	71	62	9			10	19	10	3	9	3	1	0	3	0	2	2	0	0
1139	176	159	17				47	38	11	15	17	7	9	6	1	4	4	0	0
1143	143	124	19					39	9	19	16	9	13	6	2	4	3	2	2
1146	55	55	0						15	15	6	4	2	9	1	0	2	0	1
1149	185	165	20							65	29	5	20	14	5	15	6	3	3
1153	157	140	17								56	13	16	16	2	12	13	1	11
1156	83	70	13									21	13	12	3	2	9	0	9
1159	176	156	20										68	27	7	23	7	4	20
1163	146	130	16											60	12	19	16	5	18
1166	58	48	10												10	18	7	6	7
1169	168	140	28													55	32	11	42
1173	146	121	25														64	11	46
1176	63	45	18															20	25