Markov Chain Analysis of Student Learning Progression in a Quarter Academic System

Jhon Lawrence G. Quimio, Anthony A. Sanchez,
Kianna Denise C. Villapando, Rene D. Estember
School of Industrial Engineering and Engineering Management
Mapúa University
Manila, Philippines
jlgquimio@mymail.mapua.edu.ph, aasanchez@mymail.mapua.edu.ph,
kdcvillapando@mymail.mapua.edu.ph, rdestember@mapua.edu.ph

Abstract

In the field of education, student learning progression is structured as a hierarchical organization, wherein lower grade levels are set to proceed to higher levels as their knowledge advances. However, their progression is stochastic in nature due to various reasons such as difficulty and number of units of courses. With this, the present study aims to develop a Markov Model to examine the flow of Industrial engineering students in a quarter system. The data used in this research were the enrolled subjects of Industrial engineering students of admission batch 2019 from the first term of their first year up to the third term of the second year, as well as their marks for the said courses. This scenario was modeled as an Absorbing Markov Chain. In the analysis, it was determined that if a student starts his first term in the university, it is expected that he spends an average of 15.5574 terms in the span of the seven terms. Also, if a student starts his first term, there is 29.40% chance that he withdraws and 70.59% that he proceeds. If he starts in the second term, there is 24.99% chance of withdrawing and 75.00% chance of progressing. For the remaining states, the chance of eventually reaching the fourth term of the second year is 100%. Lastly, based on their responses, their failure in courses was mostly due to problems like learning environment and lack of motivation, while they take lesser courses per term due to difficulties in handling multiple courses.

Keywords
Markov Analysis, Markov Chain, Student Progress

1. Introduction
1.1 Background
In the field of education, student learning progression is organized by educational levels depending on the student's intellectual capabilities. Learning institutions are structured as a hierarchical organization, wherein lower grade levels are set to proceed to higher levels as their knowledge continues to advance (Brezavscek et al., 2017). As such, universities set that they evaluate the chance that one student would stay at a given level, move up to another level, drop out, or graduate. This process allows differentiation among learners and would allow them to have and be given the knowledge for them accordingly. However, due to several reasons, the chance of progressing from one level to another, up to the chances of graduating, is uncertain and could be random (Corner, 1993); for instance, Alawadhi and Konsova (2010) stated that college students stay longer in their courses due to the difficulty and the large credit unit in their programs. Also, other factors such as changes in the learning environment could influence student progress (Crossen, 2017). Because these reasons are inevitable and uncontrollable, having no strategic plans with regards to the educational system results in many delayed and dismissed students. (Adam, 2015). Hence, it is important for institutions to study and assess their student's progress.

Student learning progression is indeed uncertain due to various reasons (Corner, 1993). Especially for undergraduates, the possibilities of progressing from one level to another, up to the chances of graduating, are more prone to be erratic due to the increased difficulty and number of credit units compared to the preceding levels (Alawadhi and Konsova, 2010). Due to this, the behavior of the situation could be characterized as stochastic, whereas the chances of progressing and graduating has a random distribution.

Granted this scenario, the researchers have decided to model the problem by utilizing Markov Analysis - an algebraic approach used to analyze stochastic processes through determining expected means for the number of hitting times as well as their equilibrium distributions (Pfannkuch & Budget, 2016). Mainly, it is a method used to estimate the value of the variables whose predicted value is obtained through its present state. Simply stated, Markov Analysis establishes a framework to model decision making (Durand et al., 2011). The said approach would be utilized by the researchers in determining how students under the School of Industrial Engineering and Engineering Management in Mapua University progress in learning by having a quarter system implemented.

1.2 Gap of Missing Information

Previous studies had utilized Markov analysis in the study of student learning. Also, several reviews and related literature have already applied the said tool in analyzing student performance and progress. However, it was observed that these research articles mainly focused on student progress only on a yearly basis. There remains paucity in research papers which were centered on a detailed analysis of student progress, such as looking into a per term or semestral basis.

1.3 Objectives

The general objective of this study is to develop a Markov Model to examine the performance of Industrial Engineering students on a quarter system from the first quarter of their stay up to their third term of their second year. Specifically, this research aims to determine the average number of terms the students under the School of Industrial Engineering and Engineering Management will stay in each term before transitioning to absorbing states. It also aims to determine the probability of a student being absorbed to either withdrawal from the program or progression to second year fourth term. Lastly, this research investigates the factors that affect the progression of students enrolled in different year levels.

