PREPARING SYSTEMS ENGINEERING AND COMPUTING SCIENCE STUDENTS IN DISCIPLINED METHODS, QUANTITATIVE, AND ADVANCED STATISTICAL TECHNIQUES TO IMPROVE PROCESS PERFORMANCE

BY

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DISSERTATION

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Abstract

The research was prompted by a need to conduct a study that assesses process improvement, quality management and analytical techniques taught to students in U.S. colleges and universities undergraduate and graduate systems engineering and the computing science discipline (e.g., software engineering, computer science, and information technology) degree programs during their academic training that can be applied to quantitatively manage processes for performance.

Everyone involved in executing repeatable processes in the software and systems development lifecycle processes needs to become familiar with the concepts of *quantitative management, statistical thinking, process improvement methods* and how they relate to process-performance. Organizations are starting to embrace the *de facto* Software Engineering Institute (SEI) Capability Maturity Model Integration (CMMI®) Models as process improvement frameworks to improve business processes performance. High maturity process areas in the CMMI model imply the use of analytical, statistical, quantitative management techniques, and process performance modeling to identify and eliminate sources of variation, continually improve process-performance; reduce cost and predict future outcomes.

The research study identifies and provides a detail discussion of the gap analysis findings of process improvement and quantitative analysis techniques taught in U.S. universities systems engineering and computing science degree programs, gaps that exist in the literature, and a comparison analysis which identifies the gaps that exist between the SEI's "*healthy ingredients*" of a process performance model and courses taught in U.S. universities degree program. The research also heightens awareness that academicians have conducted little research on applicable statistics and quantitative techniques that can be used to demonstrate high maturity as implied in the CMMI models.

The research also includes a Monte Carlo simulation optimization model and dashboard that demonstrates the use of statistical methods, statistical process control, sensitivity analysis, quantitative and optimization techniques to establish a baseline and predict future customer satisfaction index scores (outcomes). The American Customer Satisfaction Index (ACSI) model and industry benchmarks were used as a framework for the simulation model.

Dedication

I dedicate this research to my parents Wilmon Sr. and Mary McCray, siblings Patricia Heard, Derek Smith, Brenda McCray Nobles, Carol McCray Singleton, Schenita McCray, Geneva McCray, Pamela Hill, Anthony Sr., Chevelle McCray-Ward, Lynnise McCray, my nephews, nieces, relatives, friends, and colleagues.

Wise Saying (Proverbs 23:22-25 Good News Translation)

Listen to your father; without him you would not exist. When your mother is old, show her your appreciation. Truth, wisdom, learning, and good sense—these are worth paying for, but too valuable for you to sell. A righteous person's parents have good reason to be happy. You can take pride in a wise child. Let your father and mother be proud of you; give your mother that happiness.

The Conclusion of the Matter (Ecclesiastes 12:12-13 Good News Translation)

My child, there is something else to watch out for. There is no end to the writing of books, and too much study will wear you out. After all this, there is only one thing to say: Have reverence for God, and obey his commands, because this is all that we were created for. God is going to judge everything we do, whether good or bad, even things done in secret. "Life is useless, all useless. You spend your life working, laboring, and what do you have to show for it?" Ecclesiastes 1:3

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First and for most, I thank God for giving me wisdom, knowledge, and the opportunity over several decades to develop expertise in diverse engineering disciplines. It is through God's grace, at this appointed time in my life, I was able to complete the dissertation and contribute to the body of knowledge in software engineering, systems engineering, computer science, information technology, and customer satisfaction research.

The dissertation process took a long time to complete over the years and I would like to express my deepest appreciation to the people that were steadfast, very supportive, and believed in me. I would never have been able to finish my dissertation without the guidance of my committee members, encouragement from mentors and friends, and support from family members.

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I would also like to thank Dr. Donna Rhodes of Massachusetts Institute of Technology Engineering Systems Division. Dr. Rhodes was the original Chair of my dissertation committee. She inspired me to conduct research in systems engineering and pursue a doctoral degree.

I have several mentors to thank. I would like especially thank Dr. Leslie Lander, not only was Dr. Lander the Faculty Advisor on my committee, he has been my mentor for numerous years and have provided me with guidance, encouragement, and insight. Dr. Lander is very supportive and I credit him for cultivating my passion for software engineering. I am grateful to have Dr. Larry G. Mills as a mentor. Dr. Mills has provided me with professional career guidance at Lockheed Martin Corporation and spiritual support at Mt. Sinai Baptist Church. I would like to acknowledge and thank Software Engineering Directors Mrs. Ann Marie Bunts and Mrs. Donna Blake (deceased) of Lockheed Martin Systems Integration Owego. I would also like to thank Mr. John Vogel, Director of Enterprise Excellence, Mr. Edward Fontenot, Manager of Process Management, Mr. Warren Schwomeyer, Ms. Valerie Gundrum, and other members on the 2001 – 2009 Process Management Team at Lockheed Martin Systems Integration Division, Owego, NY.

I began developing my expertise in software and systems engineering improvement models while working at Lockheed Martin Systems Integration with Mr. Warren Schwomeyer. We co-authored a journal article (Schwomeyer et al., 2002) that described our CMMI transition experience from the software capability maturity model (CMM) to the capability maturity model integration (CMMI).

I would like to thank my best friends Mr. Larnell "Cisco" Graves, Dr. Donald Johnson, and Dr. Yolanda Carson for their support and words of encouragement. I give a special thank you to my cousin Mrs. Bernice Guimond and Mr. James Reid for the encouraging and kind words they often share.

I would like to extend a very special thank you to Mrs. Janice Kinzer, Information Specialist, EngiNet™, Binghamton University, Thomas J. Watson School of Engineering and Applied Science. Janice always reminded me that the secret to getting ahead is getting started. She encouraged me to never give up on my pursuit to achieve the doctoral degree in spite of the personal challenges I faced during the journey. Janice has become a "go to person" for students who seek advice to solve problems. Her companionate, caring, and warm spirit has enriched my learning experience.

Finally, I would like to thank my mother, siblings, nephews, nieces, cousins and other family members for their support.

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List of Abbreviations

Abbreviation	Definition
ABET	The Accreditation Board of Engineering and Technology
ACM	The Education Board of the Association for Computing
ACSI	The American Customer Satisfaction Index
AHP	Analytical Hierarchy Process
AITP	Association of Information Technology Processionals
ANCOVA	Analysis of Covariance
ANOVA	Analysis of Variance
ASAC	Applied Science Accreditation Commission
ASQ	American Society for Quality
c	c Chart
CAC	Computing Accreditation Commission
CL	Capability Level
CLT	Central Limit Theorem
CMF	CMMI Model Foundation
CMM	Capability Maturity Models
CMMI	Capability Maturity Model Integration
CMMI-ACQ	CMMI for Acquisition
CMMI-DEV	CMMI for Development
CMMI-SVC	CMMI for Services
COBIT	Control Objectives for Information and Related Technology
CS	Computer Science
CSI	Customer Satisfaction Index /Indices
CSS	Customer Satisfaction Survey
EAC	Engineering Accreditation Commission
ETVX	Entry-Task-Validation-Exit
Expcty	Customer Expectancy
GE	General Electric Company
GP	Generic Practice
GSwERC	Graduate Software Engineering Reference Curriculum
GUI	Graphical User Interface
HML	High Maturity Level
i.i.d.	Identical Independent Distributions (Homoscedasticity / Homogenous Data Sets)

Abbreviation	Definition
ImR	Individual Moving Range
INCOSE	International Council of Systems Engineering
ISE	Industrial and Systems Engineering
ISO	International Organization for Standardization
IT	Information Technology
ITIL	Information Technology Infrastructure Library
LC	Lifecycle Models
MANNOVA	Multivariate Analysis of Variance
MSCHE	Middle States Commission on Higher Education
ML	Maturity Level
NESC/CIHE	New England Association of Schools and Colleges Commission on Institutions of Higher Education
n.i.i.d	Non-Normal Independent and Identically Distributed Distributions (Heteroscedasticity /Heterogonous Data Sets)
NC/HLC	North Central Association of Colleges and Schools The Higher Learning Commission
NWCCU	Northwest Commission on Colleges and Universities
np	np Chart
OCSI	Overall Customer Satisfaction Index
p	p Chart
PA	Process Areas
PAT	Part Average Testing
Perf	Ideal Performance
PG	Process Governance
PPQA	Product and Process Quality Assurance
QMS	Quality Management Systems
RABQSA	Registrar Accreditation Board and Quality Society of Australasia
RD	Requirements Development
SACSCOC	Southern Association of Colleges and Schools Commission on Colleges
Sat	Customer Satisfaction
SCAMPI	Standard CMMI Appraisal Method for Process Improvement
SDLC	Software and Systems Development Lifecycle
SE	Systems Engineering
SEI	Software Engineering Institute
SLT	Senior Leadership Team
SOCSI	Simulated Overall Customer Satisfaction Index
SP	Specific Practice
SPC	Statistical Process Control

Abbreviation	**Definition**
SW	Software Engineering
SWEBOK	Software Engineering Body of Knowledge
u	u Chart
WASC	WASC Senior College and University Commission
XmR	Individual Moving Range

Introduction

The business landscape is constantly changing in the new economy in two primary ways, namely, companies are competing for business in a competitive global marketplace, and customers' demands for unique products or services are increasing. Advances in technology are creating a demand for systems and software integrators that can respond rapidly to changing market demands, and can horizontally integrate enterprise processes across difference business units. Product lifecycles are getting shorter, product development teams are decentralized, and companies are no longer the single solution provider on large-scale projects. In other words, there is a marked trend in moving away from single-source providers to systems integrators of software-intense systems. Managing the acquisition process to acquire subsystems and software-intense components has often suffered from poor product quality, cost overruns, and schedule slips.

Companies are faced with an increased competition for experienced personnel and well-defined organizational processes that can be measured and continuously improved via process improvement initiatives or benchmarked against recognized industry process improvement standards in order to achieve successful product and process delivery and expected business performance outcomes. Recognized industry standards such as, Capability Maturity Model Integration (CMMI®), International Organization for

Standardization (ISO) standards, Information Technology Infrastructure Library (ITIL), Control Objectives for Information and related Technology COBIT, etc.

Everyone in the organization involved in following processes to create customer unique value needs to become familiar with the concepts of "Statistical Thinking" and how they relate to the concepts of "Process Management" and "Process-Performance".

Chapter 1: Research Overview

This chapter provides an overview and background discussion of the research purpose.

1.1 Background

In today's competitive environment, systems integrators and software developers are being challenged to develop and improve integrated "not stove-piped", agile, flexible, repeatable and measurable business processes that can be used by practitioners to deliver customer-unique and perceived value (e.g., customer satisfaction). Managing the performance of enterprise business processes and other intangible core competencies such as intellectual capital (skilled and knowledge workforce of practitioners) are becoming a central issue in America today to successfully compete in globally competitive markets. Optimizing processes that are agile and innovative depends on the participation of an empowered workforce aligned with the business values and objectives of the organization.

The organization's ability to respond to changes and opportunities is enhanced by finding ways to accelerate and share learning. Improvement of the processes is inherently part of everybody's role, resulting in a cycle of continual improvement. Enterprise business processes and sub-processes must be well understood by practitioners. Knowing when to tailor (modify) work products or decouple business processes is essential. Cross-trained and empowered practitioners are vital assets in such a demanding environment. When business processes are not compliant, stable or in control—generally not performing well, it is difficult for even the best practitioners to perform well using the process.

As the twenty-first century unfolds, more and more organizations involved in the development and acquisition of systems and software-intense products and services are starting to adopt recognized industry process improvement standards support from *green belts, black belts, and statisticians* in an effort to improve quality and reduce cost. Organizations are starting to embrace the Software Engineering Institute (SEI). Capability maturity models (CMMs) and other process improvement models to focus their attention on measuring business processes for performance using analytical, statistical, and quantitative management techniques to identify and eliminate sources of variation and continually improve process-performance. Enterprise business processes are repeated (hopefully, in a systematic way) in every company on a daily basis by people performing the process to create customer-unique value.

1.2 **Problem Description**

One of the most perplexing problems facing practitioners involved in continual process improvement, or process management, is determining the applicable analytical techniques to apply to analyze measured process-performance data from various types of distributions. Unlike most continuous manufacturing processes, engineering, transactional, and other business processes where people are involved often yield non-normally distributed data sets that sometime contain a high degree of variability. CMMI trained appraisers, system engineers or software engineer practitioners are generally not familiar with analytical, quantitative management, or statistical data analysis techniques that can be applied to analyze process variation or measure the performance effectiveness or efficiency of a sub-process.

Many practitioners not familiar with the theoretical principles of statistical process control (SPC) chart techniques are using 2σ control limits and other unorthodox methods to trigger action due to assignable cause of process variation (Paulk and Chrissis, 2002). The use of 2σ control limits to manage process variation is not a good practice. Besides SPC methods, other techniques exist that can also be used to examine process variation. Junior practitioners on projects are often assigned the responsibility to manage and report the project's measurement data with no training in measurements or SPC. Some organizations that are familiar with SPC are using improper control charts to plot and manage non-normally distributed data sets.

Most software and systems engineering curricula do not offer academic training focused on measuring the software or systems engineering process for improvement. In fact, there is not a lot of literature available on measuring the systems and software engineering process. Panel members on the 1996 Committee on Applied and Theoretical Statistics Board on Mathematics Science National Research Council concluded, during their discussion, there is a need for collaboration between systems / software engineers and statisticians. Systems and software engineers need to develop an understanding of what statisticians can and cannot do; conversely, statisticians will need to develop an understanding of the life cycle processes. Participants that attended the March 2008 CMMI High Maturity Measurement and Analysis Workshop (Stoddard et al., 2008) shared a similar concern, "…statistical experts lacked sufficient domain knowledge and created models that had little value to the organizations and projects". There has not been much academic research performed in this area, apparently, because the problems have not been perceived as being significant or addressed by the academic community. Offering academic training courses that focus on applying the applicable statistical techniques to the systems and software engineering process will provide significant training to future systems and software engineers.

In most statistical process control textbooks, the logical sequence of events to stabilize a process is as follows: (1) identify and remove "assignable cause of process variation" anomalies, (2) perform "root cause analysis" to prevent the anomaly from recurring, and (3) re-establish control limits that contain only inherent common causes of process variation.

A study can be conducted, if it is cost effective, to optimize (specifically, minimize) process variation assuming assignable causes have been removed from the process. The CMMI high maturity level 4 and 5 process areas and generic practices do not follow a methodical sequence. The current CMMI definition and approach to optimizing a process is misleading – the intent is correct; however, the high maturity model components are not. Chapter 2 provides an overview on the CMMI models, process areas, and maturity levels.

1.3 Research Objectives

The objective of this research is to assess the body of knowledge in process improvement, quality management, data analysis, and advanced quantitative and analytical techniques students in systems engineering and the computing science disciplines receive during their academic training that can be applied to analyze and quantitatively manage processes for performance. To demonstrate the use of advanced quantitative / analytical techniques to predict future outcomes of customer satisfaction survey indices.

The research will focus on identifying applicable quantitative, exploratory data analysis, visualization, and statistical techniques that can be used to analyze and manage process variation in a systems engineering, software engineering, or support business processes that yield non-normally distributed distributions.

To apply statistical thinking to a process, the reader will first be provided with a definition of a process and what is being inferred to as “Statistical Thinking” to help the reader understand measured data can be collected from the process (e.g., simple or complex) every time it is executed. Often, when a person thinks of measuring a process for performance, the first notion that comes to mind is to use traditional Shewhart SPC charts applicable for homogenous data sets (e.g., Gaussians distributions). Manufacturing processes are repetitive, repeatable, and are traditionally monitored using traditional Shewhart SPC techniques to monitor, manage, and analyze variable and attribute data sets from continuous manufacturing processes. These processes are homogenous in nature and can be characterized as identical independent distributions (i.i.d.). Non-manufacturing processes are repeatable and can be measured using quantitative and statistical techniques to monitor process performance, as well. Most non-manufacturing processes yield data sets that can be characterized as non-normal and non-i.i.d.

Simply restated, the research objective is to educate the systems and software engineering community in the use of visualization techniques, exploratory data analysis techniques, other analytical techniques, and statistical approaches that can be used to analyze, monitor, and optimize process-performance of the software and systems engineering product development process(es).

The research will address the following questions of interest:

- Do academic programs in the U.S. in software engineering, systems engineering, computer science, and information technology programs provide formal training in quantitative, analytical, or statistical analysis principles and methods centered on process improvement to students during their academic studies?
- Which statistical techniques can be apply in meaningful ways to stabilize and optimize the software engineering, systems engineering, and support processes?
- Which analytical techniques can practitioners use to analyze, monitor, control, and improve process variation?

- Can practitioners use Shewhart statistical process control (SPC) charts to manage and control process variation? If so, which types of control charts are applicable?
- What analytical techniques can be applied to analyze, monitor and improve Customer Satisfaction Survey data sets?
- Can advanced SPC techniques be used to measure process-performance? If so, which advanced techniques?
- Can bivariate and other multivariate techniques be applied to software and systems engineering process data sets?
- Can off-line statistical techniques be used to model and optimize process-performance? If so, which techniques (e.g., capability analysis, design of experiment, response surface design, central composite design, discrete event Monte Carlo simulation, inferential statistical techniques, Taguchi's techniques, etc.) are applicable?

1.4 Significance of Research

Increase awareness of the importance to provide college students in systems engineering and the computing science discipline with exposure to statistical thinking, quality management concepts, and advanced quantitative / analytical techniques that can be applied to optimize a business process for performance. Includes the demonstration of a simulation model and use of statistical process control (SPC) to stabilize and predict future outcomes of customer satisfaction survey indices.

Green belt, master black belt, and other metrics practitioners not familiar with the use of various statistical, quantitative and analytical techniques to analyze non-normal data sets will be able to use the techniques included in this research as a framework.

The research will also increase awareness in academia amongst faculty responsible for developing degree programs (e.g., software engineering, systems engineering, computer science, and information technology) of the need to include quality management courses in their curricula that focus on the quality management of software and systems engineering product and process. A quality management course that places emphasis on the use of quantitative analysis, statistics, and predicative modeling methodologies and techniques.

In industry, most projects yield small sets of *heterogeneous* process data. It is important to industry to have practitioners on the team that have an understanding of process measurements, quality management, and the systems development lifecycle processes. Quantitative, analytical, and statistical analysis is becoming an important skill for systems and software engineering practitioners. Systems and software engineers face new challenges in the twenty-first century (Muhammad, July 2006) and their roles are being constantly redefined.

1.5 Overview of Dissertation Chapters

This section provides the reader with an overview of the content contained in Chapters 2 -5, which briefly describes the published literature, research methodology, research results, limitations, and recommended future research.

Chapter 2 contains the literature review, notable academic research, and sets the context of this research. The chapter provides a brief description of the CMMI history, model foundation, and process areas. The focus of this research centers on the CMMI "high maturity" process areas (Level 4 & 5) and the challenges organizations have establishing analytical techniques and predicative models to stabilize and optimize process-performance. The chapter provides the definition of a process and describes the typical lifecycle phases of a systems and software engineering process. The chapter provides a brief overview on the data analysis approach. The chapter also examines the type of quantitative, statistical, and analytical techniques systems engineering, computer science, and information technology (IT) students tend to receive during their academic development.

Chapter 3 presents the research methodologies and analytical techniques that will be used in the research.

Chapter 4 contains the gap analysis results from conducting an assessment of the body of knowledge of process improvement and quantitative / analytical techniques practitioners need to know. Also includes a simulation model and demonstrated use of SPC to stabilize and predict future outcomes of customer satisfaction survey indices.

The chapter also includes a review of academic degree programs in the U.S. in systems engineering, software engineering, computer science, and information technology that includes required and electives courses that prepares the students with basic knowledge in quantitative analysis methodologies and techniques that can perhaps be applied to analyze a process for improvement.

Chapter 5 contains a summary of the dissertation, limitation, and recommendations for future research.

Chapter 2: Literature Review

Chapter 2 provides the reader with an overview of the literature that formed the basis of this study.

2.1 Literature

Extensive literature research was conducted to develop the research basis and provide the reader with insight on industry recognized process improvement models that are used to assess / evaluate the systems and software engineering business processes, applicable academic and industry research, and challenges facing practitioners involved in process improvement activities. The literature review points out a common theme; little academic or scholarly research has been conducted to address the research questions.

Everyone involved in executing repeatable processes in the software and systems development lifecycle (SDLC), or also referred to as software development lifecycle process needs to become familiar with the concepts of Quantitative Management, Statistical Thinking, Quality Management, Process Improvement techniques, and how they relate to process-performance. Practitioners should also have an understanding of customer expectations and satisfaction.

Process improvement model frameworks such as the CMMI (Capability Maturity Model for Integration) and ISO (International Organization for Standardization), "imply the use of analytical and quantitative management techniques to identify and eliminate sources of variation, reduce cost, and continually improve process-performance. Often, practitioners involved in performing metrics / measurement analysis are not trained in advanced applicable quantitative, statistical, or analytical techniques that can be used to analyze non-normal data sets" (McCray and Santos, 2009).

Most software engineering, systems engineering, computer science, and information technology curricula do not offer academic training focused on measuring the SDLC for improvement. Knowledge of how to apply the applicable quantitative and statistical techniques to manage the software and systems engineering processes is becoming increasingly important (McCray and Santos, 2009).

Briefly described below is an overview of each section in this chapter:

Section 2.2 provides a synopsis of the notable published academic research in which simulation and statistical techniques have been applied to predict software engineering processes.

Section 2.3 provides an overview of the CMMI history, CMMI model foundation , CMMI process areas, capability and maturity levels, and an understanding of high maturity Level 4 (quantitatively managed) and Level 5 (optimizing process) areas.

Section 2.4 provides general definitions of a process and emphasizes the importance of a process infrastructure, governance, and quality assurance approach to process improvement. In general, all organizations have a myriad of business processes. An overview of the SDLC models and processes are also included in this section.

Section 2.5 outlines the tenets and principles of statistical thinking and variation control, a view of measurement scales and data types, enumerative study versus an analytic study, and non-normal data.

Section 2.6 provides a brief discussion on variation analysis, approaches to exam data, non-normal data, and outliers; data visualization techniques, and fitting empirical data to useful probability distributions. This section also contains an analysis which shows how the CMMI models overtime has de-emphasized and placed less emphasis on the well-known terminology used for decades to describe process variation.

Section 2.7 provides insight on the lack of process improvement training in the systems engineering and computing science disciplines in courses from U.S. colleges and universities. The section also provides a discussion on issues regarding lean six sigma and black belt training programs.

Section 2.8 provides a discussion on prediction modeling and the use of modeling and simulation of the systems and software engineering processes.

2.2 Notable Academic Research

Researchers in academia have conducted very little research on applicable qualitative and quantitative analytical techniques that can be used to improve performance, or demonstrate high maturity as implied in the Capability Maturity Models (CMMIs) of the systems and software engineering processes. Few master's and doctoral dissertations have been published that focus on the use of applicable statistical, quantitative and optimization techniques to enable process improvement of the systems and software engineering processes and business processes, in general.

Madachy (1994) used systems dynamics simulation to explore software engineering project cost, schedule, and risk issues (i.e., cost overruns, schedule slips, etc.) to predict relative changes. Tvedt (1996) explored the use of systems dynamics simulation to evaluate the impact of process improvement on software development cycle time. Raffo (1996) demonstrated the use of modeling and simulation approaches in his dissertation to assess the impact of potential process performance changes (i.e., effort, cycle-time, and defect levels) of software engineering processes. Paulk (2005) conducted an empirical study of the software engineering process discipline in which he applied multi-regression and other statistical techniques to analyze software quality. Rogers (2006) applied discrete event simulation modeling to model small team software engineering projects from a role playing perspective to provide students with insight on how processes work and can be managed. Richard (2010) administered a survey to assess for need of a project tracking tool for six sigma projects. Biswas (2009) administered a survey to information technology (IT) managers and used randomized complete block (RCBD) design of experiment techniques to evaluate the effectiveness of outsourcing and off-shoring IT software process. Gerali (2008) explored the use of a multi-dimensional model approach using Likert Scale, Delphi technique, and the box plot to predict software quality. Earnest's (2011) research involved examining the similarity of patterns for systems engineering process tailoring and reuse and suggested that generic processes need to be sufficiently general for reuse must provide contextual instructions. A research study regarding *process tailoring and reuse* can also prove to be rather interesting if the focus was on the outcome of the process (i.e., does reuse processes deliver the same process-performance outcome?).

2.3 Capability Maturity Models

The sub-sections in 2.3, provides the reader with an overview of the history of the CMMI and other legacy systems and software engineering models. The subsequent sub-sections also provides the reader with a synopsis of the CMMI model constellation, an overview of process areas, capability and maturity levels, and an understanding of a quantitatively managed and optimizing HML process areas.

2.3.1 History of Capability Maturity Models for Process Improvement

The history of capability maturity models for software and systems engineering process improvement models began in the early 1990s, as illustrated in Figure 2.1, Humphrey Watts, Ron Radice, and others at the Software Engineering Institute (SEI) are acknowledged (CMMI Product Team, 2006; Chrissis, Konrad, and Shrum, 2006) for developing the Capability Maturity Model for Software Engineering (also known as

CMM and SW-CMMs) to assess / evaluate software engineering processes for improvement. Watts Humphrey adopted and applied the Quality Management Maturity Grid (QMMG) and quality management philosophies established by Philip Crosby (1979) as a basis to develop the Process Maturity Framework (Humphrey, 1989)—a precursor to the Capability Maturity Model (SW-CMM), other legacy discipline-specific process models, and the CMMI models. The QMMG and SW-CMM models both have five (5) levels of maturity.

From 2006 – 2009, as illustrated in Figure 2.1, the SEI released three (3) CMMI models, version 1.2 (SEI Models & Reports): CMMI for Development (CMMI-DEV), CMMI for Acquisition (CMMI-ACQ), and CMMI for Services (CMMI-SVC). The SEI revised and released the 3 models as version 1.3 in November 2010. According to the CMMI Product team (CMMI/SEI-2010-TR-033, 2010), the CMMI models were updated to make them consistent and provide more clarity to improve the high maturity practices.

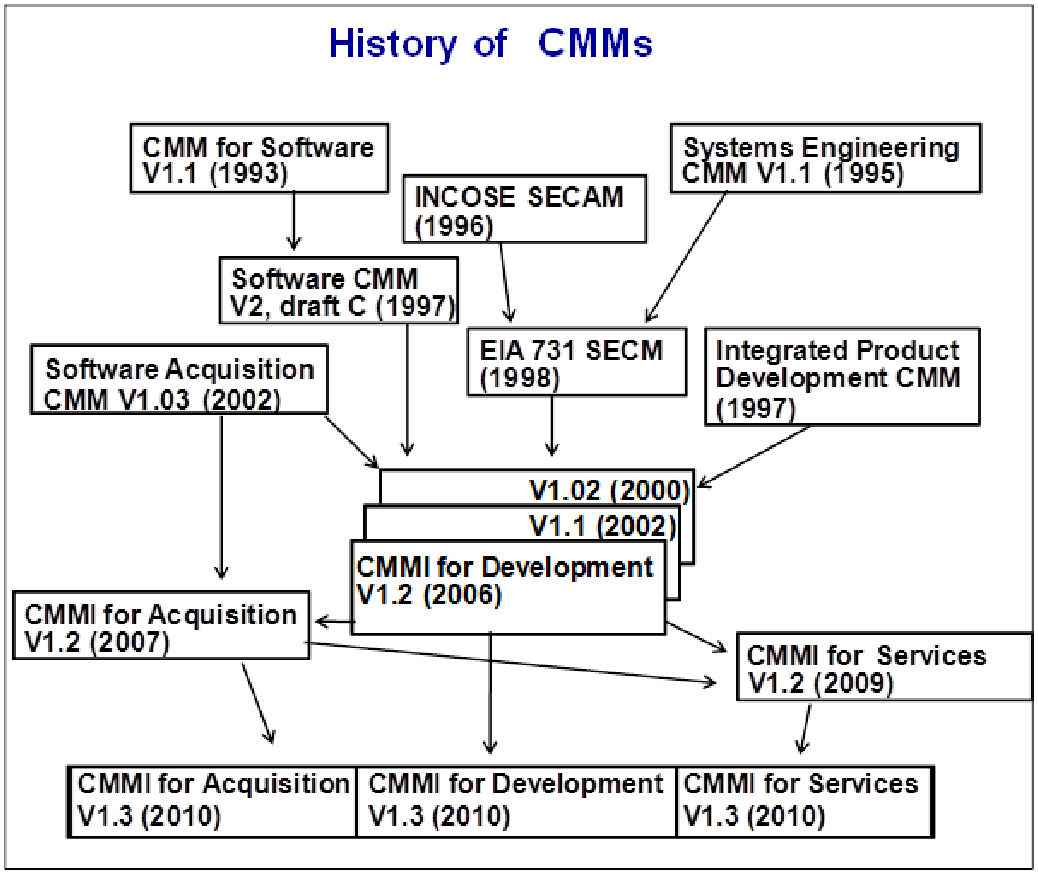


Figure 2.1: The History of CMMs

Source: CMMI-DEV, v1.3, (p.13)

An organization pursuing enterprise-wide process improvement can use the model(s) to conduct a gap analysis, identify best practices, appraise its organizational maturity or process area capability, establish priorities for process improvement, and guidance to implement process improvement initiatives.

2.3.2 CMMI Models, Process Areas, & Maturity Levels

Sections 2.3.2.1 -2.3.4 provide the reader with an overview of the CMMI models, the model foundation, process areas, capability levels (CL) and maturity levels (ML), and a brief discussion of high MLs.

2.3.2.1 CMMI Models

The SEI describes the CMMI models as a process improvement approach that provides organizations with the essential elements of effective processes. CMMI models consist of a collection of best practices that help organizations to benchmark, evaluate, and develop a systemic approach to establish strategies to guide process improvement initiatives across a project, a division, or an entire organization. There are three CMMI models:

- CMMI for Development (CMMI-DEV)
- CMMI for Services (CMMI-SVC)
- CMMI for Acquisition (CMMI-ACQ)

The focus of this paper is on analytical and quantitative techniques taught in college courses that enable process improvement at the HMLs. Readers that are interested in learning about the CMMI models can obtain a copy of the particular model from the SEI's website (http://www.sei.cmu.edu/library/abstracts/reports/10tr033.cfm'CMMI Models and Reports').

2.3.2.2 Process Areas

The SEI (CMMI Product Team, 2006) defined a process area, "…as a cluster of related practices in an area that, when implemented collectively, satisfies a set of goals considered important for making improvement in that area". Process areas are evaluated to determine process institutionalization—how well the process is ingrained within an organization. Process institutionalization is an important concept in process improvement (CMMI Product Team, 2006)

As shown in the depiction below, Figure 2.2, provided by Process Governance Consulting Group, LLC (McCray, 2009a), each CMMI model contains between 22 – 24 core and specific process areas. The common or core process areas to all CMMI models are part of what is termed the CMMI Model Foundation (CMF) used for process improvement. The CMF consist 16 core process areas that spans across the three CMMI models. The diagram also depicts the ML in each process area. Each process area contains generic and specific goals and practices that are assessed.

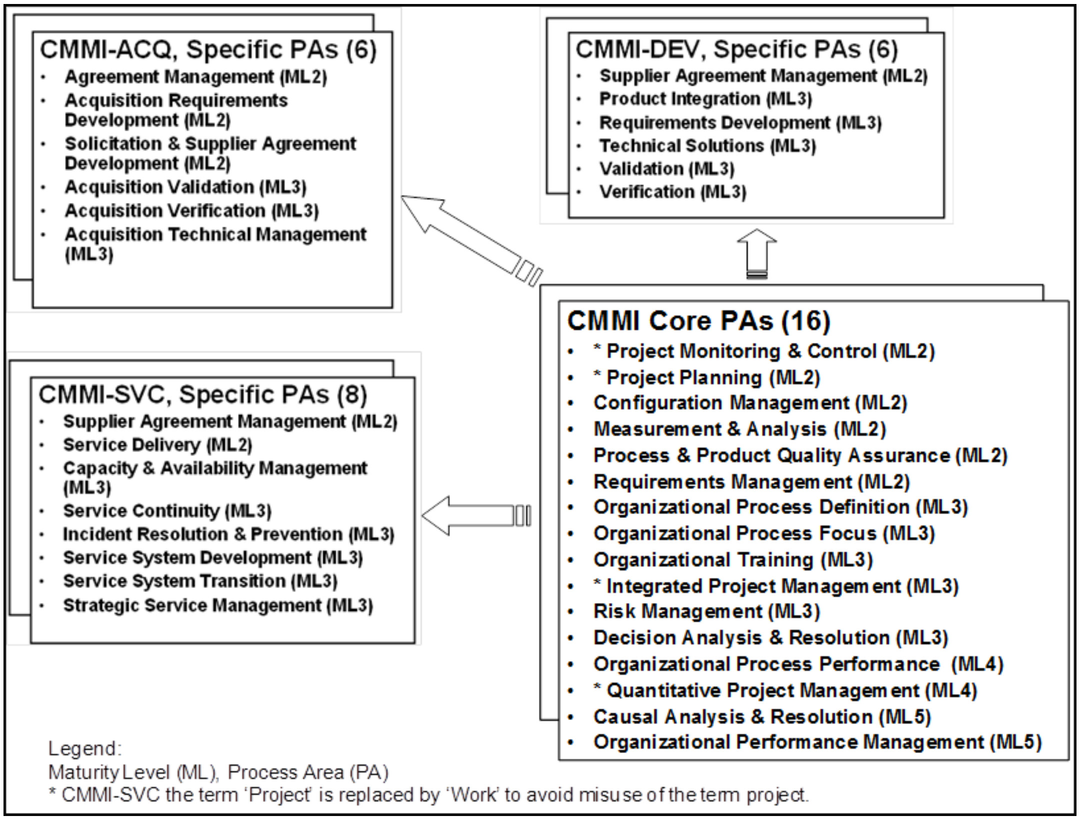


Figure 2.2: CMMI CMF, Process Areas, & Maturity Levels

2.3.3 CMMI Model Capability and Maturity Levels

As illustrated in Figure 2.3, the SEI's CMMI model structure consists of two model representations (continuous and stage representation) that organizations can use to baseline or assess their processes for improvement. Each representation uses levels to gauge an organization's process maturity. The continuous representation uses Capability Levels and the stage representation use Maturity Levels to measure the level of a process area.

In the continuous representation, there are four (4) capability levels, numbered 0-through-3 and described as incomplete, performed, managed, or defined. The stage representation uses five (5) maturity levels numbered 1-through-5 to rate a process and levels are delineated as initial, managed, defined, quantitatively managed, and optimized.

Level	Continuous Representation (Capability Levels)	Stage Representation Maturity Levels	High Maturity: Process Area	High Maturity: Generic Practice	Focus	Process Characterization
5	Optimizing	Optimizing	Causal Analysis & Resolution	**GP 5.2	Process Optimization & Continuous Process Improvement	Consistent, Effective, Efficient, Controlled
			Organizational Performance Management	**GP 5.1		
4	Quantitatively Managed	Quantitatively Managed	Quantitative Project Management	**GP 4.2	Quantitative Management (Variation reduction)	
			Organizational Process Performance	**GP 4.1		
3	Defined	Defined		GP 3.1 GP 3.2	Process Standardization (Repeatability)	Risk, Inconsistent, un-controlled
2	Managed	Managed		GP 2.1-2.10	Project Mgmt	
1	Performed	Initial		**GP 1.1	Ad hoc, chaotic	
0	Incomplete	N/A				

Note: **High maturity generic practice (GP) not applicable in the Stage Representation

Figure 2.3: CMMI Model Capability& Maturity Levels

2.3.3.1 Process Characterization of CMMI Levels

The diagram also denotes the process characterization of a high maturity process. The higher the level is rated is an indication of how well the process is ingrained (e.g., institutionalized) in the organization. Processes characterized at Level 4 and 5 are consistent, efficient, controlled, quantitatively managed and continuously improved to deliver optimal results. Lower rated processes are inconsistent, un-controlled, non-mature, and have inherent risk.

Processes characterized at level 0 are incomplete. Processes characterized at the Performed/Initial (Level 1) are as best ad hoc, chaotic, unpredictable, and poorly controlled. Managed Process (Level 2), projects ensure that processes are planned and basic infrastructure is in place to support the process. A managed process is reactive and relies on skilled people to produce the desired outputs. A Defined Process (Level 3) implies that standardize processes are well understood and described in procedures used to establish consistency. A Quantitatively Managed (Level 4) process implies that the organization and projects establishes and monitors quantitative objectives for quality and process-performance for selected sub-processes. Specific measures of process-performance are collected and statistically analyzed using predictive, quantitative, and statistical management techniques. Emphasis is placed on managing and improving the predictability of organizational performance measurements. “Performance models are used to set performance objectives for performance and to help achieve business objectives” (CMMI Product Team, 2010.). An Optimizing (Level 5) process focuses on the use of quantitative approaches to understand the variation inherent in the process and the causes of process outcomes. The focus is on continuous process improvement of the overall organizational process-performance measurement baseline(s) through incremental and innovative process technological improvements and changes. “The effects of deployed process improvements are measured using statistical and other quantitative techniques and compared to quality and process-performance objectives” (CMMI Product Team, 2010).

2.3.4 Maturity **Level 4 & 5 ‘High Maturity’ Process Areas**

The stage representation of the CMMI model has four (4) “High Maturity Process Areas”. The high maturity process areas focus on the use of statistical and quantitative techniques to analyze and improve process-performance. High maturity process areas are categorized as “Quantitatively Managed Process” and “Optimizing Process.” In the sub-sections that follow, detailed definitions and concepts of a quantitatively managed and optimizing process are given. Table 2.1 shows the high maturity categories, maturity levels, and process areas.

Table 2.1: High Maturity Process Areas

Category	Maturity Level	Process Area
Quantitatively Managed Process	ML4	Quantitative Project Management (QPM)
	ML4	Organizational Process-performance (OPP)
Optimizing Process	ML5	Causal Analysis & Resolution (CAR)
	ML5	Organizational Performance Management (OPM)

The CMMI model, just like other process improvement methods, focus on the "what" and not on "how to" apply applicable analytical techniques to monitor and improve process-performance. The research focuses on the use of analytical and quantitative management techniques that can be used to improve process-performance of repeatable engineering processes that yield non-normal data.

It is implied that processes and sub-processes rated at "ML 4 & 5" are quantitatively managed using statistical management techniques, and optimization methods, to manage process variation and improve, or optimize, process-performance. The term "statistical management" implies statistical thinking and the correct use of statistics, statistical process control, and other analytical techniques to stabilize a process or sub-process by identifying and eliminating one or more assignable causes of process variation.

2.3.4.1 Quantitatively Managed Process

In the CMMI model the term quantitatively managed process is used to describe a process that is controlled using statistical and other quantitative techniques, "The term quantitatively managed implies using appropriate statistical and other quantitative techniques to manage the performance of one or more critical sub-processes so that the performance of the process can be predicted" (CMMI Product Team, 2006). In other words, from a quality management statistical process control point-of-view, a quantitatively managed process focuses on the *voice of the process* in which appropriate analytical techniques are used to identify, stabilize, manage, control and eliminate special causes of process variation and prevent them from reoccurring.

As indicated in Section 2.3.4, Table 2.1, process areas described as Level 4 are quantitatively managed. In other words, the measured outcomes of the selected business / engineering process or sub-process is considered stable and *assignable cause of process variation* (i.e., voice of the process) is under control.

2.3.4.2 Optimizing Process

The term *optimize process* is used to describe the continuous improvement of a process. "In a process that is optimized, common causes of process variation are addressed by changing the process in a way that will shift the mean" (CMMI Product Team, 2006). It is implied that process optimization focuses on the voice of the customer and continual process improvement to achieve the optimum level of process-performance that is cost effective by implementing process changes. An optimized process focuses on continually improving process-performance by incremental and innovative technological improvements.

Processes rated at Level 5 are analyzed to continuously improve process capability by optimizing common cause of process variation (voice of the customer) to achieve the process-performance objectives of the internal or external customer.