1.4 Significance of the Study

This study will contribute mostly to the institution in a way that it will provide information or details that are relevant and will help in assessing the effectiveness of the setup that they are in; this study will help improve the system of learning, since this could be helpful for schools such that they will be able to design an effective educational policy

1.5 Scope and Limitations

This study will only focus on the students of Mapua University, School of Industrial Engineering in Intramuros, Manila. In addition, the present study would be getting the data from only one batch: Batch 2019–2020. Furthermore, this study focuses on the first, second, third, and fourth terms of the academic year 2019-2020 and first, second, and third terms of academic year 2020-2021.

2. Literature Review

2.1 Student Progress

2.1.1 Student Progress between Levels

Educational institutions are designed as a hierarchical organization wherein students either stay at a given level or transfer from a higher one depending on their capabilities and performance; however, due to several reasons, the chances of progressing from one level to another, up to the chances of graduating, could be random (Brezavscek, 2017). Indeed, student performance is influenced by several factors (Hlavaty & Domeova, 2014). For instance, in a study by Alawadhi and Konsova (2010), the difficulty of courses, as well as the large number of credit units, cause students to stay longer in their courses. Also, factors such as the university, student motivation, and student disposition greatly affect completion of programs (Mapuranga, 2015).

Aside from this, the emergence of the virtual learning environment could be a factor in the uncertainty concerning the learning progression of students (Baziukaite, 2004). In addition, in a study by Crossen (2017), it is evident that for a variety of causes, many students' performance inadequacies are vividly detected and actualized at the university level; transitioning from a home-reporting educational context to an autonomous setting, a lack of a sympathetic support structure, or a variety of behavioral situations that accentuate hidden academic weaknesses are all possible factors. As these aforementioned factors could be unavoidable and uncontrollable, having no strategic plans with regards to the educational system results in many delayed and dismissed students. (Adam, 2015).

2.1.2 Student Withdrawal

In addition to the problems regarding the delay of students, a study by Gorbunova (2019) stated that course withdrawals due to academic failure are also prevalent. Withdrawal poses significant consequences for both students and the institutions (Bernardo et al., 2017). Hence, dropping out of a university program has a serious effect not only for the student who quits, but also for the institution where the withdrawal happens. As a result of this phenomena, higher education institutions must conduct more in-depth research on why such things happen in order to develop effective prevention strategies in the future to lessen this kind of problem (Bernardo et al, 2017). That is why it is critical for universities and institutions to assess student progress, since by doing so, if students proceed from one year level to the next, the rate of withdrawal lowers and the rate of graduation rises (Muhammed et al., 2019).

2.2 Markov Analysis Application in Student Progress

The scenario presented in this study possesses stochastic characteristics that make them suitable for modeling with Markov Analysis, since students don't always transfer between years of study in a predictable manner (Corner, 1993). In the study of Durand et al. (2011), it is stated that Markov decision processes are commonly utilized to investigate a wide range of optimization problems such as the student advancement from various courses; it is a tool that is appropriate for modeling decision-making.

Markov Analysis has been used in the past to analyze student growth or progress. Hlavaty et al. (2014), for example, used the tool to create a model of how students progressed during the course using a semestral system and the Markov chain approach. On the basis of assessments, he calculated the likelihood of success at the end of the course in the study. Furthermore, the use of Markov Models to anticipate enrollment awarded is not new (Jayarathma and Chamara, 2012). Lastly, in the study of Khamparia et al. (2019), the tool was used to analyze and improve learner performance based on psychological and environmental aspects.

3. Methods

3.1 Conceptual Framework

Throughout the study, the researchers were guided by the following conceptual framework. Figure 1 represents the graphical representation of the Markov Chain Model that forms the outcome of the study. The numbers 1 to 7 are the states that a student can go through to pass a certain term, while the P_{11}, P_{12}, P_{22}, P_{23}, P_{33}, P_{34}, P_{44}, P_{45}, P_{55}, P_{56}, P_{66}, P_{67}, and P_{77} indicates the probability of moving from and to the specified states. On the other hand, P_{1W}, P_{2W}, P_{3W}, P_{4W}, P_{5W}, P_{6W}, and P_{7W} are the probabilities that a student will withdraw from their program. Lastly, P_{7P} is the probability that a student will pass the certain term and become on time. The states P, which denotes passed, and W, which denotes withdrawal, are considered as absorbing states.

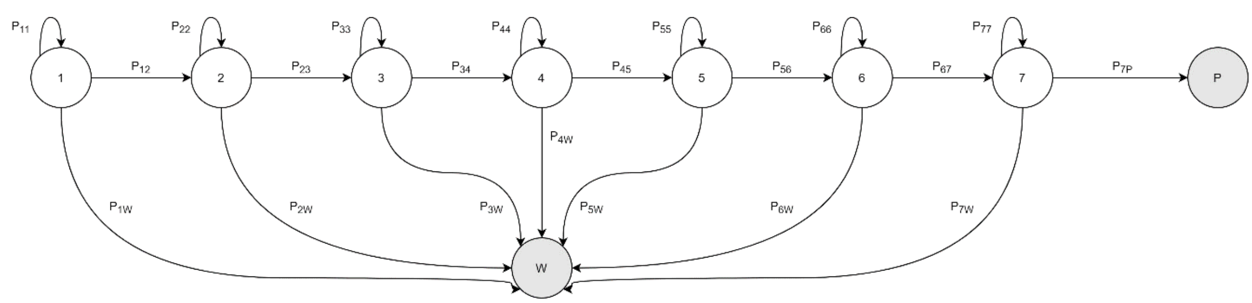

Figure 1. Conceptual Framework

3.2 Analysis and Evaluation Procedure

3.2.1 Tools for Analysis

In the present study, an absorbing Markov Chain was applied in the analysis of student progression in a quarter system. Mainly, this approach helped the researchers determine the expected number of terms a student stays in each term before progressing to the next state. The equation for the fundamental matrix is shown in equation 1.

$$\mathbf{F} = [\mathbf{I} - \mathbf{N}]^{-1} \quad \text{(Equation 1)}$$

In the said equation, N represents the non-absorbing matrix, while I denotes the identity matrix with the same size as N. Furthermore, to determine the probability that a student withdraws from the course at any given term, Equation 2 establishes the matrix, where A is the absorbing matrix.

$$\mathbf{B = FA} \quad \text{(Equation 2)}$$

3.3.2 Model for Markov Analysis

The university where the present research took place currently implements a quarter system. Every academic year consists of four terms with 11 weeks each. Since the main concern in the study is the transition of the students from each term, the states used for the analysis are the following:

S_1 = student is enrolled in first term of the first year
S_2 = student is enrolled in second term of the first year
S_3 = student is enrolled in third term of the first year
S_4 = student is enrolled in fourth term of the first year
S_5 = student is enrolled in first term of the second year
S_6 = student is enrolled in second term of the second year
S_7 = student is enrolled in third term of the second year
S_P = student is on time and is able to take the fourth term of the second year
S_W = student has withdrawn from the program

4. Data Collection

The data used in this research were obtained from the survey responses of Mapua University Industrial Engineering students, batch 2019–2020. A total of 40 out of 60 respondents, or about 66.67% of the population, were obtained. For the sampling technique, purposive non-probability sampling technique was utilized; the researchers have only targeted the specific students involved as they are the population of concern for the present study.

With regards to the questionnaire, the first part had collected the demographic profiling of the students. The second part, on the other hand, had asked the students regarding their enrolled subjects from the first term of their first year up to the third term of the current year, as well as their marks for the said courses. Meanwhile, the third part contained questions about the possible reasons for failure and underload of the Industrial engineering students. The said questionnaire was distributed online.

5. Results and Discussion

5.1 Presentation of Results

Primarily, before applying the Markov Analysis, the data collected from the survey were summarized based on the frequency distribution of the students who were on time, were not on time, and had permanently withdrawn from the course. In the present study, only the data from the first term of the first year up to the third term of the second year were obtained. This is since the respondents were mainly the Industrial engineering students of batch 2019 and they were approximately just on their second year during the period of the study. The results are shown in Table 1.