2.4 What is a Process?

In the literature, several authors (Harrington, 1991; Oakland, 1993, Martin, 1996; Davis, 2001; Bynal and Foong, 2002) use different but similar definitions to describe the basic Input-Process-Output (IPO) process model. The definitions were synthesized to form the following explicit meaning of a process:

A process is a transformation. A process is the transformation of inputs (which can include people, tools, information, material, methods, and operations people, tools, information, procedures, and methods)—through a logical sequence of repeatable tasks, events, or interrelated activity steps—to produce a desired output in the form of a product, service, or information that meets the internal or external customer needs, expectations, and requirements.

H. James Harrington (1991) commented that, "In all companies, there are literally hundreds of business processes going on every day. Over 80 percent of them are repetitive, things we do over-and-over-again. John S. Oakland (1993) surmised that everything we do involves a process, which is the transformation of a set of inputs into the desired outputs, and in each area or function of an organization there will be many processes taking place. Quality chains can be traced through business or service processes. In every organization, there are some key, critical business-processes that must be performed especially well if the mission and objectives are to be achieved."

2.4.1 **What Is A Process Procedure?**

In all organizations, ad-hoc and well-defined *repeatable and not necessarily repetitive* business processes and sub-processes—things we do over-and-over again are executed to deliver unique product and service value to the customer. The quality of a product or service is highly dependent on a process-based approach, the quality and performance of the processes, sub-processes, and procedures used to create it.

In a narrative form, a "process-procedure" describes the process, tasks, and systematic sequential (step-by-step) activities that implements a process. Process-procedure activity outputs (e.g., information, products, services, etc.) are often referred to as deliverables.

As noted in Section 2.4, a process transforms a set of inputs or series of logically related tasks / activities into the desired outputs which defines at a high level in a graphical depiction (e.g., a process flow diagram to show the decomposition and connection between interrelated sub-processes) "What" and not "How" each task will be performed. Process Inputs and Outputs are described as nouns. As illustrated in Figure 2.4, notional process procedure diagram, a process or sub-process consists of tasks that are further decomposed into sequential procedural activity steps. Sequential activity steps, sometimes called procedures or methods, are written in the form of a verb-noun and describe the "how", "who does what activity", and the interrelationship between tasks. Section (2.4.2) titled, Process Governance includes additional attributes of a "process-procedure".

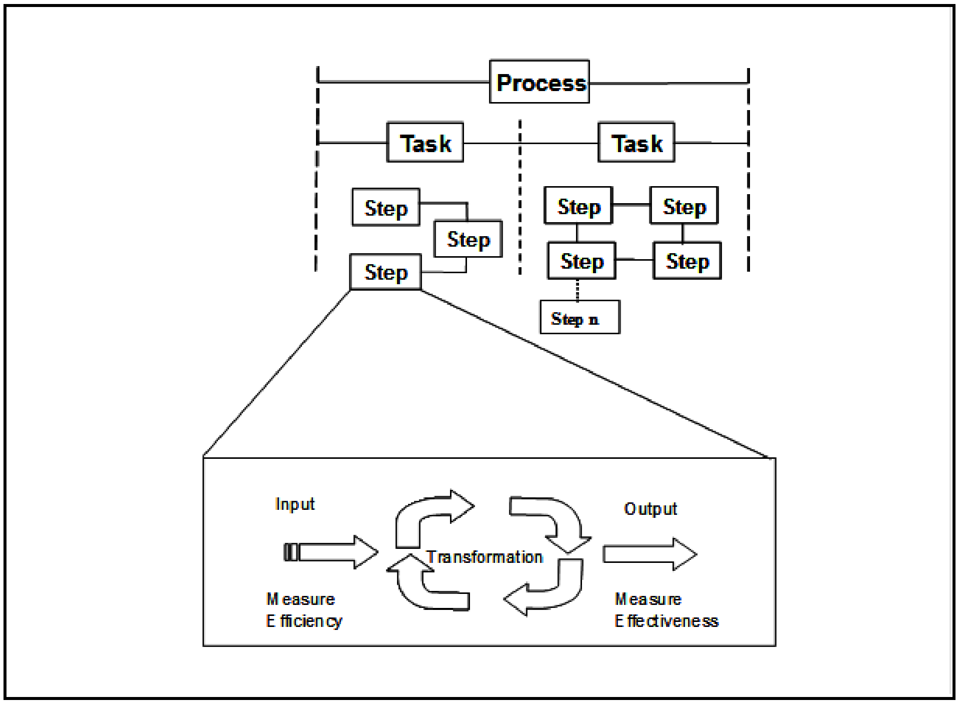


Figure 2.4: Notional Process-Procedure Diagram

2.4.2 **Process Governance**

The World English Dictionary defines the term "Governance"—as the action, manner, or system of governing. Jeston and Nelis (2008) pointed out that process governance is the most important dimension for the continued sustainability and success of creating a process-focused high performance management organization and summarized that, "process governance provides a means for the alignment of business strategy and the highest performance management of the organization via its business processes."

Jeston and Nelis (2008), Richardson (2006), and Bilodeau (2010) are all in agreement in order to establish a process-focused governance structure will involve a paradigm shift; traditionally, most organizations have been operating and managing their business processes in functional silos and will encounter obstacles and challenges associated with cross-departmental collaboration and management of business processes. Gardner (2004) explains managing cross-functional business processes as something traditional organizations do not do very well. A Process Governance (PG) approach will require executive sponsorship, oversight, and end-to-end business process ownership from members of the Executive or Senior Leadership Team (SLT) Council.

Continuous process improvement models, such as ISO 9001 and CMMI models emphasize a process-focused approach. In general, the frameworks place emphasis on identifying and creating the necessary defined organizational standard processes, understanding the interactions between processes, continuous process improvement and process management, establishing quality policies, objectives, quality management system (QMS), a quality assurance and document management system; and frequent adequacy, effectiveness, and efficiency management reviews of the QMS by members on the SLT. Several consultants of Process Governance Consulting Group, LLC (W. McCray, personal communication, May 10, 2011) stated that an organization must first establish a process architecture, process infrastructure, and quality management systems (QMS) with well-defined business processes assets that are easily understood (institutionalized or ingrained in the organization and when executed yield measurable, repeatable, and sustainable business results).

The CMMI model provides guidance on the attributes of a well-define process-procedure. A well-defined business process-procedure framework, at a minimum, should clearly identify (Persse 2006; CMMI Product Team, 2010) the ”Policy, Purpose, Inputs, Entry (E) Criteria, Task (T) Activities, Roles, Measures, Verification (V) Steps, Outputs, and Exit (X) Criteria”, as illustrated in Figure 2.4. The diagram in Figure 2.5 also denotes that measures of efficiency (inputs) and effectiveness (outputs) of well-defined process-procedures can be evaluated for process-performance and improvement.

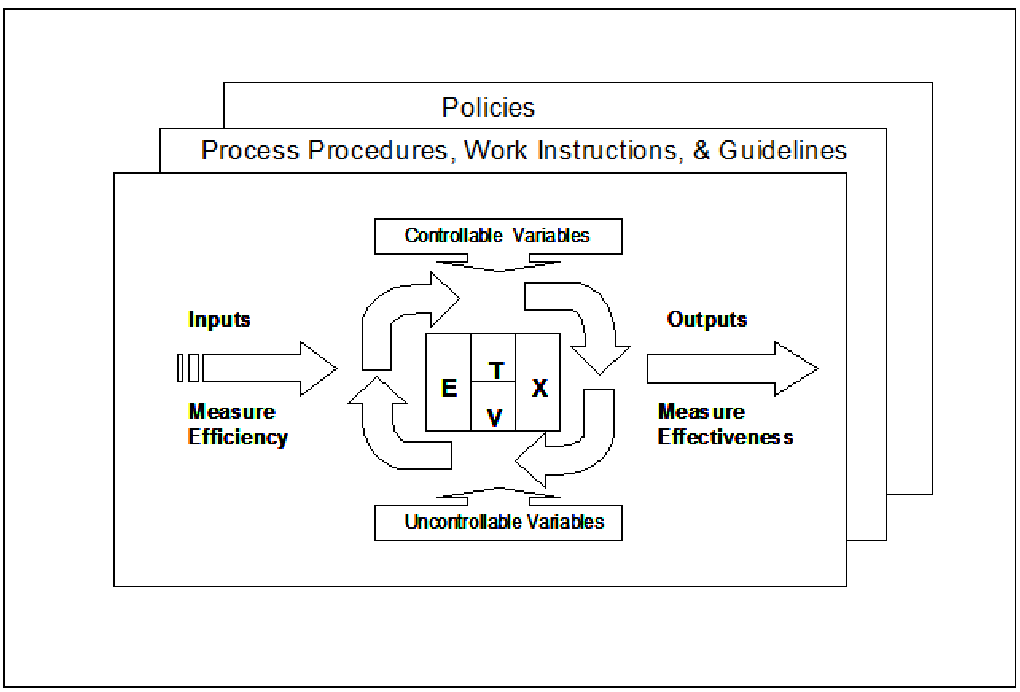


Figure 2.5: Typical Attributes of a Defined Process-Procedure

Harrington (1991) pointed out that a process left unregulated or not monitored will change and not necessarily be for the best interest of the organization or customer. A strategy of prevention should be adopted to monitor and control the input efficiencies, rather than one of detection—measuring and monitoring the effectiveness of the output. According to Oakland (1993), this will concentrate all the attention on the front end of any process—inputs—and changes the emphasis to making sure the inputs are capable of meeting the requirements of the process. The inputs critical to the process—which can be in the form of people, tools, information (data), procedures, and methods—can be analyzed for efficiency using multivariable and optimization techniques.

2.4.3 Software and Systems Engineering Process

Software and systems engineers use numerous life-cycle (LC) models as frameworks to guide the design and development process to develop customer desired products or services. The models consist of phases that define the LC—the logical order of design phases a product or service goes through from inception to phase-out (i.e., cradle to grave). The waterfall, spiral, rapid prototyping, incremental, iterative, and V-Model are examples of commonly used LC models—there are similarities and differences to each LC design approach.

The waterfall model is based on using the entire LC phases in a sequential approach on large-scale development project; rarely today are products developed using the entire LC phases. Today, several methodologies are used in systems and software engineering development: incremental, iterative, spiral, rapid application development, prototyping, object-oriented, agile, and scrum methodology. The V-Model, Figure 2.6, shows the notional LC phases included in a systems engineering and software engineering development process. Throughout each LC phase, work products are produced and peer reviewed. Process improvement can occur in each sub-process LC phase by evaluating products for conformity and process for compliance.

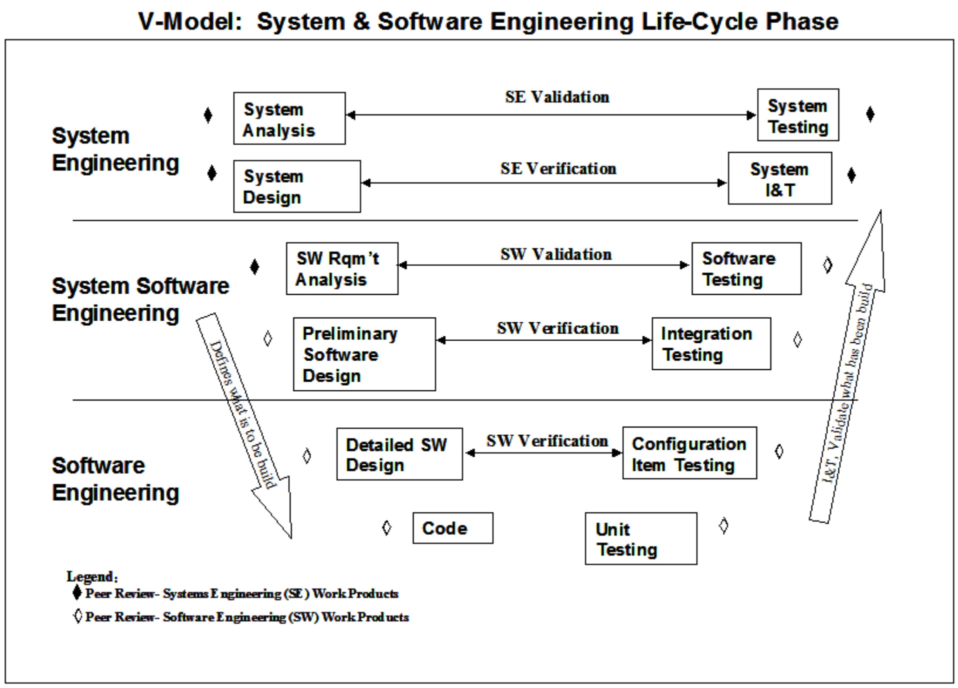


Figure 2.6: V-Model: System & Software Engineering Life-Cycle Phase

2.4.4 Product and Process Quality Assurance

Product and Process Quality Assurance (PPQA) is a ML2 overarching support process area (PA) in the CMMI model. As denoted in Section 2.3.2.2, Figure 2.2, it is a "common" PA. An internal audit system is the foundation of a PPQA process.

The intent of PPQA is to act as the eyes and ears of the enterprise and provide the SLT with objective insight (i.e., governance) into process compliance, product conformance, opportunities for improvement, best practices, and noncompliance / nonconformance issues through independent internal and external evaluations / audits. PPQA ensures that the organization's policies (i.e., guiding principles), processes, procedures, and methods are implemented, institutionalized, and sustained.

The PPQA process supports all process areas (CMMI Product Team, 2010) by objectively evaluating performed processes, work products, and service against business processes, procedures, methods, and standards. Audit findings, opportunities for improvement and best practices provide input into SLT management review meetings.

Many organizations do not quantitatively manage their PPQA processes for performance improvement. An internal audit process offers a wealth of qualitative and quantitative data that organizations can analyze and leverage to drive continuous process improvement. A PPQA process evaluates the efficiency and effectiveness of a process to produce outcomes that meet customer desired expectations. Internal and external auditors not trained in lean six sigma methodologies (e.g., value stream mapping, process mapping, expected / desired outputs, and etc.) cannot objectively evaluate the efficiency of a process. RABQSA (Registrar Accreditation Board and Quality Society of Australasia) trained auditors learn how to audit processes for conformance and effectiveness not efficiency.

2.4.5 **Peer Review Process**

In the CMMI model *testing and peer reviews* are essential components of the verification methods. Verification is a Maturity Level 3, PA in the CMMI-DEV model. As denoted in Section 2.4.3, Figure 2.6, peer reviews are conducted incrementally throughout the SDLC to ensure selected interim products, work products, and service offerings meet their requirements. A peer review is a type of verification method or in-process inspection performed to ensure that specified requirements are satisfied.

Software and systems engineering practitioners are often confused regarding the deference between the verification and validation process— they are similar but address different issues. Validation demonstrates that the product, as provided (or as it will be provided), will fulfill its intended use, whereas verification addresses whether the work product properly reflects the specified requirements. In other words, verification ensures that “you build it right”; whereas, validation ensures that “you build the right thing” (CMMI Product Team, 2010). Many software organizations collect and monitor defect density as a metric but rarely do the practitioners apply quantitative *analysis techniques to* obtain a better understanding of the data.

2.5 Statistical Thinking

Statistical thinking is the methodology of using *statistical methods* to identify and eliminate special cause and analyze common causes of variation in a process with an objective to improve customer value (e.g., delivery of products and services).

The term “statistical thinking” was first used by W. Edwards Deming during a NBC broadcast titled “If Japan Can Why Can't We” in June 1980. Evans and Lindsay (1993) pointed out that “statistical thinking” was only a portion of Deming’s quality management philosophies. Deming focused on the improvement of products and services by reducing uncertainty and process variation in the design and manufacturing processes.

The tents of statistical thinking and process variation are not new. Walter A. Shewhart developed a paradigm for process variation of a product or process by characterizing the difference between “common cause” and “special cause” of process variation in the 1920s at Bell Laboratories (see Section 2.6.5).

The Statistics Division of the American Society for Quality (ASQ 1996) published the below definition of “*statistical thinking*” in their glossary and tables for statistical quality. Hoerl and Snee (2001) helped to popularize the concept of *statistical thinking* by developing an eight step approach, as shown in Figure 2.7, to implement statistical thinking.

Statistical Thinking Definition

> "All work occurs in a system of interconnected processes,
> Variation exists in all processes, and Understanding and reducing variation are keys to success."

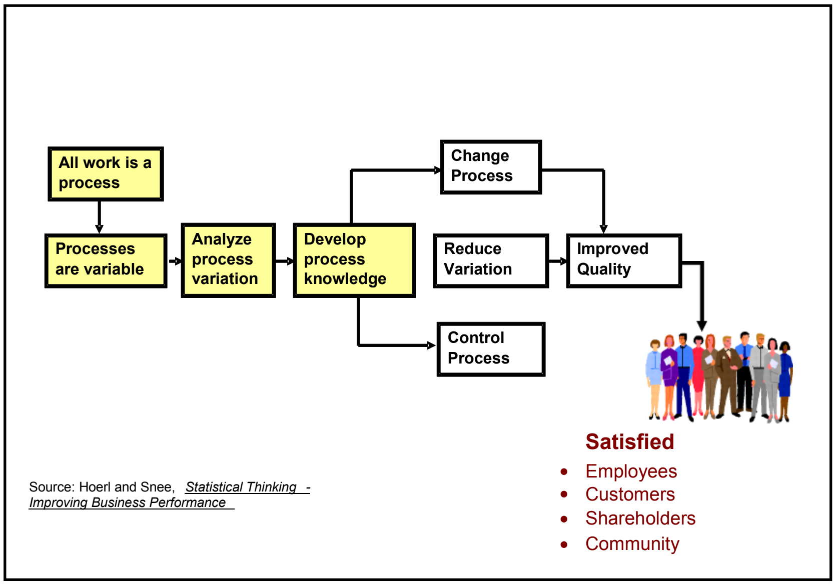


Figure 2.7: Steps in Implementing Statistical Thinking

2.5.1 **Measurement Scales and Data Types**

Measurement scales and data types are very important concepts that are not often understood by practitioners that have no formal training in data analysis techniques or exposure to qualitative and quantitative analytical methodologies, principles, and techniques. The four measure scales in Table 2.2, nominal scale, ordinal scale, interval scale, and ratio scale (Hair and et al., 1998; Berenson and Levine 1999; Kolarik 1999; Black 2004) are commonly used to characterize measures in practice.

Nominal and ordinal data are non-metric, categorical, data that are often characterized as qualitative or attribute—counted data if something occurs. Mendenhall et al. (1999) explained, “Quantitative variables are generally numerical data, whereas qualitative variables are generally categorical data. However, even qualitative variables can generate numerical data if the categories are numerically coded to form a scale”. Nominal data can be described as a “base-measure”. A base-measure (McGarry et al., 2001) is a measure of a single attribute defined by a specified measurement method. Base-measures are obtained from the total count of categorical data and are independent of other measures. Statistical techniques to analyze nominal data are limited and “enumerative studies” are conducted to quantify the base-measure being studied. Attributes data generally provide the analyst with less information than measurement (variables) data would for the same process. The mode can be used to describe central tendency of “nominal data”. The mode or median can be used to describe central tendency of “ordinal data”.

In contrast, interval and ratio data are measurements often characterized as quantitative or variable data. Ratio data is made up of two or more base-measures, or derived measures. Analytic studies are conducted using variable data in order to predict performance of a metric. The mode, median, or mean can be used to describe central tendency of interval and ratio data. The mean is the best measure of central tendency of interval / ratio for data that are not skewed. For skewed interval / ratio data, use the median.

Table 2.2: Measurement Scales and Data Types

Measurement	**Data Type**	**Measurement Scale / Level**	**Characteristic**	**Example**
Base Non-metric	Qualitative Attribute/**Variable	Nominal (Lowest)	Number of occurrences, or *count*, in each *category* in which no ordering is implied	Summary of counted (numerical) data by category. Number of...
Ranking Non-metric	Qualitative Attribute	Ordinal (Low)	Ranking of data into ordered *categories*, characteristic or dimension, in which ordering is from lowest-highest, or highest-lowest	Survey questionnaire ranking implies only which category is "Unsatisfied, Neutral, Fairly Satisfied, Very Satisfied"--not by how much
Numeric Metric	Quantitative Variable Data	Interval (Next Highest)	The data is numerical and have equal intervals between numbers; the "zero" value is arbitrary, not real, and just another point on the scale	Temperature
Numeric Derived Metric	Quantitative Variable Data	Ratio (Highest)	Ordered scale with defined intervals between measurements----have a true and fixed zero point	Proportion, Percentage, Rate, or Ratio

** Counts of entities that represents the size of total population should always be treated as variables data, even though they are instances of discrete counts (Florac & Carleton, 1999, p. 79)

2.5.2 Enumerative Study versus Analytic Study

A fundamental step in performing data analysis is to determine the data type (e.g., attribute and variable), measurement scale, and the type of analysis to be performed (e.g., enumerative study or analytic study). Florac and Carleton (1999) provided an eloquent analogy and rationale on understanding the importance of an *enumerative study* versus an *analytic study*. Florac and Carleton (1999) pointed out that, "the aim of an enumerative study is descriptive—to determine *how many* as opposed to *why so many*". Enumerative studies are not conducted to predict results or provide insight to process changes. Florac and Carleton (1999) also stated that "the aim of an analytic study" is *to predict or improve the behavior of the process in the future*. Analytic studies use data from existing process to make an inference or predict characteristics of future outcomes or performance from the same or similar process. Most process-performance studies are analytic studies.

2.5.3 Understanding Central Limit Theorem and Non-Normality

The Gaussian distribution (bell shaped or normal curve) is often use as a classical approach to explain the shape and clustering / convergence of data points clustered about the mean. In general probability and statistics, quality management, and black belt training courses emphasis is place on understating of the classical principles of the Gaussian distribution. Less emphasis or discussion, if any, is placed on understanding rational subgroups, delineation between homoscedasticity / homogenous [independent and identically distributed (i.i.d.)] and heteroscedasticity / heterogonous or [(non-normal independent and identically distributed (n.i.i.d)] distributions of random variables, and an understanding of the central limit theorem (CLT).

In the literature (Montgomery and Runger 1994; Brenson and Levine, 1999; Mendenhall et al., 1999), statisticians agree that the CLT is one of the most useful statistics theorems to describe normality of continuous distributions (e.g., normal, uniform and exponential) and make statistical inference about a population mean. The CLT states (Montgomery, 1991), "the sum of independent and identically distributed random variables is approximately normally distributed". In other words, the means of samples (of size 4 or large) taken from a non-normal distribution will tend to be normally distributed around the population mean.

Wheeler (1995) explained distributions for subgroup averages look more alike as the subgroup sizes increases. The CLT applies to subgroup averages and not subgroup ranges; therefore, it shall not be applied as the bases for control charts.

2.5.4 Non-Normally Distributed Data Measures of Central Tendency

As mentioned in Section 2.5.3, the normal or Gaussian distribution is often used in statistical textbooks to illustrate the theoretical principles, and measures of central tendency (e.g., mean, median, and mode), or location of symmetric numerical data. The mean is the measure used to describe central tendency of normally distributed data sets. With non-normal (asymmetric) data sets, the median, kurtosis, and skewness are better measures to use to describe central tendency. Extreme values or outliers do not affect the median as strongly as they do the mean.

2.6 Data Visualization Using Exploratory and Statistical Analysis

Section 2.6 sub-sections provide the reader with applicable approaches that can be used to examine data sets, discussion on useful probability distribution and distribution fitting of empirical data, and variation reduction and optimization techniques.

2.6.1 Examining Data Sets

Examining data sets involves the methodology of data collection, aggregation, data cleaning, and the use of quantitative, statistical, and analytical methods, techniques and tools that can be used to analyze and obtain an understanding of data that can be used to drive decision.

The appropriate techniques must be used to analyze univariate, bivariate, and multivariate data. When examining data sets an initial step involves determining if the data set is unimodal (e.g., normal or Gaussian) bimodal, trimodal, multimodal, non-normal and the shape and type of distribution the data resemble. A dot plot, stem-and-leaf plot, or histogram is a useful visualization technique to use to examine univariate data. In general, the plotted data points will provide a visualization of the distribution shape (normality should never be assumed because the data points could resemble a non-normal distribution). This can lead to inaccurate statistical analysis of the data.

Descriptive statistics (e.g., measure of central tendency and measures of dispersion); summary measures, tables (e.g., numerical summaries) and graphs are useful tools to use to examine data sets. Scatter plots, analysis of variance, and regression analysis are useful techniques to examine the correlation or relationship between bivariate data. There are several types of multivariate data analysis techniques that can be used to examine multiple variables in a single relationship or set of relationships.

2.6.2 **Analyzing Non-Normal Data**

Not all process data collected from business processes yield normal data sets. Several transactional and engineering business processes yield non-normal data. Simply restated, commonly taught statistical and analytical methods and approaches are based on the assumption of normality (e.g., normal distribution). To avoid costly analytical mistakes, caution should be exercised when selecting classic and traditional statistical test, analytical methods, and statistical process control techniques to analyze data sets.

When assessing normality and non-normality of data sets, the shape, symmetry, skewness, and kurtosis are important visual / graphical indicators from a histogram. In most cases, a non-normal data distribution is asymmetrical and often depicted on a graph as being right or left skewed (there exist a few exceptions to the rule), as opposed to a normal or Gaussian distribution in which the data is symmetrical.

Kolarik (1999) described the use of various non-traditional SPC methods and models that are appropriate for monitoring identically distributed independent (i.i.d.) non-normal data. Kolarik suggests the transformation and autocorrelation of residuals to convert data from i.i.d. to near normal data streams. Kolarik (1999) also stated that, in the case of high autocorrelation, it is not easy to separate common and special cause of variation.

Deshapande et al. (1995) described several useful statistical inference, (e.g., non-parametric or distribution-free) methods and techniques (e.g., empirical distribution function, U-statistics, asymptotic distribution, etc.) appropriate for analysis of non-normal data.

2.6.3 **Useful Probability Distributions**

Hines and Montgomery (1980) asserted that probability and inferential statistics is a branch of statistical science that deals with the analysis of data and the process of making decisions. Hines and Montgomery (1980) described probability as “a methodology that permits the description or random variation in systems. Inferential statistics uses sample data to draw general conclusion about the population from which the sample was taken".

In probability and statistics textbooks (Montgomery and Runger, 1994; Wheeler, 1995; Rossman and Chance, 1998; Mendenhall, Beaver, and Beaver, 1999), a probability distribution is often described as, a function of a discrete or continuous random variable yielding the probability or likelihood of the set of possible outcomes (values) that the variable will have a given value. The given value is expressed as the ratio of the number of actual occurrences to the total number of possible occurrences. The usefulness of random variable concept depends upon the ability to determine the probability that the values of the random variable occur in a given set of real numbers (Allen, 1978).

Blanchard and Fabrycky (1990) explained that probability distribution models, pattern of probabilities over all possible outcomes, provide a means for assigning the likelihood of occurrences of all possible values, and that a "probability distribution is completely defined when the probability associated with every possible outcome is defined."

As mentioned in previous sections, well-defined business processes and process procedures are executed and adhered to deliver repeatable business outcomes. Breyfogle (2003) stated," that the output of many processes are subject to the effects of chance, and that companies need to consider chance, or probability, when they make assessment of how well they fulfill customer expectations."

Florac and Carleton (1999) provide a discussion on the binomial and Poisson distributions their relationship to n, np, c, u, XmR control charts, and their use, cautions, and conditions that must be satisfied in order to monitor and control software defects and defect density. The "X" in XmR chart is also known as an individual chart. An individual chart is plotted without the moving range.

Kan (2003) provides insight on how the Rayleigh and exponential distribution, which are special cases of the Weibull distribution, are used to model and analyze defect profile patterns in a phase-based approach throughout the SDLC model. Gaffney (1984) was one of the first practitioners to use the Rayleigh model to predict software related performance of large-scale systems. Kan (2003) also mentioned that no good universal software reliability model exists. Kan conducted an experiment using the Rayleigh model on "software field defect rate" and his findings were conclusive to a similar experiment conducted by Wiener-Ehrlich, Hamrick, and Rupolo (1984) "man-loading scores of a software project at the tail end"—the Rayleigh model underestimates the tail end of the distribution of software data.

Kan also mentioned, "in general, there is a lot of room for improvement in the data quality in the software industry". The Rayleigh is a good overall model for quality management and reliability studies---it promotes detection of defects / failure early in the lifecycle phase (i.e., upstream in a process). The Rayleigh curve can be used as a phase-based lifecycle model to assess the defect profile of a business-value-chain, or process, for process improvement.

Table 2.3, contains a list of commonly used probability distributions that can be applied to monitor the performance of software and systems engineering defects for process improvement of non-normal data sets. In an event, when in doubt of which distribution to use, Florac and Carleton (1999) and Kan (2003) would advocate the use of several probability distribution models to validate assumptions. If both probability distribution models point to the same conclusion, one is unlikely to be led astray.

Table 2.3: Probability Distributions

Useful Probability Distributions		
Distribution	**Discrete / Continuous**	**Application(s)**
Binominal	Discrete	• Testing - Pass / Fail Test • Use a p chart to study code practices
Rayleigh	Continuous	• Resource and staffing demand; used for projecting the latent software defect discovery/prevention and defect removal patterns. • Software development lifecycle (SDLC) phase defect patterns • Reliability growth
Uniform	Continuous	• When little knowledge about the random variable is available
Poisson	Discrete	• U chart to count the number of defects found in modules during inspection or testing. *Note: Defects per module or defects per test are ratios and not based on equal opportunities.*
Exponential	Continuous	• Defect arrival patterns • Software reliability growth
Weibull	Continuous	• Describe increasing or decreasing software failure rates
Triangular	Continuous	• Cost and schedule

2.6.4 Distribution Fitting of Empirical Data

Most empirical data (e.g., numerical outcome or frequency of occurrence) collected from non-repetitive processes in the real world are not normally distributed. The data or data sets, which describe the frequency or probability of events, are plotted in a histogram, box and whisker, stem and leaf, or other visual technique to obtain a pictorial view of the empirical distribution shape, skewness, curve, or profile. To assess the fitness of data to a straight-line, one can use a probability plot as another visual technique; this is highly useful for small data sets wherein a histogram does not provide a good understanding of the distribution of the values. Summary or descriptive statistics also provide useful information about a distribution. The empirical distribution does not always resemble the true underlying population (Evans and Olson, 1998), profile, or curve, of a theoretical distribution because of sampling error and attempts should be made to fit the data and statically verify goodness of fit.

There are many useful distribution-fitting software applications on the market that automatically and accurately fit and determine which useful probability distribution (as described in Section 2.6.3) best represent the empirical data set, display distribution comparison charts, and perform statistical and goodness-of-fit tests. It is a good practice to fit empirical data to more than one theoretical distribution for comparison.

2.6.5 **Variation and Capability Analysis**

The philosophy of quality gurus such as, W. Edwards Deming, Joseph M. Juran, and Genichi Taguchi, all focus attention on ways to reduce variation in process outputs. Identifying, measuring, and finding ways to reduce, improve, and manage variation is important for the success of a business. Variation exists in all processes (e.g., products, processes, and service designs) and consists of both non-inherent signals (special cause) and inherent noise (common cause of variation) in the process / system.

The following terms are often used to describe the variation of non-inherent signals in data sets:

- Non-random variation
- Special cause of variation
- Assignable cause of variation
- Outliers
- Shifts
- Trends
- Cycles

Managing special cause of variation requires analyzing and hopefully removing the unusual special cause. The synonyms "random variation, common cause of variation, and chance cause" are used to describe the variation of inherent noise in a data set. Managing common cause variation requires shifts and incremental improvements of the process. Walter A. Shewhart (1931) originally used the term assignable-cause and W. Edwards Deming later coined the term "*special-cause*" to describe out of control process variation, which is not inherent in the process / system. Deming identifies two sources of improvement in any process: reducing common cause of variation inherent in the production system, and eliminating isolated "*special causes*" identifiable with a specific individual, machine, or batch of material" (Evans and Lindsay, 1993). A process governed by common cause is stable, remains constant overtime, and can be predicted.

The CMMI model or the SEI measurement and analysis training does not include content on how to establish specification limits. Neither do they cover the concept of capability analysis and capability ratios. A capability analysis study can be used to assess whether an optimized process is statistically able to meet a set of specifications (e.g., voice of the customer). A capability analysis study can be performed on a process that is statistically stable and does not have any special causes of variation present to predict the future performance of the system or process.

Donald Wheeler (1995) commented, "...the term *capability* denotes the predictable outcome of a process which displays a reasonable degree of statistical control", i.e. a well-defined stable process. Evans and Lindsey (1993) emphasized that process capability is the range over which the natural variation of a process occurs as determined by the system of common causes and is measured by the proportion of output that can be produced within design specification. Evans and Lindsey (1993) also mentioned, that, "process capability has three components: (1) the design specifications, (2) the centering of the natural variation, and (3) the range, or spread, of variation". Caution must be exercised not to make the specifications *to tight or to lose* in order to achieve the quality objectives. A capability analysis, a peak performance, process characterization, or a component variability study is sometimes performed as types of *statistical analysis of process variation* studies.

Wheeler (1995) argues that specification limits are actually artificial boundaries used to make arbitrary decision about the product or process and naïve attempts to deal with the problems created the variation of product / process characteristics. Wheeler's point of view regarding specification limits can have its detractors, including the author of this dissertation. *Specification limits* are not necessarily artificial boundaries, often they are the numerical values or *established boundaries / requirements* within which a product or process are expected to conform. Conformance to specification as a concept of quality, although necessary, is not sufficient to remain competitive in today's world. Wheeler (1995) surmised that world class quality has been defined by "On Target with Minimum Variance" for the last 30 years. Conformance to requirements, Zero Defects, Six-Sigma Quality, Cost of Quality and all other specification-based nostrums miss this point. Dr. Taguchi's concept of a more realistic loss function (On Target with Minimum Variance) leads unavoidably to a new definition of world-class quality. Wheeler (1995) stated that with predictable processes, the natural process limits, the specified tolerance, the distance to the nearest specification and the mean square deviation about target can be used to characterize different aspects of the process and will be indicative of both the past and future as long as the process continues to display statistical control. The elaborations in the CMMI model do not provide a discussion on the use of offline statistics and analytical techniques.

The revised CMMI models, v1.3, eliminated important quantitative and optimization concepts contained in the following generic practices (GP) and specific practices (SP), see Table2.4 below.

Table 2.4: Removal of Important Variation Analysis Concepts

Practice	Number	Description
Generic Practice	GP 4.1	Establish and maintain quantitative objectives for the process, which address quality and process performance, based on customer needs and business objectives.
Generic Practice	GP 4.2	Stabilize the performance of one or more subprocesses to determine the ability of the process to achieve the established quantitative quality and process-performance objectives.
Generic Practice	GP 5.1	Ensure continuous improvement of the process in fulfilling the relevant business objectives of the organization.
Generic Practice	GP 5.2	Identify and correct the root causes of defects and other problems in the process.
Specific Practice	QPM, SP 2.2	Establish and maintain an understanding of the variation of the selected subprocesses using the selected measures and analytic techniques.

As illustrated in Table2.5, CMMI model, v1.3, de-emphasized the terminology used in a previous version to explain "process variation". When, in fact, more rather than less emphasis needs to be elaborated in the model in order for practitioners not trained in quantitative and statistical techniques to obtain a better appreciation and approaches to reduce variability and improve predictable outcomes, quantitatively manage and optimized a process for performance.

Table 2.5: De-Emphasis on Process Variation Terminology

Terminology	CMMI-SE/SW/IPPD/SS, V1.1 Mar-02	CMMI-DEV, V1.2 Aug-06	CMMI-DEV, V1.3 Nov-10
Process Variation			
Common Cause	16	19	7
Chance Cause	0	0	0
Special Cause	33	39	9
Assignable Cause	3	3	0
Outliers	0	0	2
Process Capability Analysis			
Natural Bounds	26	26	7
Control Limits	0	0	0
Voice of the Process	1	1	1
Voice of the Customer	0	0	0
Specification Limits	0	0	0
Process Capability Analysis*	1	1	1

Note:
* Where the term appears, the emphasis is not related to quantitative analysis

2.6.6 **Analyzing Outliers**

Outliers can provide useful information about a process. As previously mentioned in Section 2.6.5, outliers are non-inherent signals or observation of extreme values (i.e., special causes of variation) that lie outside or a distance from the majority of data points in a distribution. Practitioners that have the responsibility of performing data analysis must carefully examine outliers or extreme values before considering to "include or exclude" them from data sets.

Hair, Anderson, Tatham, and Black (1998) re-iterate the point that it is imperative that analysts examine data sets for the presence of outliers to determine their type of influence and the information they provide. Hair et al. (1998) identified four (4) classes in which outliers can be classified and methods used for detecting outliers in univariate, bivariate, and multivariate data sets. The first class, "procedural errors" that occur in the data cleansing stage. The second-class of outlier occurs from the "uniqueness of an extraordinary event" and the decision centers on deletion or retention of the observed data point(s). The third class of outlier comprises of "extraordinary observations that cannot be explained". The fourth class of outlier contains "observations that fall within the range of values but have unique values across the variables" (i.e., observable shifts, patterns, or trends within the data set).

Buxton and Tabor (2003) provides a discussion on outlier detection techniques and mentioned "when presented with a real-life data population it is far more difficult to establish a reliable definition of what constitutes an outliner." Buxton and Tabor (2003) also mentioned that practical outlier detection methods are based on median or percentile calculations and the Automotive Electronics Council developed a technique called Part Average Testing (PAT) used for outlier detection analysis in the manufacture of semiconductor devices. The PAT technique uses static and dynamic test limits to identify outliers. The PAT techniques can also be applied to detect outliers that exist in non-manufacturing processes data sets as well.

2.6.7 Variation Reduction and Optimization

Variation reduction and optimization analysis focuses on the use of various quantitative, statistical and analytical techniques, methodologies, and tools to analyze and improve common-cause of process variation for optimal process-performance.

Taylor (1991) presented several optimization and variation reduction techniques to improve product and process-performance. The variation and optimization techniques (e.g., multivariate charts, variance component analysis, analysis of means, variation transmission studies, capability analysis, and parameter design, etc.) can be applied during the design process to prevent problems and later on to continuously improve any product or process. Taylor also noted, "…the key to measuring variation is multiple measurements", and the analyst must first understand the means of measuring variation before you can begin the path to variation reduction. Reducing statistical variation (e.g., range and standard deviation) means reducing the deviation or distance between the target value, mean / median, and specification limits.

2.7 Training in Quantitative and Process Improvement Methodologies

Sub-sections 2.7.1 and 2.7.2 that follows provides the reader with an overview of the type of quantitative and process improvement training, and lack thereof, practitioners receive. Sub-section 2.7.1, provides a brief overview of studies conducted to assess gaps in process improvement courses taught in systems engineering and computing sciences courses in U.S. colleges and universities. Sub-section 2.7.2, provides an overview discussion on the training emphasis in lean thinking and six sigma training programs.

2.7.1 Systems Engineers, Software Engineers, Computer Science, and Information Technology Practitioners

Simply restated, in the literature, there has not been a lot of academic research conducted to address the gap in-process improvement and quantitative analysis, methods, and techniques taught to students in systems engineering and the computing science disciplines in universities and colleges in the United States. McCray and Santos (2009) stated that most software engineering, systems engineering, computer science, and information technology curricula surveyed do not offer academic training focused on measuring the SDLC for improvement. Knowledge of *how to apply the applicable quantitative and statistical techniques* to manage the software and systems engineering processes is becoming increasingly important in industry. The problems have not been perceived as being significant or there is a lack of awareness in the academic community. In 2007 - 2008, Stevens Institute of Technology (Pyster et al., 2008) conducted a study on 28 graduate software engineering degree programs to determine the current state of software engineering master's level degree programs. As a result, a coalition from academia, industry, and government was formed to develop a Graduate Software Engineering Reference Curriculum (GSwERC). The study conducted by Stevens Institute of Technology also identified, as one of the findings, a gap in the lack of software quality courses taught in graduate software engineering degree program curricula.