Table 1. Frequency Distribution of the Progression of IE Students

Term	% On Time	% Not on Time	% Withdrawn	Total
Year 1 Term 1	32	6	2	40
Year 1 Term 2	6	30	2	38
Year 1 Term 3	6	30	0	36
Year 1 Term 4	16	20	0	36
Year 2 Term 1	19	17	0	36
Year 2 Term 2	19	17	0	36
Year 2 Term 3	18	18	0	36

From the frequency distribution table, the percentage of students who have successfully progressed from a given term onto the next term was calculated. The results in Table 2 were then used as a reference to estimate the values for the transition probability matrix. To explain the behavior of the numbers of on time and delayed students, there was a sudden increase in regular students during the first year fourth term because during that time, the university had given opportunities for failed students to take courses with prerequisites. However, during the second year, there was a decrease in regular students from second term to third term because the school had started implementing a can pass, can fail policy.

Table 2. Percentage Distribution of the Progression of IE Students

Term	On Time	Not on Time	Withdrawn	Total
Year 1 Term 1	80.00%	15.00%	5.00%	100.00%
Year 1 Term 2	15.79%	78.95%	5.26%	100.00%
Year 1 Term 3	16.67%	83.33%	0.00%	100.00%
Year 1 Term 4	44.44%	55.56%	0.00%	100.00%
Year 2 Term 1	52.78%	47.22%	0.00%	100.00%
Year 2 Term 2	52.78%	47.22%	0.00%	100.00%
Year 2 Term 3	50.00%	50.00%	0.00%	100.00%

Consequently, Table 3 shows the values for the transition probability matrix based on the percentage distribution of student progression obtained in Table 2. In addition, the variables represent the states, wherein states S_1, S_2, S_3, S_4, S_5, S_6, and S_7 implies first year first term, first year second term, first year third term, first year fourth term, second year first term, second year second term, and second year third term, respectively.

Meanwhile, S_W, which denotes withdrawn, and S_P, which denotes on time and being able to take the next term, are considered as absorbing states such that permanent withdrawal from the program as well as the official progression of students to the fourth term will not enable the students to move between the other states. Because there is an absorbing state in the study, the researchers have also partitioned the matrix into identity, null, absorbing, and non-absorbing matrices.

Table 3. Transition Probability Matrix

From/To	S_W	S_P	S_1	S_2	S_3	S_4	S_5	S_6	S_7
S_W	1	0	0	0	0	0	0	0	0
S_P	0	1	0	0	0	0	0	0	0
S_1	0.0500	0	0.1500	0.8000	0	0	0	0	0
S_2	0.0526	0	0	0.7895	0.1579	0	0	0	0
S_3	0	0	0	0	0.8333	0.1667	0	0	0
S_4	0	0	0	0	0	0.5556	0.4444	0	0
S_5	0	0	0	0	0	0	0.4722	0.5278	0
S_6	0	0	0	0	0	0	0	0.4722	0.5278
S_7	0	0.5000	0	0	0	0	0	0	0.5000

$$N = \begin{bmatrix} 0.1500 & 0.8000 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.7895 & 0.1579 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.8333 & 0.1667 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.5556 & 0.4444 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.4722 & 0.5278 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.4722 & 0.5000 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0.5000 \end{bmatrix}$$

Figure 1. Non-absorbing Matrix

$$F = \begin{array}{c} \\ S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \\ S_7 \end{array} \begin{bmatrix} S_1 & S_2 & S_3 & S_4 & S_5 & S_6 & S_7 \\ 1.1765 & 4.4706 & 4.2353 & 1.5882 & 1.3375 & 1.3375 & 1.4118 \\ 0 & 4.7500 & 4.5000 & 1.6875 & 1.4211 & 1.4211 & 1.5000 \\ 0 & 0 & 6.0000 & 2.2500 & 1.8947 & 1.8947 & 2.0000 \\ 0 & 0 & 0 & 2.2500 & 1.8947 & 1.8947 & 2.0000 \\ 0 & 0 & 0 & 0 & 1.8947 & 1.8947 & 2.0000 \\ 0 & 0 & 0 & 0 & 0 & 1.8947 & 2.0000 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2.0000 \end{bmatrix}$$

Figure 2. Fundamental Matrix

Since there is an absorbing state established in the study, it is important to determine both the fundamental and conditional matrices. First, the non-absorbing matrix is needed for determining the fundamental matrix. Then, based on equation 2, the said matrix was subtracted from the identity matrix with the same size. After then, the inverse of the resulting matrix was computed. Figure 2 shows the non-absorbing matrix, while Figure 3 represents the final fundamental matrix.