2.7.2 **Lean Six Sigma, Green Belt, Black Belt, and Master Black Belt Training**

Schroeder et al. (2008) pointed out that lean six sigma has been gaining momentum in industries over the last two-and-half-decades; there have been books written and articles published on the Internet by consultants and practitioners, and very few articles published in scholarly journals. Scholarly research is needed to develop an in-depth, scientific understanding of six sigma and separate fact from fiction (Schroeder et al., 2008).

Lean thinking or principles (Womack and Jones, 2003; Breyfogle, 2003) place emphasis on customer value, with a focus on mapping the value / non-value activities of a core set of end-to-end processes that efficiently deliver value to the customer; and letting the customer pull product as needed to pursue perfection through continuous process-improvement. The goal of the lean methodology focuses on "muda" waste stream elimination of overproduction, waiting, transportation, inventory, over-processing, motion, and defects.

In 1986, Bill Smith of Motorola Corporation coined the phrase "six sigma" to describe process variability in terms of standard deviations. A six sigma quality level is equal to 3.4 defective parts per million. The philosophy of six sigma focuses on the elimination and reduction of variation using statistical process control, statistics, analytical techniques, and project management techniques to foster process improvement.

In the mid-1990s, independently both AlliedSignal and Maytag introduced six sigma and lean methods as a business initiative. They combined the methodologies, created a project framework, and cross-trained their employees in lean six sigma principles and techniques. In 1995, Jack Welch, General Electric (GE) company, initiated, highlighted the benefits, and popularized the implementation of six sigma throughout GE (Breyfogel, 2003).

Today, with companies trying to do more with less, in practically all business sectors, are adopting, training, and certifying their employees in the lean six sigma quality improvement methodologies and principles. Employees interested in quality improvement attend "*yellow belt, green belt, black belt, or master black belt*" training class and receive certification from the company or an outside organization that offers training. The lean six sigma training methodologies, principles, and certification vary from company to company. There is no standardized *green belt, black belt, and master black belt training* or certification governance body in place. In most lean six sigma training programs, more emphasis is placed on the lean principles and traditional six sigma methodologies as opposed to advanced statistical or quantitative analysis techniques. Chakravorty (2009) advocated that there is an increasing concern across industries regarding the failure and a planned approach of implementing of six sigma programs. Chakravorty developed a “Six Sigma Implementation Model” and pointed out that studies have identified five (5) key elements to a successful six sigma program (i.e., management commitment, levels of six sigma training, performance metrics, implementation systematic approach, and project selection / prioritization).

2.8 Prediction Modeling of Software and Systems Engineering Process

As previously stated in Sections 2.3.4 – 2.3.4.2, and Table 2.1, high maturity process areas are quantitatively managed and optimized to demonstrate stability and continual process improvement. In the CMMI model, the Organizational Process-performance (OPP) process area advocates the use of “process-performance models” (i.e., prediction modeling). The CMMI, v1.3 glossary describes a process-performance model as “a description of relationship (CMMI Product Team, 2010) among the measurable attributes of one or more processes or work products that is developed from historical process-performance data and is used to predict future performance.” The CMMI model also states (CMMI Product Team, 2010) that “process-performance models include statistical, probabilistic and simulation based models that predict interim or final results by connecting past performance with future outcomes”. The CMMI model is not prescriptive in the use of modeling and simulation models. The term “Monte Carlo” appears one time in CMMI, v1.3, Organization Process-performance process area elaborations.

Gass and Assad (2005) provided a rich history on the origin of "Monte Carlo simulation". The term Monte Carlo was coined in 1947 by Nicholas Metropolis (Metropolis and Ulam, 1949) and used as a code name for computer computations / simulations of nuclear fission during the development of the atomic bomb. Evans and Olson (1998) added, "Monte Carlo simulation is basically a sampling experiment whose purpose is to estimate the distribution of an outcome variable that depends on several probabilistic input variables". Monte Carlo and discrete event simulation modeling techniques and methods are often taught in decision science, systems science, systems and industrial engineering, and mathematics and statistics departments with an operation research focus. With the affordability of software and faster computers in the early 1990s, Monte Carlo simulation gained use by decision-makers in a variety of industries.

There has not been a lot of academic research on the use of predictive modeling of the software and systems engineering processes for performance. Kellner et al. (1999) provided a broad perspective in a journal article on the why, what, and how to simulate and model software engineering processes using systems dynamics and discrete event simulation approaches. They (Kellner et al., 1999) included in the article a summary table of past work (papers and dissertation topics) by the authors from 1991-1996, and a table of 11 papers on the topic that was presented at the Process Modeling Simulation (ProSim'98) Workshop. They analyzed and characterize the simulation approaches used in the papers as rule-based, state-based, or systems dynamics simulation approaches and pointed out that no one modeling approach or tool work in all situations

Kan (2003) pointed out how the Rayleigh, exponential distribution, and reliability growth models have been used since 1986 to predict software reliability.

In 2006 and 2007, the SEI Measurement and Analysis group developed and offered a series of measurement courses to practitioners and Lead Appraisers to better communicate the intention of a process-performance model which is described as being statistical, probabilistic, or simulation based.

In 2010, the Software Engineering Institute (SEI) Measurement and Analysis Working Group prepared a compilation of high maturity process-performance modeling approaches that were presented by practitioners during the second and third Measurement and Analysis Workshops in November 2008 and March 2009 (Stoddard and Goldenson, 2010). The report contains25 examples of statistical, probabilistic or simulation models and techniques used in high maturity organizations. The category of process-performance modeling approaches used are summarized in Table 2.6 .

Table 2.6: Process-Performance Modeling Used in High Maturity Organizations

Summary from 2010 SEI Series of Workshops on Approaches to Process Performance Modeling	
Number of Models	**Description of Model and Analysis Technique**
3	Discrete Event Simulation
5	Monte Carlo
7	Other Simulation Approaches (e.g., game theory, Bayesian methods, algebraic, probabilistic, eigenvalue structure matrices, reliability growth models, and etc.)
10	Statistical Models

2.9 Summary

In summary, extensive literature research was conducted to develop the research basis and to provide the reader with insight into how industry recognized process improvement models such as the CMMI and ISO standards are used to assess and evaluate systems and software engineering business processes for performance. The high maturity process areas in the CMMI models "imply the use of analytical, statistical, and quantitative management techniques to identify and eliminate sources of variation, reduce cost, and continually improve process-performance." Section 2.3, provides an overview of the CMMI history, CMMI models , CMMI process areas, capability and maturity levels, and an understanding of maturity Level 4 (quantitatively managed) and Level 5 (optimizing process) areas.

The literature review also points out that, often, practitioners involved in performing metrics / measurement analysis are not trained in advanced applicable quantitative, statistical, or analytical techniques that can be used to analyze non-normal data sets yielding from systems and software engineering business processes. Researchers in academia have conducted very little research on applicable qualitative and quantitative analytical techniques that can be used to improve performance, or demonstrate high maturity as implied in CMMI quantitatively managed and optimized process areas (see Sections 2.3.4.1 and 2.3.4.2). Section 2, also provides a discussion of an enumerative study versus an analytic study, examining data sets, data visualization techniques, useful probability distributions, non-normally distributed data measures of central tendency, variation reduction and optimization analysis, and approaches to analyze outliers.

Most software engineering, systems engineering, computer science, and information technology curricula do not offer academic training focused on measuring the SDLC for improvement. Knowledge of "how to apply the applicable statistical thinking methodologies (Section 2.5) and quantitative and statistical techniques" to manage the software and systems engineering processes is becoming increasingly important. Section 2.2 provides a synopsis of the notable published academic research in which simulation and statistical techniques have been applied to predict software engineering processes.

Section 2.4, provides general definitions of a process, process procedure, and emphasizes the importance of a process infrastructure, governance, and quality assurance approach to process improvement. This section provides the reader with an understanding of the importance of establishing and monitoring business processes, business process infrastructure, and process architecture. Section 2.4, also reinforces the notional idea that the quality of an organization's products and services are highly dependent on its business processes and governance. Process governance is the most important dimension for the continued sustainability and success of creating a process-focused high performance management organization. A process governance approach requires executive sponsorship, oversight, and end-to-end business process ownership from members of the Executive or Senior Leadership Team (SLT) Council. Section 2.4, provides a brief overview of SDLC models and a quality assurance framework (e.g., peer reviews and PPQA). The intent of PPQA is to act as the eyes and ears of the enterprise and provide the SLT with objective insight into process compliance, governance, best practices, non-conformance, and opportunities for improvement. Many organizations do not quantitatively manage their PPQA processes for performance improvement.

Section 2.7, provides an insightful discussion based on a study conducted which examines the lack of process improvement and quality management courses taught in systems engineering and the computing science disciplines curricula in U.S. colleges and universities. The section also provides the reader with awareness on issues regarding lean six sigma and black belt training programs, and challenges companies are facing while implementing a six-sigma strategy. In most lean six sigma training programs, more emphasis is placed on the lean principles as opposed to advanced statistical or quantitative analysis techniques.

Section 2.8, provides a brief overview and applicable research that has been conducted on the use of applying prediction techniques to model and analyze the software and systems engineering processes. There has not been a lot of academic research on the use of predictive modeling of the software and systems engineering processes for performance.

Chapter 3: Research Methodology

This chapter outlines the research methodology and approaches.

3.1 Significance of Research

The previous chapters provided general background information regarding the motivation of this study, a review of related literature, its significance to the software and systems engineering community and academia. This chapter further describes the proposed methodologies and approaches that will be applied to the research. The research focuses on collecting, analyzing, and mixing both qualitative and quantitative data in a single study or series of studies to address the research questions and yield results. The research will add to the body of knowledge and heighten awareness of issues that are not readily apparent to the academic community with regards to providing courses that provide the body of knowledge and skills engineering practitioners that are responsible for process improvement will need in industry. The research also demonstrates the use of statistical methods applied to analyze customer satisfaction survey results.

3.2 *Re*-Statement of the Research Questions

Most software engineering, systems engineering, computer science, and information technology curricula do not offer academic training focused on measuring improvements in the software and systems development life cycle (SDLC), or also referred to as software development lifecycle. Knowledge of "how to apply the applicable quantitative and statistical techniques" to manage the software and systems engineering processes is becoming increasingly important (McCray and Santos, 2009). Academic researchers have conducted little research on applicable qualitative and quantitative analytical techniques that can be used to improve performance or demonstrate high maturity as implied in the Capability Maturity Models (CMMIs) of the systems and software engineering processes.

The research focuses on the following questions of interest summarized below:

- Do academic programs in the U.S. in software engineering, systems engineering, computer science, and information technology programs provide formal training in quantitative, analytical, or statistical analysis principles and methods centered on process improvement to students during their academic studies?
- Which statistical techniques can be applied in meaningful ways to stabilize and optimize the software engineering, systems engineering, and support processes?
- Which analytical techniques can practitioners use to analyze, monitor, control, and improve process variation?
- Can practitioners use Shewhart statistical process control (SPC) charts to manage and control process variation? If so, which types of control charts are applicable?
- What analytical techniques can be applied to analyze, monitor and improve Customer Satisfaction Survey data sets?

- Can advanced SPC techniques be used to measure process-performance? If so, which advanced techniques?
- Can bivariate and other multivariate techniques be applied to software and systems engineering process data sets?
- Can off-line statistical techniques be used to model and optimize process-performance? If so, which techniques (e.g., capability analysis, design of experiment, response surface design, central composite design, discrete event Monte Carlo simulation, inferential statistical techniques, Taguchi's techniques, etc.) are applicable?

3.3 Assessment of Systems Engineering and Computing Science Degree Programs in U.S. Colleges and Universities That Offer Courses in Process Improvement Quantitative Analysis Techniques

Researchers in academia have conducted little research on applicable qualitative and quantitative analytical techniques that can be used to improve performance or demonstrate high maturity of systems engineering and computing science processes.

The objective will involve conducting a review of colleges and universities systems engineering and computing science (e.g., software engineering, computer science, and information technology) degree-programs that offer courses that provide the students with domain knowledge and application on how to measure, analyze, and implement software and systems engineering process-performance and quality improvements. "Students typically have little understanding of how to plan and track their personal work or how to measure and manage software quality" (Humphrey et al., 2008). There certainly are needs in industry (McCray and Santos, 2009) for software and systems engineering practitioners that can apply the applicable analytical and quantitative techniques. The focus of the research is to identify the gaps in analytical and quantitative techniques taught in college courses that enable process improvement at the high maturity levels.

The research will employ a variety of methodologies to illustrate the use of qualitative descriptive methods, mapping matrices comparative analysis, and information gathering through direct observation, personal interviews, documents, published materials, and similar information gathering methods to identify coherent patterns and gaps.

3.3.1 **Research Sample U.S. Colleges and Universities**

The research sample consists of a subset of colleges and universities in the United States (U.S.) that offers bachelor's, master's, and doctoral degree programs in systems engineering and the computing science disciplines (e.g., software engineering, computer science, and information technology). Several different sources (e.g., INCOSE list of systems engineering schools, Peterson's Guide to colleges and universities online database, ABET database of accredited programs by commission, Council for Higher Education Accreditation (CHEA) database of regional accredited institutions, etc.) will be used to determine which colleges and universities to include in the study .

The researcher conducted random queries using the online databases and retrieved relevant information pertaining to institutions that offer systems engineering and the computing science disciplines degree programs. The data gathered was placed in MS

Excel spreadsheets (matrices) for filtering and analysis to determine which schools to include in the study. The data was sorted by the university enrollment size from largest to smallest and the admission difficulty from "very difficult to non-competitive". The study size and decision criterion for inclusion is contained in Table 3.1. The data collection method, in Section 3.3.4., contains additional or secondary criteria that were used in the study to identify required and elective courses in degree programs that develop domain knowledge and skills of quantitative management techniques (e.g., analytical and quantitative techniques) that can be applied to improve, predict, and sustain process-performance. This study is comprehensive and does not focus on any particular university.

Table 3.1 and Table 3.2 contain the number of colleges and universities included in the study. The university's enrollment size and difficulty of admission based on Peterson's criteria were used as decision criteria to determine the study sample size (see Table 3.1). The overall university minimum and maximum enrollment sizes, as listed in Table 3.1, were used as a decision criterion to determine the computing science degree programs to include in the study. To demonstrate that the study is not biased by degree mills and accreditations mills a mapping was conducted of CHEA regional accrediting organizations and included in Appendix A through D. The U.S. Department of Education higher education opportunity act ("Diploma Mills and Accreditation", 2014) defines a diploma mill as an entity that offers, for a fee, degrees, diplomas, or certificates; and lacks accreditation by an accrediting agency or association that is recognized as an accrediting agency or association of institution of higher education.

The study includes a mapping of the institution's ABET program and regional accreditation in Appendix A through D. Figure 3.1, shows the number of U.S. accredited ABET programs by commission as of November 1, 2012, and the number of ABET accredited programs in the study. The intent of Figure 3.1, is to illustrate the number of ABET degree programs in the study and not to compare by proportion to the U.S. accredited ABET programs by commission. The ABET commission listed below accredits degree programs. It is not surprising that a lot of institutions engineering programs are not ABET accredited. According to ABET representative, ABET program accreditation by commission is not mandatory.

- Applied Science Accreditation Commission (ASAC) accredits information technology (IT) degree programs at the bachelor's and master's level.
- Computing Accreditation Commission (CAC) accredits computer science (CS) degree programs at the bachelor's level only.
- Engineering Accreditation Commission (EAC) accredits software engineering and systems engineering degree programs at the bachelor's and master's level.

As indicated in Table 3.1, Table 3.2, and Appendix A through D, the study will assess a total of 266 bachelor's, master's, and doctoral curricula in 145 different college and university degree programs (McCray and Santos, 2009).

The International Council of Systems Engineering (INCOSE) maintains a list of colleges and universities in the U.S. that offer systems engineering degree programs. Only 54%

of the consolidated list of schools identified in the Peterson's database and INCOSE list of colleges and universities that offer systems engineering degree programs was included in the study. The university enrollment sizes and admission difficulty in Table 3.1 for systems engineering were not used as decision criteria. Institutions that did not offer degree programs that focus on the body of knowledge and principles of systems engineering were removed from the consolidated list. The principles of systems engineering are used to guide the engineering of complex systems from inception to phase-out and disposal throughout the lifecycle phases (e.g., needs analysis, concept exploration, concept definition—analysis of alternatives, trade studies, functional and physical architecture, requirements development and management; system design and technical solution—preliminary and detailed design, code and unit test; system integration and test; post development—production, deployment, operation and support; and disposal, etc.). It is noteworthy to mention that not all schools included in the INCOSE list of degree program focus on the principles of systems engineering; therefore, the researcher will exclude the schools from the study (see 3.3.2 Research Exclusions and Limitations).

Peterson's Guide to colleges and universities in the U.S., Canada, and many international schools has been a trusted and valuable resource for over 4 decades. The Peterson's database offers a significant amount of useful information. This study will use a subset of the information of computing science degree programs (e.g., 45% computer science, 63% software engineering, and 40% information technology) listed in the Peterson's database to narrow down the number.

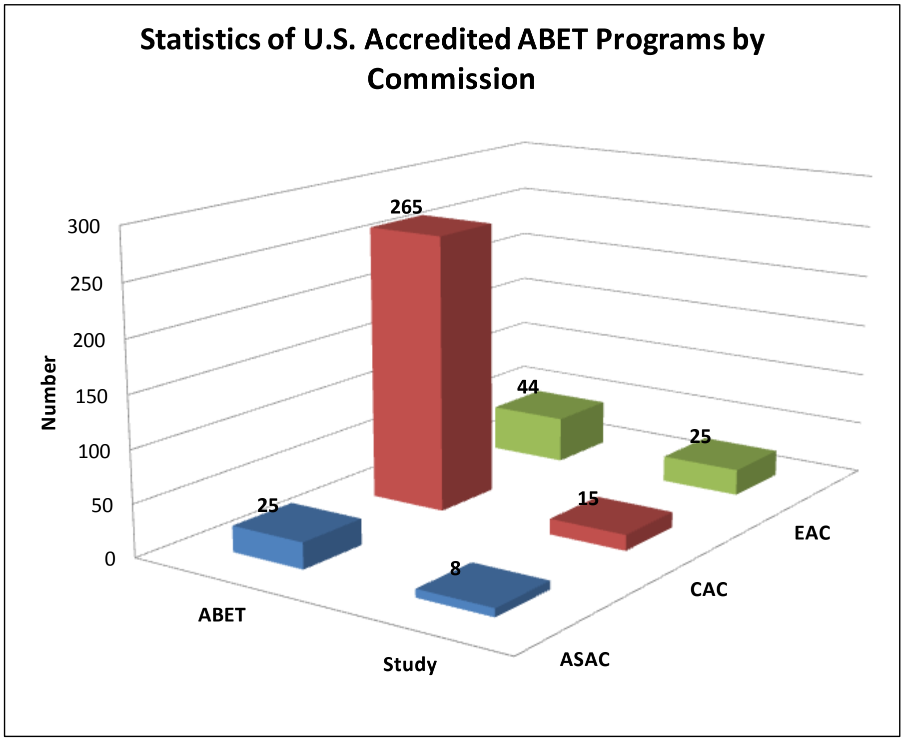


Figure 3.1: U.S. ABET Accredited Degree Programs by Commission Used in the Study

Table 3.1: Study Size and Decision Criteria for University Selection

Degree Program	Study Size	University Enrollment Min.	Max.	Range	Admission Difficulty
Software Engineering	40	1832	21646	19814	Very difficult-10% Moderately difficult-35% Minimally difficult-8% Date not available-47%
Systems Engineering	43	N/A	N/A	N/A	N/A
Computer Science	40	2801	31589	28788	Very difficult-98% Moderate dificult-2%
Information Technology	49	3291	42910	39619	Very difficult-4% Moderately difficult-69% Minimally difficult-8% Non-competitive-18%

Legend:
N/A - Not applicable

Coincidently, 26 of 28 graduate software engineering degree programs listed in the 2007-2008 study performed by Stevens Institute of Technology (Pyster et al., 2008), which identified the lack of software quality courses taught are also included in this study.

Table 3.2: Number of Universities Reviewed by Discipline

Number of Colleges & Universities Reviewed By Discipline					
		No. of Curriculums Included in the Study			
Colleges & Universities	**Degree Program**	**BS**	**MS**	**Ph.D.**	**Total**
40	Software Engineering	21	31	3	55
43	Systems Engineering	9	41	10	60
40	Computer Science	40	24	18	82
49	Information Technology	47	18	4	69
	Total	**117**	**114**	**35**	**266**
Note: the above number of colleges and universities do not total 145. Some of the schools included in the study offer degree programs in multiple disciplines.					

The researcher will also develop a comparison matrix (see Section 4.2) of the "SEI's Healthy Ingredients – Statistical Methods and Optimization Approaches" to the quantitative skills and methods taught in U.S. universities' systems engineering and computing science discipline courses.

3.3.2 Research Exclusions and Limitations

Systems engineering degree programs, as identified in the INCOSE list of schools ("Directory of Systems Engineering Academic Programs", 2013) , which do not offer courses in the principle of systems engineering (SE) were excluded from the study (e.g., degree programs with a focus in industrial technology, industrial engineering with specialization in human factors / ergonomics and cognitive engineering, manufacturing and operations research, agriculture and environmental systems, management science, industrial power systems, systems control theory, geosensing systems, bioproducts and biosystems engineering, and electrical engineering with a systems focus or specialization in electronic systems). Institutions that offer certificates only in SE will be excluded from the study as well.

Institutions identified in the study that cannot be verified as CHEA regionally accredited will be excluded. Degree mills and accreditation mills institutions will not be included in the study.

The study will not contain any engineering universities outside of the U.S. A percentage (see Section 3.3.1) of computing science degree programs in U.S. universities will be included in the study. Universities with enrollment size lower than the minimum and higher than the aforementioned maximum, and did not meet the admission difficulty criteria selections (see Section 3.3.1, Table 3.1) will be excluded from the study.

3.3.3 Confidentiality

The research does not involve confidentiality issues. The information used in the research resides in the public domain on websites, pamphlets, and course catalogues.

3.3.4 Artifacts Data Collection and Instrumentation

The data collection instruments consist of Microsoft Excel workbooks. To determine which schools to include in the research, with the exception of the systems engineering degree programs, the research will perform queries using Peterson's Guide to U.S. colleges and universities online database to identify schools that offer degree programs in each computing science discipline. The query results will be place into a Microsoft Excel spreadsheet workbook and ranked to determine the schools to include in the study. The school's entrance difficulty (very difficult, most difficult, moderately difficult, minimally difficult, not available, and non-competitive) and enrollment size will form the ranking basis.

The Microsoft Excel workbook with spreadsheet tabs for each discipline will be used as a data collection instrument to manage, store, and analyze the un-structured data. The spreadsheet column headings will contain the school name, department / telephone number, website, degree offered (i.e., bachelor's, master's, or doctoral). In some cases, the research will include the degree program area of focus.

The data collection process will involve reviewing various artifacts to extrapolate information on required and elective courses that focuses upon developing foundation knowledge of quantitative management, process improvement, software quality assurance methodologies and techniques. The Microsoft Excel spreadsheets will be populated with the information collected.

The data collection process will involve an in-depth review and collection of course catalogs, online degree programs curricula and syllabi to identify required and elective courses that develop domain knowledge and skills of quantitative management techniques (e.g., analytical and quantitative techniques) that can be applied to improve, predict, and sustain process-performance. Email request will be sent to program coordinators and professors to obtain copies of their course outline (syllabi) not available on-line.

3.3.5 **Data Analysis of Universities Included in the Study**

Each Microsoft Excel spreadsheet will contain summary statistics of the number of degree programs included in the study along with their required and elective courses that focuses and develop foundational knowledge on the application and applicability of quantitative management and process improvement skills and techniques taught in courses. The spreadsheet will also illuminate the gaps that appear in the academic degree programs by discipline.

3.3.6 Validity and Reliability

Several approaches will be used to validate the research. The content of courses in question will be validated by conducting telephone interviews and exchanging email messages with professors and program coordinators. The gaps in process improvement courses identified and the comparison matrix will be presented at the Software Engineering Institute, Measurement and Working Group workshop and at other relevant conferences to obtain feedback and validation amongst colleagues.

3.4 Software Development Organization Customer Satisfaction Survey Analysis

The purposes of this component of the research are to: (1) develop a customer satisfaction survey (CSS) for a company that develops case management software applications and analyze the results using statistical methods and techniques, and (2) demonstrate the use of analytical and quantitative techniques to show how customer satisfaction indices (CSI) can meet the Software Engineering Institute Capability Maturity Model Integration (CMMI) requirements as a high maturity metric.

In today's competitive economy, delivery of high quality software products and services is a key to sustaining a competitive advantage. In the global economy, customers are demanding higher quality in products and services than ever before and companies must deploy methods to improve business performance by measuring and monitoring customer satisfaction, customer expectations, and perceived values in order to gain a competitive advantage in the marketplace.

Implementing a CSS is a useful method that can be used to obtain insight into the "voice-of-the-customer" level of perceived quality, perceived values, and customer expectations. CSS results often divulge non-functional requirements or implied customer expectations regarding product and service requirements that customers expect to receive in a product or service obtained. Figure 3.2, the American Customer Satisfaction Index model (www.theacsi.org) illustrates factors that influence CS and customer loyalty all which can impact profitability.

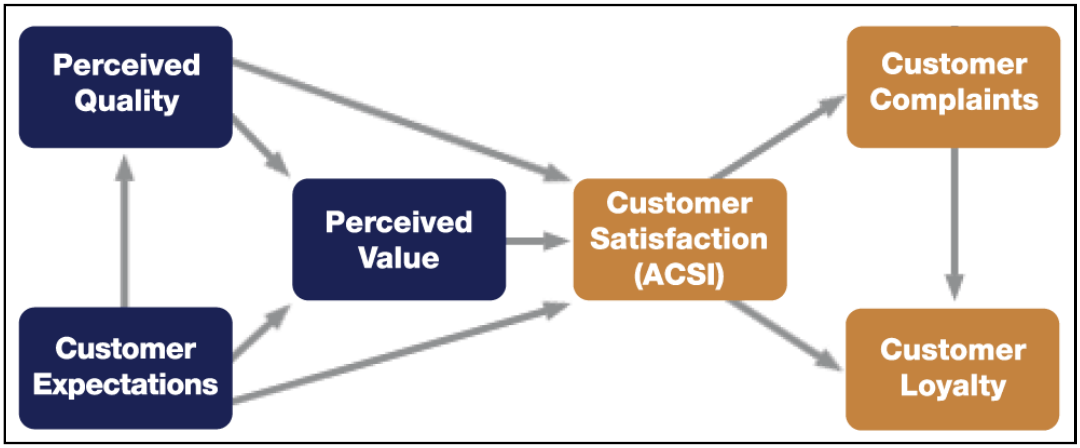


Figure 3.2: The American Customer Satisfaction Index (ACSI) Model

Source: The American Customer Satisfaction Index

3.4.1 Research Sample of Customer Satisfaction

The research is being targeted to users of a case management software application in order to obtain their expectations, perceived quality and value. The survey will be sent to approximately 1500 users.

3.4.2 Customer Satisfaction Research Methodology

The vice president of the company will establish and designate senior managers in the organization to be members of the CSS Team. CSS Team objective is to develop a CSS to obtain insight, customer expectations and perceive value of company. The CSS Team will consist of the researcher and three (3) senior managers from the company that design case management and other business software applications.

The researcher will develop a project schedule and facilitate an initial CSS kickoff meeting with the CSS team members. The research will prepare a CSS overview presentation deck and present it to the CSS Team. The research shall provide clarity to the CSS Team members during the question and answer session at the end of the presentation.

Working together, the researcher and CSS Team members will prepare draft objectives of the CSS and survey questionnaire that will be administered to respondents. The survey design must have a balance of open and closed ended questions. The CSS Team will also obtained questions from members within the organization that interface with external customers on a regular basis. The draft survey design will be emailed to consultants on the Technical Advisory Board to obtain their feedback comments, recommendations and approval of the survey design.

The CSS Team will conduct a pilot survey to collect feedback on the survey design prior to sending it out to hundreds of respondents. The CSS Team will select and administer the pilot survey to a small group of people from different departments within the company that directly interface with the customers. The results and feedback from the pilot survey will be used to tweak questions in the survey questionnaire, evaluate the amount of time it takes to complete the survey, and the overall quality of the survey. The survey questionnaire will be emailed to the respondents using SurveyMonkey.

The researcher will also assess the use of the terminology “Customer Satisfaction” in the CMMI models to evaluate the model emphasis on customer satisfaction.

3.4.3 Research Exclusions and Limitations

The customer satisfaction survey will be administered to a subset of the population identified.

3.4.4 Customer Satisfaction Survey Confidentiality

Each participant will be made aware that participation in the survey is on a volunteer basis. To protect the respondent's confidentiality their name and any other identifying information will not be collected. The respondent’s identifying information will remain anonymous and not directly associated with any data.

The names of the businesses that participate in the CSS shall remain confidential in order to protect the company's sensitive quality assurance and marketing information. A coding scheme will be employed to identify subgroups by demographics. The raw survey data will not be included in the research in order to protect the confidentiality of the organization.

3.4.5 Customer Satisfaction Survey Design and Instrument

SurveyMonkey will be used as the platform for the survey instrument. The survey questionnaire consists of a combination of 13 open and closed ended questions that measures "perceived quality, perceived value, customer expectations, customer satisfaction, and customer loyalty". The survey will also include demographic questions and a comment section on selected open-ended questions to obtain additional feedback. The closed-ended questions, with the exception of those used to rate overall customer satisfaction, will be rated on a "1-to-5 Likert Scale" from "Very Dissatisfied, Dissatisfied, Neutral, Satisfied, Very Satisfied". The survey instrument will also contain matrix and rating type questions. The three (3) core questions, "customer satisfaction, customer expectation, and perceived value" that forms the basis of the American Customer Satisfaction Index (www.theacsi.org) will be slightly re-written and used to measure on a continuum ten-point Likert Scale (1-very dissatisfied to 10-very satisfied) overall CS. The overall CS scores will be used to calculate the CSI. Conditional logic will be used in the survey instrument design to allow respondents to skip certain questions if the questions do not apply, based on other responses. The survey will also be pilot tested with a small sample of the user population.

A process mapping matrix will be designed using Microsoft Excel spreadsheet as a tool to record the mapped CS information. The matrix will include column headings of the three CMMI models (e.g., CMMI-DEV, CMMI-SVC, and CMMI-ACQ) mapped against the applicable process areas.

3.4.6 CMMI Model and Customer Satisfaction

Assessment of customer satisfaction in the CMMI models will be performed by conducting a "where used" search in the models. The results will be compiled and placed in a matrix using Microsoft Excel spreadsheet.

The data collected from the pilot survey will only be used to make improvements to the final questionnaire prior to sending it out to the general population. The CSS questionnaire will be administered via email server to a selected subset of the population understudy. The responses will be automatically collected in the survey instrument. Email reminders will be sent to respondents that do not take the survey by a predetermined point in time. The survey will have a cutoff time and date. The survey data will be collected and exported into spreadsheet and/or statistical software package for analysis.

The researcher will conduct a "where used" word search to identify all the places where the word "customer satisfaction" appears in the CMMI, v1.3, models. The data will be collected and entered into the spreadsheet mapping matrix for comparative analysis.

3.4.7 Customer Satisfaction Survey Data Analysis

The CSS raw survey data will be analyzed using various statistical techniques and statistical software packages (e.g., Minitab 16, Microsoft Excel worksheets, and Excel random number generator, etc.) to convert the data into useful information. The mean overall customer satisfaction, customer expectation, and perceived value scores will be used to calculate the Customer Satisfaction Index (CSI) score. According to Hair et al. (1998), the maximum likelihood estimation procedure has proven to provide valid results.

The research will also include an examination and analysis of the empirical data set of surveyed CSI scores. Microsoft Excel random number generator or Monte Carlo simulation will be used to generate random numbers between 1 and 10 to calculate and model theoretical CSI scores to predict future CS outcomes. The outcomes will be plotted in a statistical process control chart to assess stability. Analysis of variance (ANOVA) and other quantitative comparative analysis techniques will also be used to analyze the attributes of the survey question to detect significant differences. Normality tests will be conducted to evaluate skewness and kurtosis of the data. Correlation matrix will be used to inspect multicollinearity between variables.

3.4.8 Customer Satisfaction Survey Validity and Reliability

As illustrated in Table 3.3, a validity check will be performed by the CSS Team and Technical Advisory members on the questionnaire to ensure the survey design includes mix of open and closed ended questions, questions pertaining to the areas of focus and measures of customer satisfaction indices.

There is no historical CS data available to conduct a comparison analysis. This will be the first time the organization conducts a CSS with its external customers (e.g., users of the case management software application). The survey results and analysis will form a CSS baseline for the organization. The CSI score will be benchmarked against the

American Customer Satisfaction Index for comparison The survey results will be presented to senior management and members in the organization that interface with external customers to obtain their concurrency of the findings.

Table 3.3: Survey Questionnaire Validity Check

Customer Satisfaction Survey Questionnaire Validity Check			
Area of Focus	**Measure of Satisfaction**	**Number of Questions**	**Likert Scale**
Problem Resolution	Customer Commplaints		
Sales	Customer Expectation		
Rate Expectations	Customer Expectation	1	1 to 10
Customer Recommendation	Customer Loyalty		
End-user usage	Customer Loyalty		
Rate Overall CS	Customer Satisfaction	1	1 to 10
Software End-User Usage	Customer Satisfaction		
Training	Customer Satisfaction		
Demongraphics	General	2	
Design/Process Change	Perceived Quality		
Quality	Perceived Quality		
Software Implementation	Perceived Quality		
Technical Support	Perceived Quality		
Training	Perceived Quality		
Rate Comparison to Ideal Software	Perceived Value	1	1 to 10
Sales	Perceived Value		

3.5 Summary Methodology

In summary, the research will add to the body of knowledge by making aware issues and gaps that are not readily apparent to the academic community and engineering practitioners responsible for applying analytical and quantitative techniques to measure, monitor, and improve the software and systems engineering processes. The research will also demonstrate the use of different analytical and quantitative techniques that can be used to baseline, quantitatively manage, and optimize a “Customer Satisfaction” process.

Chapter 4, will include the research methodology results: Gap analysis findings of process improvement and quality management courses taught in the systems engineering and computing science disciplines in U.S. colleges and universities; and a matrix that shows the mapping of the SEI Healthy Ingredients analytical techniques” (e.g., statistical methods, optimization approaches, visual and decision techniques) mapped to quality management and statistical courses taught in the computing science and systems engineering disciplines. The results of quantitatively managing the customer satisfaction process by applying quantitative, analytical, and SPC techniques. Chapter 4 will also provide a brief discussion of the term *customer satisfaction* and its emphasis in the CMMI model.

Chapter 4: RESULTS AND DISCUSSION

The previous chapters provided general background information regarding the motivation of this study and a review of related literature. This chapter describes the research findings of the study; it also serves to provide its significance to researchers, the academic community, software and systems engineering process improvement practitioners, and also delineates contributions to the body of knowledge.

The research findings of this study are presented in four (4) major sections. Section 4.1 summarizes the results from conducting a gap analysis of process improvement and quality management skills taught to students in the systems engineering and computing science disciplines in U.S. universities. Section 4.2 delineates the results from conducting a comparison analysis of the *Software Engineering Institute's (SEI) healthy ingredients of process performance models and analytical methods* against the *gaps identified in the process improvement courses taught in the systems engineering and computing science disciplines*. Section 4.3 provides a demonstration using modeling and simulation, statistical process control, advanced statistical and quantitative approaches and methods, and optimization techniques to show how an organization can select customer satisfaction sub-process as a measurement business objective and achieve Capability Maturity Model Integration (CMMI) high maturity rating. Section 4.3 also includes a *customer satisfaction index score dashboard* that was developed as a result of the research. The research contributions are described in Section 4.4.

4.1 Gap Analysis Findings of Process Improvement & Quantitative Management Skills Taught in Computing Science and Systems Engineering Disciplines

This section of the research provides a discussion and the results from conducting a gap analysis study to address the question, "Do academic programs in the U.S. in systems engineering (SE), software engineering (SW), computer science (CS), and information technology (IT) programs provide formal training in quantitative, analytical, or statistical analysis principles and methods centered on process improvement to students during their academic studies?"

4.1.1 Study of U.S. "Colleges and Universities Systems Engineering and Computing Science Degree Programs That Offers Courses in Process Improvement Quantitative Analysis Techniques" Assessment Results

The focus of the research was to identify the gaps that exist in analytical and quantitative techniques taught in college courses that provide students with the body of knowledge and skills needed to be able to perform process improvement and quality management tasks. Everyone involved in executing repeatable processes in the software and systems development life cycle (SDLC), or software development life cycle process (McCray and Santos, 2009) needs to become familiar with the concepts of *quantitative management, statistical thinking, quality management, process improvement techniques,* and how they relate to process-performance.

As indicated in Table 4.1, the gap analysis included the review of 266 curricula in 172 degree programs. The study involved in-depth reviews of course catalogs, curricula, and syllabi to identify required and elective courses. Degree programs were analyzed with an eye towards on courses that primarily focused on the application of quantitative management techniques (e.g., use of statistical and quantitative techniques), process improvement, and software quality disciplined methodologies that can be applied to improve software and systems engineering products and processes for performance. The content of syllabi and course descriptions in questions were validated with program coordinators and professors via telephone conversations and emails. The names of the U.S. colleges and universities included in the study are listed in Appendix A through D.

Table 4.1: Number of Colleges & Universities Reviewed By Discipline

		No. of Curricula Included in the Study			
Colleges & Universities	**Degree Program**	**BS**	**MS**	**Ph.D.**	**Total**
40	Software Engineering (SW)	21	31	3	55
43	Systems Engineering (SE)	9	41	10	60
40	Computer Science (CS)	40	24	18	82
49	Information Technology (IT)	47	18	4	69
	Total	117	114	35	266
Note: The above number of colleges and universities do not total 145. Some of the schools included in the study offer degree programs in multiple disciplines.					

4.1.1.1 Software Engineering Study Assessment Results

In the U.S. colleges and universities SW degree programs are interdisciplinary and have a broad focus. The first Bachelor of Science degree was awarded by Rochester Institute of Technology in 1996 (Bagert and Ardis, 2003). Master's of Science degrees in SW have been in existence longer and have been awarded since the late 1970s (Bagert and Ardis, 2003; Mead, 2009). In 1989 (Ardis and Ford,1989) the SEI conducted a workshop and invited several software engineering educators to attend the workshop to develop a master's of science in software engineering degree curriculum. The names of the participants that attended the SEI workshop are listed in Table 4.2:

Table 4.2 SEI 1989 MS in Software Engineering Degree Curriculum Design Team

SEI Representative	University Representative
Mark Ardis	Jim Collofello, Arizona State University
Lionel Deimel	Dick Fairley, George Mason University
Gary Ford	Jeff Lasky, Rochester Institute of Technology
Norm Gibbs	Larry Morell, College of William and Mary
Bob Glass	Tom Piatkowski, State University of New York at Binghamton
Harvey Hallman	Tom Kraly, IBM
Scott Stevens	Jim Tomayko, The Wichita State University

In 2004, the Joint Task Force on Computing Curricula, IEEE Computer Society, and Association for Computing Machinery Steering Committee developed "A Curriculum Guidelines for Undergraduate Degree Programs in Software Engineering" (SE2004), and the IEE Computer Society (Abran and Moore, 2004) published a "Guide to the Software Engineering Body of Knowledge (SWEBOK)". In 2007 - 2008, Stevens Institute of Technology (Pyster et al., 2008) conducted a general study on 28 graduate SW degree programs to determine the current state of software engineering master's level degree programs, identified gaps in the programs, and developed a recommended Graduate Software Engineering Reference Curriculum (GSwERC). The study conducted by Stevens Institute of Technology also identified a gap in the lack of software quality courses taught in graduate SW degree program curricula and point out the importance of SW core body of knowledge (e.g., value and costs of quality, quality models and characteristics, quality improvement, software quality management process) to software engineering education.