Upon adding the elements per row, the expected time before a student is absorbed by the absorbing states given that he or she starts in a given state is shown in Table 4.

Table 4. Expected Duration for the States

Starting State	Expected Terms before Absorption
S_1	15.5574
S_2	15.2797
S_3	14.0394
S_4	8.0394
S_5	5.7894
S_6	3.8947
S_7	2.0000

After establishing the fundamental matrix, these were multiplied by the absorbing matrix. The resulting matrix then represents the conditional probabilities of moving from non-absorbing states to the absorbing state. Figure 4 shows the results of the analysis.

$$B = \begin{array}{c} \\ S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \\ S_7 \end{array} \begin{bmatrix} S_W & S_P \\ 0.2940 & 0.7059 \\ 0.2499 & 0.7500 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \end{bmatrix}$$

Figure 3. Conditional Probability Matrix

5.2 Discussion of Results

The Markov Analysis model had established both the fundamental and conditional probability matrices. Basically, each of the elements from the fundamental matrix indicates the expected number of terms a student is enrolled in a given term. For instance, if a student is currently enrolled in his first term during his first year in the university, it is expected that he spends 1.1765 terms for first year first term, 4.4706 terms for first year second term, 4.2353 terms for first year third term, 1.5882 terms for first year fourth term, 1.3375 terms for second year first term, 1.3375 terms for second year second term, and 1.4118 terms for second year third term. Adding these values would give 15.5574 terms. The sum denotes the expected number of terms before a student is absorbed into an absorbing state such as withdrawal or the eligibility to enroll onto the next term.

With regards to the conditional probability matrix, it was shown that if a student starts in S1, there is 29.40% chance that he withdraws and 70.59% that he proceeds. If he starts in S2, there is 24.99% chance of withdrawing and 75.00% chance of progressing. For the remaining states, the chances of eventually passing and transitioning to the fourth term of the second year is 100%.

Although the withdrawal rate is seen mostly on the first and second terms only, and that the chances of eventually progressing to the fourth term of the second year is 100 percent, it is observed that for a span of seven terms, the expected duration for an average student is about 15.5574 terms. With this, an average students would definitely be delayed.

Given this scenario, the present study had also looked into the problems encountered by the students which results in either failure or underload of the students. The following table shows the specified problems that each student faces in undertaking courses on a quarter term basis. The gathered data represents various reasons why students fail in a certain term and cause a delay in taking the next courses, as the subjects have a pre-requisite system. This data was obtained in the questions included in the survey deployed by the researchers. Overall, there were 40 respondents from the School of Industrial Engineering and Engineering Management, and this specific part of the survey had allowed multiple responses.

Table 5. Reasons for Student's Failure in Subjects

Reasons for the student's failure in subjects	Responses	Total Respondents	% Responses
Problems with Learning Environment	21	40	52.50%
Difficulties in Handling Multiple Courses	21	40	52.50%
Lack of Motivation and Commitment to Study	21	40	52.50%
Problems with Time Management	17	40	42.50%
Health Problems	6	40	15.00%
Other: Students are not encouraged by the professors	1	40	2.50%

Table 5 shows the reasons for the respondent failure in the subjects, it is depicted that majority of the students encounter Problems with learning environments, difficulties in handling multiple courses, and lack of motivation and commitment to study, having the same percentages of 52.50% each. Next is having problems with time management having 42.50%, then health problems obtaining 15%, and for the open-ended statement, one of the respondents answered that students are not encouraged by the professors – having a percentage of 2.50%. These reasons can be a factor which affects the student performance and productivity, and these results in a poor standing and failure in subjects. This then causes delays in the student's curriculum. To support the statement according to Raychaudhuri et al., (2010), numerous studies have been done to identify those who have shown factors that are affecting student's academic performance. The student's academic performance depends on several socio-economic factors like students' attendance in the class, learning environment, family income, mother's and father's education, teacher-student ratio, presence of a trained teacher in school, sex of the student, commitment of learners, and the time management.