This research study included the assessment of 55 software engineering degree programs (21 bachelor's, 31 master's, and 3 doctoral) from 40 colleges and universities. The study was performed to determine which software engineering programs offered curricula and courses that focus on developing domain knowledge and theoretical understanding on how to quantitatively manage and improve software processes for performance by applying applicable techniques. Figure 4.1, identifies the gaps in SW degree programs that do not offer required courses which focuses on software quality, quality management, or quality improvement. Gaps were noted in 16 of 21 bachelor's degree programs studied; 25 of 31 master's degree programs, and 3of 3 doctoral programs offered did not have a course on quality management, software quality assurance, or software process improvement. Five (5) of the bachelor's degree programs offered required courses focused on software quality and process improvement. Four (4) master degree programs included required courses in the curricula on software measurements /

metrics; and two (2) offered electives courses on software quality engineering, and metrics and statistical methods for software engineering.

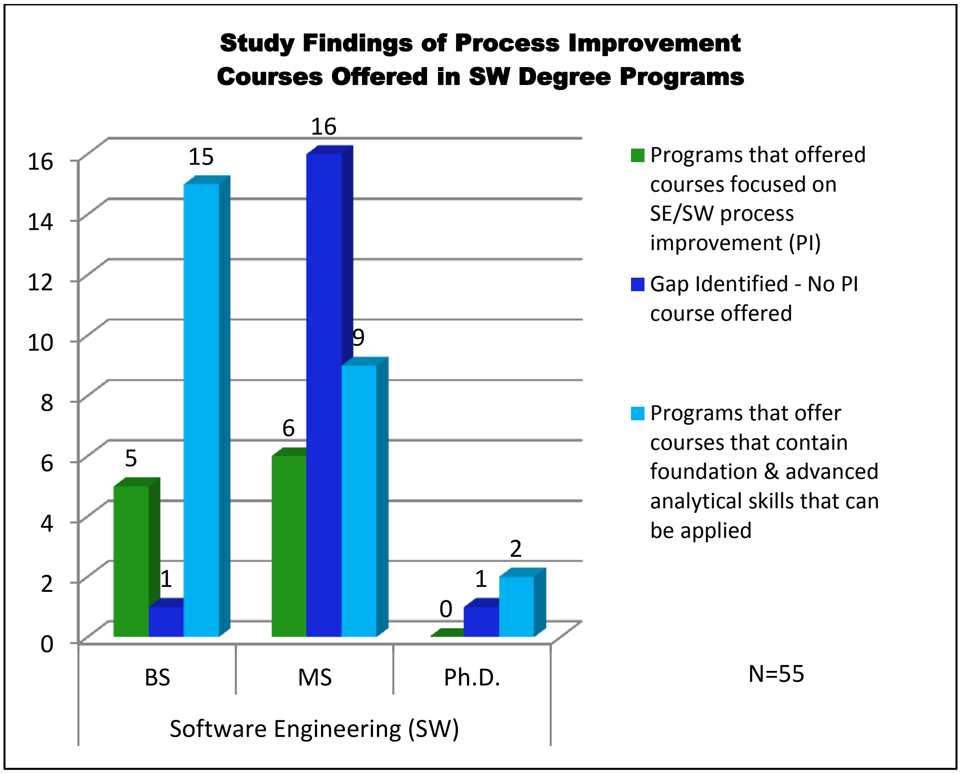


Figure 4.1: Software Engineering Degree Programs Assessment Results

4.1.1.2 Systems Engineering Study Assessment Results

The International Council on Systems Engineering (INCOSE) has defined SE as, "An interdisciplinary approach and means to enable the realization of successful systems. Systems engineers apply engineering techniques and mathematical methods to model, predict, and improve the performance of systems composed of machines, people, and procedures".

A degree in SE can be obtained at the bachelor's, master's, and doctoral degree level from several universities in the U.S. Most universities that offer a SE degree are within the industrial and systems engineering (ISE) or similarly named departments. Many people have a misconception of the term "industrial". ISE curricula are no longer restricted to manufacturing or time studies. ISE academic degree programs have a different focus today than they had 20 – 30 years ago. Most schools that offer degree programs in ISE have a large emphasis on courses that use modeling and simulation and quantitative analysis techniques for decision-making.

The academic programs in the 43 colleges and universities included in this research study have a diverse SE focus. Some of the schools have programs that provide an in-depth focus on the principles of SE and others do not. Others offer an interdisciplinary and specialized program focus (e.g., Power Systems Engineering, Operation Research, Human Computer Interface Design, Engineering Management, etc.).

As shown in Figure 4.2, the study included the assessment of 60 SE degree programs (9 bachelor's, 41 master's, and 10 doctoral) in 43 schools. A gap, which indicates evidence of no applicable software quality, quality management, or quality improvement course offered, was observed in 8 of 9 bachelor's, 27 of 41 master's, and 9 of 10 doctoral degree programs. One bachelor's degree program offered an elective course titled "Process Engineering and Improvement" which emphasizes the application of engineering principles for improving the quality of processes, products, and services. In industry, most engineering practitioners have bachelor's degrees and often are called upon to collect and analyze engineering process metrics without foundational knowledge or understanding of process improvement or quality management principles which is conclusive of the research findings. The master's degree program offered more courses focused on SE and SW process improvement. Overall, all SE disciplines studied in this research offered courses that contain foundational and advanced analytical knowledge that can be applied to obtain insight into the performance of data.

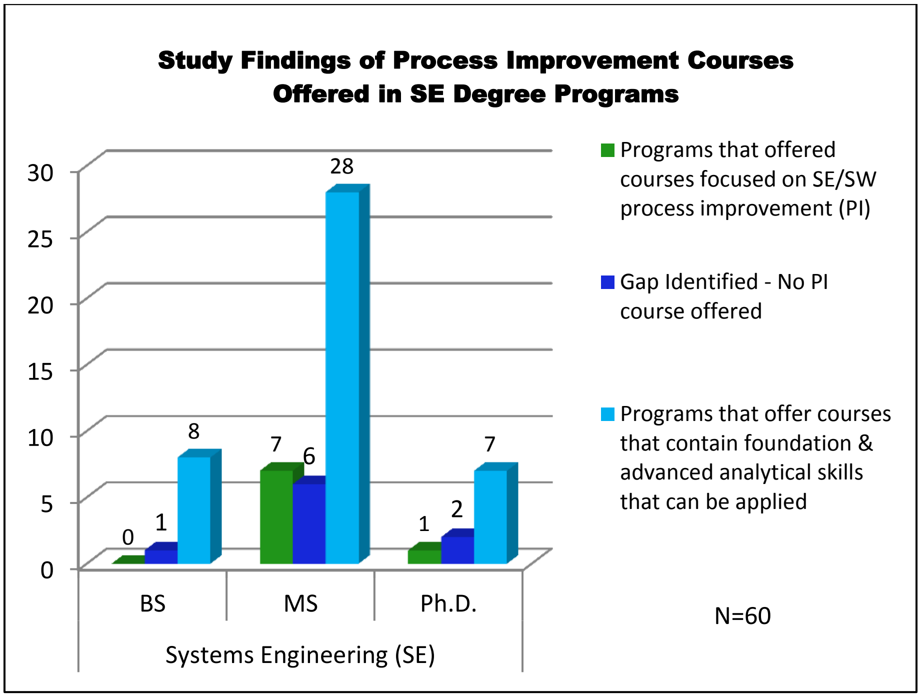


Figure 4.2: Systems Engineering Degree Programs Assessment Results

4.1.1.3 Computer Science Study Assessment Results

U.S. colleges and universities teach CS programs that tend to focus on theoretical study of computation and algorithmic reasoning (e.g., discrete math, data structures, database management, analysis and design of algorithms and their practical applications in system programming, database management, scientific visualization, telecommunications, etc.). Software engineers provide specialized knowledge and experience in developing and modifying large, complex software systems.

The findings include an assessment of 82 CS degree programs (40 bachelor's, 24 master's, and 18 doctoral) in the 40 colleges and universities included in this portion of the study. The CS programs (e.g., bachelor's, master's, and doctoral level) did not include a software quality course in the curricula.

Surprisingly, the CS disciplines studied do not offer required or elective courses in SW or SE process improvement at the bachelor's, master's, or doctoral level. As illustrated by the gaps identified in Figure 4.3, the CS programs studied do not offer a required course in software quality management or process improvement in the bachelor's, master's, or doctoral programs. Another interesting finding in the CS degree programs studied, most departments did not offer a course in the principles of systems engineering and SDLC. The bachelor's degree offered the majority of courses with foundational and advanced analytical skills that can be leveraged and applied to obtain insight to the understanding of data.

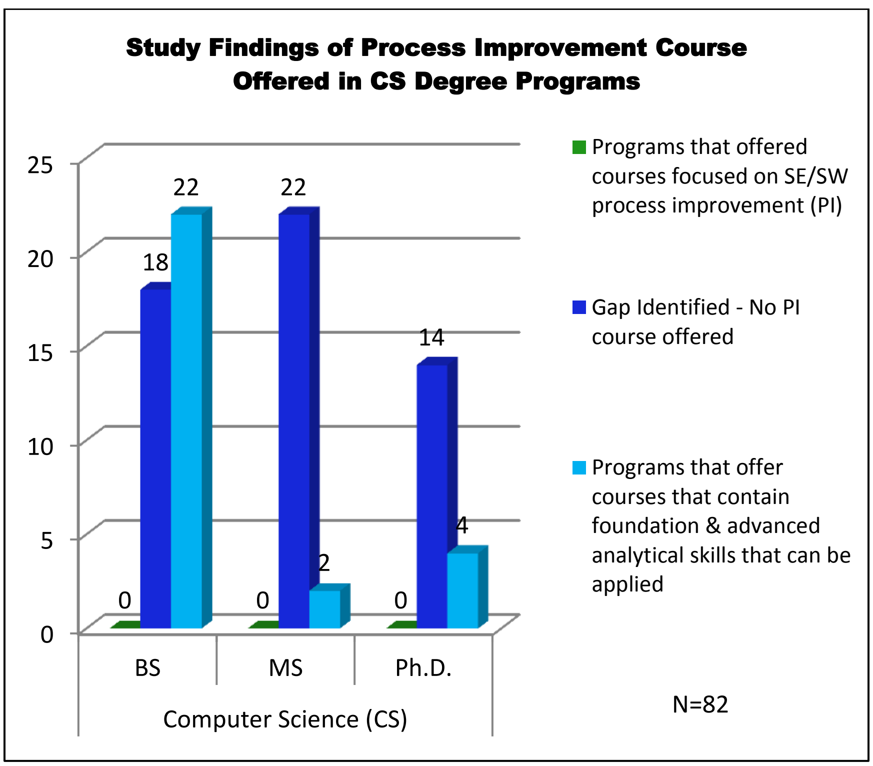


Figure 4.3: Computer Science Degree Programs Assessment Results

4.1.1.4 Information Technology Study Assessment Results

More and more students are starting to shift from CS and SW degrees to IT. The Education Board of the Association for Computing (ACM) created the first draft of The Information Technology Model Curriculum in 2005 (Barry and Ekstrom, 2008). In 2008, members of the Association for Computing Machinery and IEEE Computer Society developed Curriculum Guidelines for Undergraduate degree Programs in Information Technology (Lunt, B. M. et al., 2008).

IT degree programs are interdisciplinary and have a broad focus. IT degree programs have less focus on programming and quantitative courses as opposed to computer science. Most programs are designed to develop skills needed to prepare students for practical application of various IT assignments (e.g., network design and maintenance, information assurance and security, internet application development, business systems development, human computer interaction, and the management of IT projects). Students are interested in obtaining jobs to manage software projects and implementations.

Courses in product and process improvement, SW, and SE principles are not always included in IT curricula. Not surprisingly, as previously mentioned, the proposed curricula guidelines for undergraduate degree programs does not contain recommended courses focused on quality, process improvement of IT processes, or the fundamentals of systems engineering. This is supported by the findings in Figure 4.4.

The findings in Figure 4.4 include an assessment of 69 IT degree programs (47 bachelor's, 18 master's, and 4 doctoral) in the 49 colleges and universities included in this portion of the study. An applicable required course titled quality improvement for industry and another course titled quantitative analysis that partially focused on SW improvement was included in 2 of 47 bachelor's degree programs. The IT master's and doctoral degree programs did not include any required or elective courses as part of the curricula that provide the students with domain knowledge and skills to improve processes. Most programs did not offer courses on the principles of systems engineering and SDLC. More gaps were identified at the bachelor's level which offered more courses. The bachelor's, master's, and doctoral degree programs offered courses that contained foundational and advanced analytical skills that can to be applied to obtain insight into data.

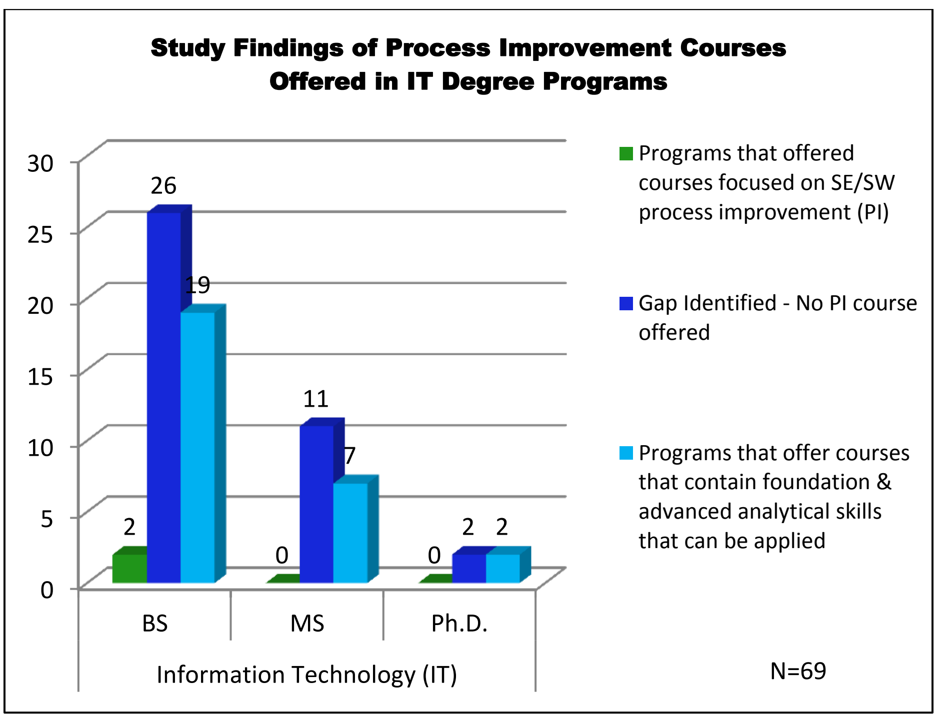
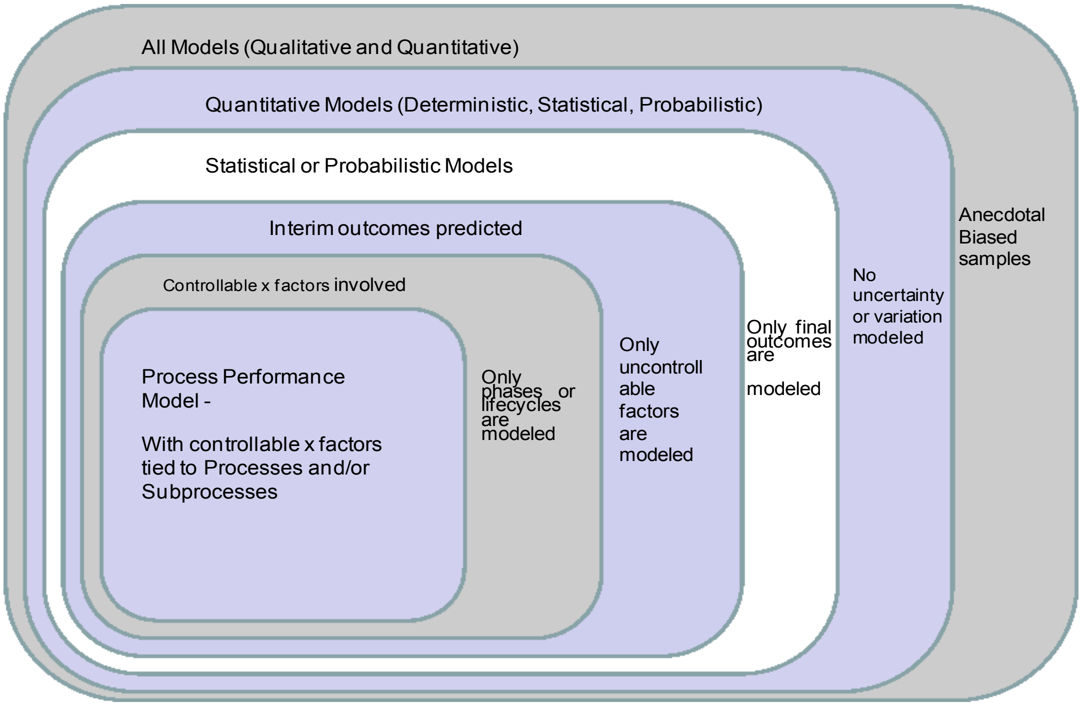


Figure 4.4: Information Technology Degree Programs Assessment Results

4.2 Comparison Analysis of "SEI's Healthy Ingredients of Process Performance Models &Analytic Methods" to "Gaps Identified In Process Improvement Courses Taught in SE & Computing Science Disciplines"

A comparison analysis was conducted to examine the process improvement and quality management courses taught in the systems engineering and computing science curricula in U.S. colleges and universities that best aligns with the "healthy ingredients" of CMMI-based process performance models and analytical methods that fosters process performance. The research findings are based on the schools included in the study.

The SEI Measurement and Analysis Working Group since 1999 have been conducting surveys, workshops, and conferences (Paulk and Chrissis, 2000; Goldenson, McCurley, and Stoddard, 2009a; Stoddard and Goldenson, 2010) to gain insight into the adoption, use of analytical methods and approaches deployed by software and systems engineering organizations. In March 2008, during the High Maturity Measurement and Analysis Workshop (Stoddard, Goldenson, Zubrow, and Harper, 2008) it was pointed out, from the data collected from 2005 – 2008, a misconceptions regarding process performance modeling, applicable analytical techniques to demonstrate high maturity needed to be dispelled. Stoddard et al. (2008) stated, "Most clients believed that the chief barrier to modeling was the need for advanced knowledge of statistics". To dispel the perception, the SEI Software Engineering and Measurement and Analysis Working Group created a framework called the "Healthy Ingredients of a Process Performance Model" (Figure 4.5) and launched a series of training workshops. The Measurement and Analysis Working Group (Stoddard and Goldenson, 2010) derived the healthy ingredients from a holistic understanding of the intent to demonstrate high maturity process performance of the CMMI models.



Source: CMU/SEI-2009-TR-021, (p. 6)

Figure 4.5: Healthy Ingredients of a Process Performance Model

In conjunction with the concept of healthy ingredients of CMMI-based process performance models the SEI also place emphasis on a set of analytical methods and techniques that are commonly used by organizations. The analytical methods (Goldenson, McCurley, and Stoddard, 2009a; McCurley and Goldenson, 2010) are grouped in four categories: statistical methods, optimization approaches, visual display techniques, and decision techniques. The analytical methods are taught in SEI measurement training courses and assessed in measurement surveys.

As illustrated in Tables 4.3 and 4.4, the research created a mapping which shows a gap between the healthy process performance model ingredients, analytical techniques, and methods taught by the SEI alignment with the required and elective analytical and quantitative courses taught at the bachelor's, master's, and doctoral level in systems engineering and computing science courses.

Table 4.5 is a summary of the number of systems engineering and computing science courses identified in the study that aligns with SEI Healthy Ingredients Methods.