Table 6. Reasons for Not Taking Full Load

Reasons for not taking full load	Response	Total Respondents	% Responses
Difficulties in Handling Multiple Courses	16	40	40.00%
Problems with Time Management	14	40	35.00%
Lack of Motivation and Commitment to Study	12	40	30.00%
Problems with Learning Environment	11	40	25.50%
Health Problems	1	40	2.50%
Other: Financial Problem	1	40	2.50%
Other: Hard to indulge all lessons together	1	40	2.50%

On the other hand, Table 6 shows the reasons of the respondents for not taking full load with their courses. The results showed that a lot of the respondents were having difficulties in handling multiple courses which is why they tend to lessen their course load, this can be a factor for them to be delayed since they aren't taking the recommended course load for the specific term. Problems with time management became the second highest reason. While health problems, financial problem, and hard to indulge all lessons together had the least response among the respondents.

6. Conclusion

In essence, the goal of the study which is to develop Markov Model to examine the flow of college students based on their performance on a quarter system was successfully accomplished. Firstly, the researchers have determined the average number of terms of the students under the School of Industrial Engineering and Engineering Management have stayed in a term: if a student starts his first year first term in the university, it is expected that he spends 1.1765 terms for first year first term, 4.4706 terms for first year second term, 4.2353 terms for first year third term, 1.5882 terms for first year fourth term, 1.3375 terms for second year first term, 1.3375 terms for second year second term, and 1.4118 terms for second year third term. Over the course of seven terms, the average student's projected length is about 15.5574 terms.

Second, in determining the probability of a student being absorbed by either of the two absorbing states, it was shown that if a student starts in S1, there is a 29.40% chance that he withdraws and 70.59% that he proceeds. If he starts in S2, there is a 24.99% chance of withdrawing and a 75.00% chance of progressing. For the remaining states, the chances of eventually passing and transitioning to the fourth term of the second year are 100%.

Lastly, the researchers had determined the factors and variables that affect the progression of the students. The failure of students was mostly due to problems with learning environments, difficulties in handling multiple courses, and lack of motivation and commitment to study. Some students also tend to take lesser courses per term mainly due to difficulties in handling multiple courses.

With that being said, transitioning from the starting level to the next level would be difficult for college students as the level of difficulty of courses may vary over time. Nevertheless, schools/universities should create an optimal plan to assist the students to progress accordingly, as the institution will be no worth without its student as the students are the most essential asset for any educational institution to survive.

Based on the methodology applied in this study, it is recommended for future researchers to use this in analyzing a wider scope of student population. For instance, in studying the whole population of college students in a given program. It is also recommended that the future researchers also take into consideration other variables such as the inactive or on leave status of students.

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Biographies

Jhon Lawrence G. Quimio at present is taking his undergraduate degree major in Industrial Engineering. He is also a member of the Philippine Institute of Industrial Engineers - Mapua University Student Chapter (PIIE-MUSC).

Anthony A. Sanchez is currently enrolled as a second-year college student at Mapua University, School of Industrial Engineering and Engineering Management, Intramuros, Manila. He is taking up Bachelor of Science in Industrial Engineering. His research interests include ergonomics, accounting, and engineering management.

Kianna Denise C. Villapando is currently enrolled as a second-year college student at Mapua University, School of Industrial Engineering and Engineering Management, Intramuros, Manila. She is taking up Bachelor of Science in Industrial Engineering. She is currently the Vice President of Internal Affairs of Philippine Institute of Industrial Engineers – Mapua University Student Chapter, as well as a member of Honor Society of Mapua. Her research interests include ergonomics, statistics, and quality management.

Rene D. Estember is a Professor in the School of Industrial Engineering and Engineering Management at the Mapua University in Manila City, Philippines. He earned his B.S. in Management and Industrial Engineering from Mapua Institute of Technology, Master's in Business Administration from Ateneo de Manila University, Master of Science in Industrial Engineering from the University of the Philippines, and finishing his Doctorate in Business Administration from the Pamantasan ng Lungsod ng Maynila (PLM), all located in the Philippines. He is presently undertaking consultancy work on quality management systems documentation and also involved as a regular resource speaker of a training company conducting technical trainings. His research interests include human factor and ergonomics, manufacturing, risk management and optimization