Table 4.3: Mapping SEI's Analytic Methods to Gaps in Courses Taught

Legend: ● Required Course ○ Elective Course ✚ Probability & Statistics ★ SW/SE Process Improvement ✯ Process Improvement	**Mapping "SEI's Healthy Ingredients - Analytic Methods" to "Gaps in Process Improvement & Quantitative Skills Taught in SE and Computing Science Courses in U.S. Colleges and Universities"**											
	Systems Engineering			**Software Engineering**			**Computer Science**			**Information Technology**		
	BS	**MS**	**Ph.D.**	**BS**	**MS**	**Ph.D.**	**BS**	**MS**	**Ph.D.**	**BS**	**MS**	**Ph.D**
SEI's Healthy Ingredients Analytic Methods												
Statistical Methods												
Individual Point SPC Charts (e.g., ImR, or XmR)	○✯	● ○✯	○✯		● ○★					●✯		
Attribute SPC Charts (e.g., c, u, p, or np)	○✯	● ○✯	○✯		● ○★					●✯		
Continuous SPC Charts (e.g., XbaR or XbarS)	○✯	● ○✯	○✯		● ○★					●✯		
Continuous Regression Analysis (e.g., bivariate, or multivariate linear regression or non linear regression)	●	○ ●✚	○ ●✚	●✚	○ ●✚		●✚	●✚		●✚	●✚	●✚
Analysis of Variance (ANOVA)	●	○ ●✚	○ ●✚	●✚	●✚		●✚	●✚		●✚	●✚	●✚
Analysis of Covariance (ANCOVA)	●	●○										
Multivariance ANOVA (MANOVA)	●	○										
Categorical Regression (e.g., logistic regression or log linear models)	●	○										
Design of Experiment	●	● ○★	● ○★		○ ●★	●						

Table 4.4: Mapping SEI's Analytic Methods to Gaps in Courses Taught

Legend: ● Required Course ○ Elective Course ✚ Probability & Statistics ★ SW/SE Process Improvement ☆ Process Improvement	**Mapping "SEI's Healthy Ingredients - Analytic Methods" to "Gaps in Process Improvement & Quantitative Skills Taught in SE and Computing Science Courses in U.S. Colleges and Universities"**											
	Systems Engineering			**Software Engineering**			**Computer Science**			**Information Technology**		
	BS	**MS**	**Ph.D.**	**BS**	**MS**	**Ph.D.**	**BS**	**MS**	**Ph.D.**	**BS**	**MS**	**Ph.D**
Optimization Approaches												
Monte Carlo Simulation	●	●★ ○☆	○	●✚								
Probabilistic Modeling	●	●	●		●★				○			
Optimization	●	●○	●○	●✚					○			
Discrete Event Simulation	●	●○	●○	●✚	○							
Markov Models	●	●○	●○									
Petri-Net Models												
Neural Networks												
Visual Display Techniques												
Pareto, Pie, Bar Charts	●✚	●✚			●✚					●✚	●✚	●✚
Histograms	●✚	●✚			●✚					●✚	●✚	●✚
Scatter Plots	●✚	●✚			●✚					●✚	●✚	●✚
Multivariable Charts	●✚	●✚			●✚					●✚	●✚	●✚
Box Plots	●✚	●✚			●✚		●✚			●✚	●✚	●✚
Categorical Mosaic Chart												
Decision Techniques												
Analytic Hierarchy Process (AHP)		○	●									
Real Options			●									
Conjoint Analysis												
Wideband Delphi												
Weighted Multi-Criteria Methods (e.g., QFD, or Pugh)		○	○									
Decision Trees		●○	●○		○							

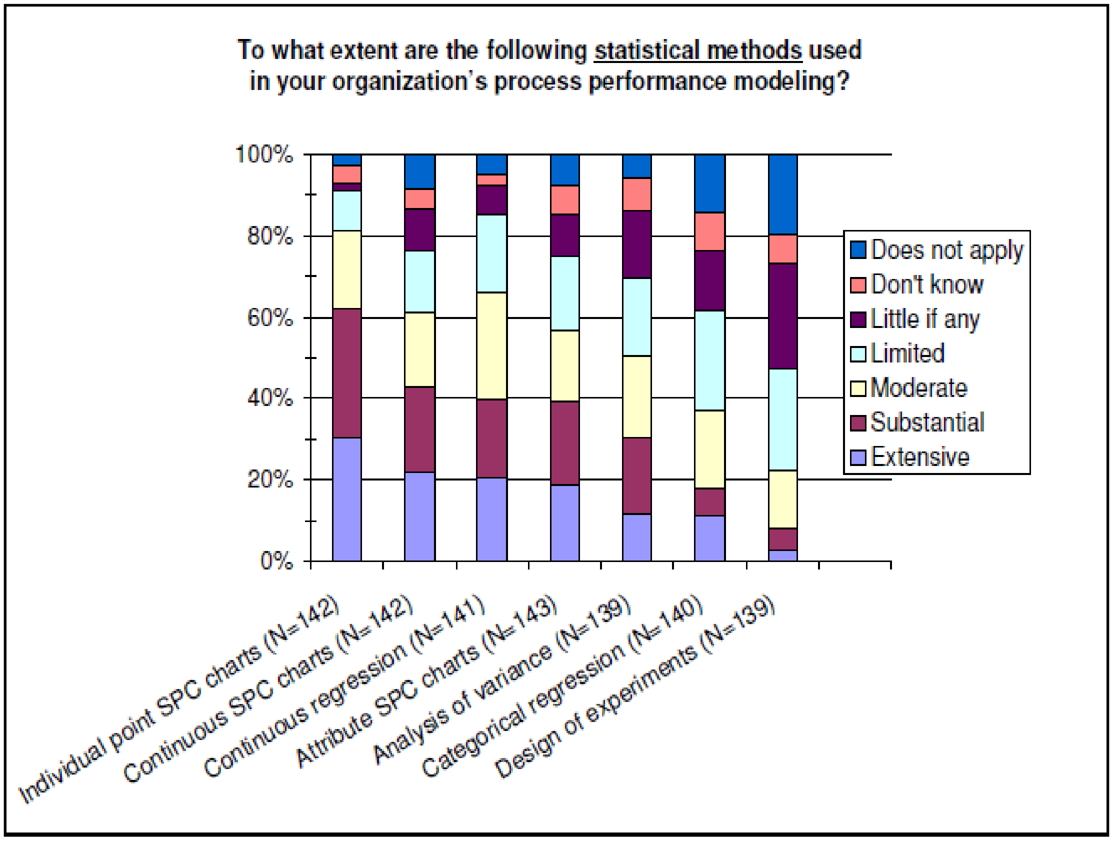
Table 4.5: Number Courses that Align with SEI Health Ingredients Methods

Summary Systems Engineering and Computing Science Courses That Align With SEI Healthy Ingredients Analytical Methods				
Category SEI Healthy Ingredients Analytical Methods	Systems Engineering	Software Engineering	Computer Science	Information Technology
Statistical Methods	49	22	8	18
Optimization Approaches	24	9	2	0
Visual Display techniques	20	10	2	30
Decision Techniques	9	1	0	0
Totals:	102	42	12	48

4.2.1 **Statistical Methods Taught**

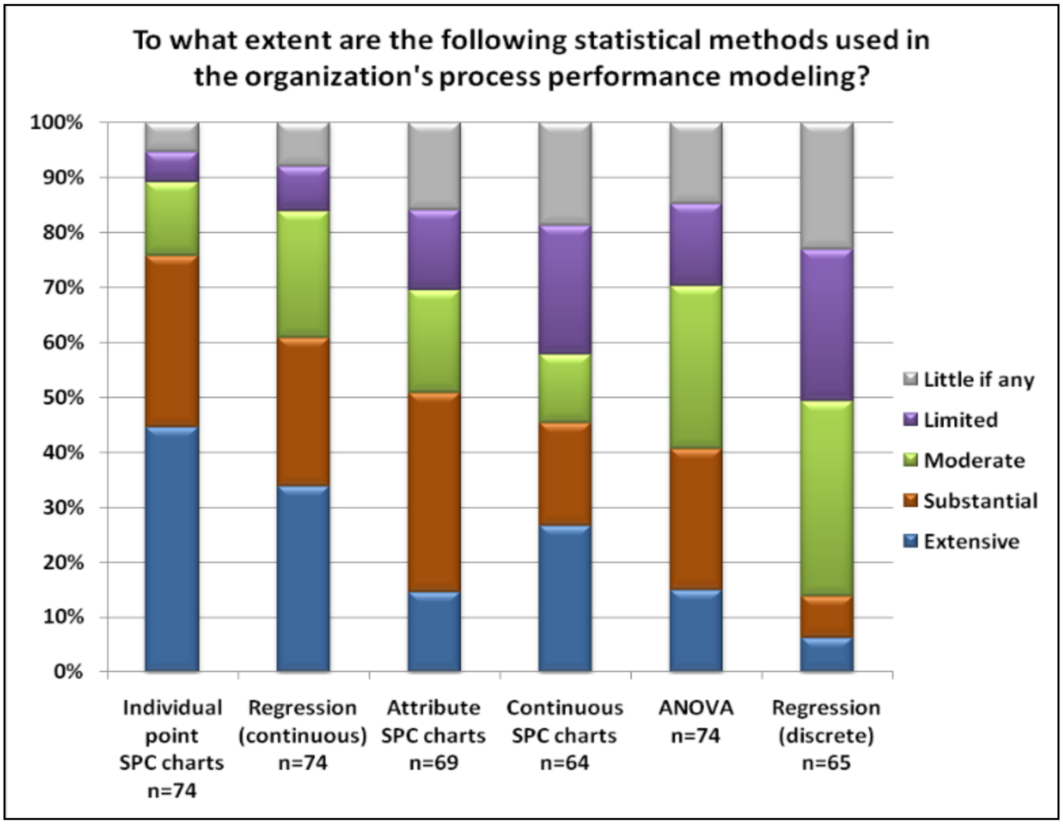
Table 4.3, in Section 4.2, contains a mapping of statistical methods taught in SEI's high maturity measurement training courses to the gaps in courses taught in U.S. colleges that foster analytical techniques that enable process improvement.

The SEI conducts surveys on the use of analytical methods used within organizations measurement programs to establish and monitor process-performance. Figures 4.6 and 4.7, respectfully, show the "use of statistical methods" results from the 2008 and 2009 surveys conducted by the SEI. The organizations surveyed extensively use "individual point statistical process control (SPC) charts and continuous SPC charts" (Goldenson, McCurley, and Stoddard, 2009a; Goldenson, McCurley, and Stoddard, 2009b;McCurley and Goldenson, 2010) as their primary statistical methods to establish and monitor process-performance. The survey results also point out that few organizations deploy extensive or substantial use of analytical methods such as categorical regression, analysis of variance, and design of experiments.



Source: CMU/SEI-2008-TR-024, (p.22)

Figure 4.6: Use of Diverse Statistical Methods



Source: CMU/SEI-2010-TR-022, (p.26)

Figure 4.7: 2009-Use of Statistical Methods in Process Performance Models

Figure 4.8 contains histograms which show the statistical methods identified in the SEI training that best aligns with the required or elective probability and statistics, SW/SE process improvement, or process improvement courses taught in U.S. colleges by discipline at the bachelor's, master's, and doctoral levels.

The research findings point out, as illustrated in the diagrams, that the SE discipline offers statistical methods courses at the bachelor's, master's, and doctoral level that best aligns with the statistical methods identified. The SW discipline does not offer a lot of courses in statistical methods at the bachelor's or doctoral level. The SW discipline offer courses at the master's level that aligns with the statistical methods identified.

The SW and CS disciplines both offer courses that develop knowledge in the principles of regression analysis and analysis of variance (ANOVA) at the bachelor's and master's level. Based upon the sample, statistical methods training is not offered in SW and CS courses at the doctoral level. The sample findings also point out that the CS discipline does not offer statistical method courses at the doctoral level. The IT discipline offers courses in statistical methods identified with the exception of categorical regression and design of experiment at the bachelor's level. Regression analysis and ANOVA principles are taught in IT courses offered at the bachelor's, master's, and doctoral level in some degree programs.

Statistical Methods

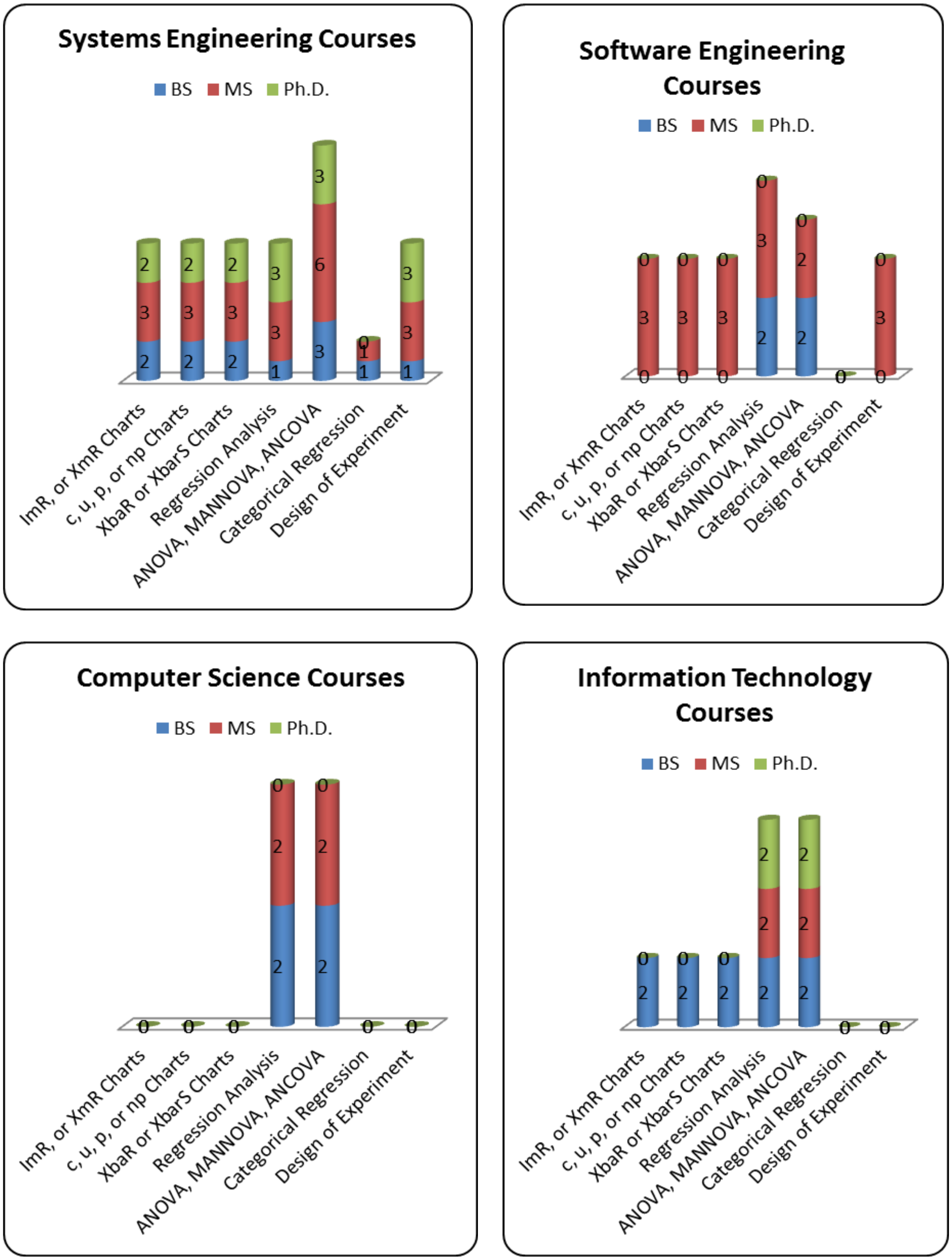
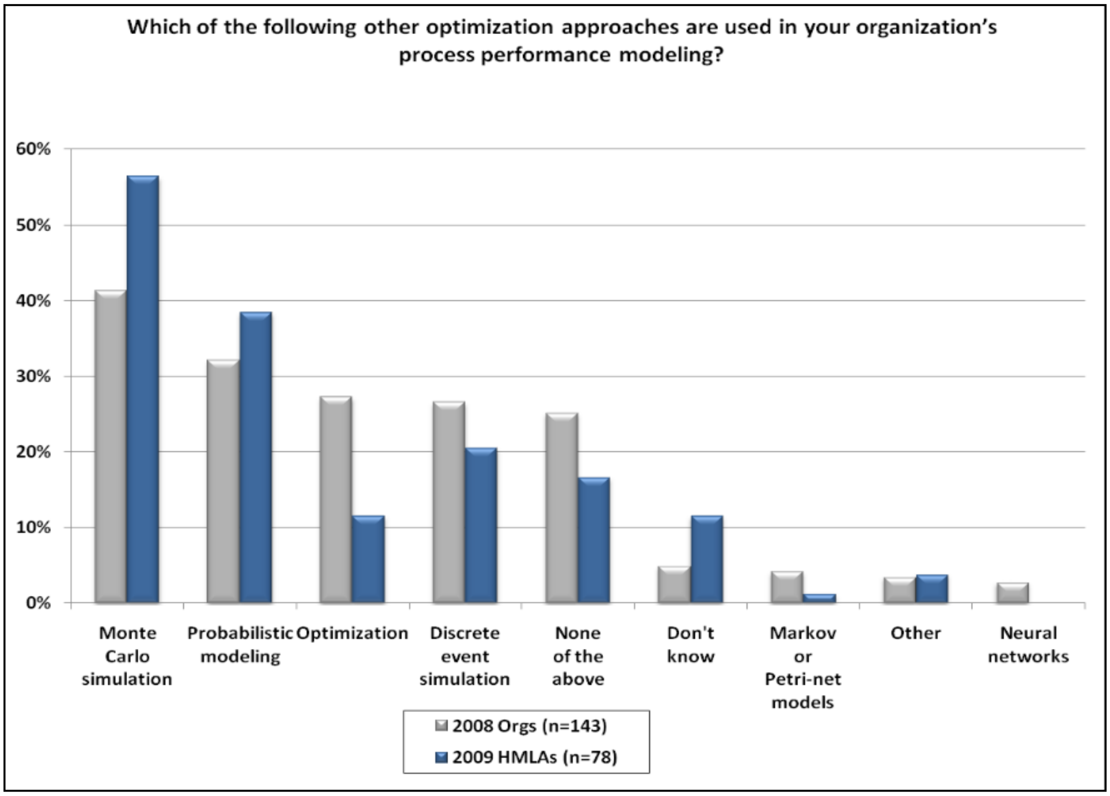


Figure 4.8: Statistical Methods Taught in College Courses By Discipline

4.2.2 **Optimization Approaches Taught**

Table 4.4, in Section 4.2, contains a mapping of optimization approaches taught in SEI's high maturity measurement training courses to the gaps in courses taught in U.S. colleges that foster analytical techniques that enable process improvement.

Figure 4.9 shows a histogram of the 2008 and 2009 survey results conducted by the SEI of "optimization approaches" organizations use to develop process-performance models and baselines. The SEI 2008 and 2009 survey results (Goldenson, McCurley, and Stoddard, 2009a; Goldenson, McCurley, and Stoddard, 2009b;McCurley and Goldenson, 2010) indicate that Monte Carlo simulation and probabilistic modeling are the most widely used optimization approaches by organizations. The 2008 – 2009 survey result comparison shows a decline in the use of optimization techniques, discrete event simulation, Markov and Petri Net models.



Source: CMU/SEI-2010-TR-022, (p.29)

Figure 4.9: 2009-Use of Optimization Techniques in Process Performance Models

The histogram in Figure 4.10 shows the "optimization approaches" taught in the SEI training courses that best align with the required or elective probability and statistics, SW/SE process improvement, or process improvement courses taught in U.S. colleges by discipline at the bachelor's, master's and doctoral level.

The research findings point out, as illustrated in Figure 4.10, that the optimization approaches identified are primarily taught in SE courses at the bachelor's, master's, and doctoral level with the exception of Petri-Net models and neutral networks in the programs included in the research study. Based on the study, there are SE degree programs that teach the principles and techniques of neutral networks and Petri-Net models not included in the study.

The SW discipline offer courses that teaches optimization teachniques and approaches. Based on the software engineering programs included in the study, Monte Carlo simulation and optimization techniques courses are taught at the bachelor's's level. Discrete event simulation is taught in courses at the bachelor's and master's level. Probabilistic modeling techniques are taught in courses at the master's level. Optimization techniques are not taught in doctoral level courses. The schools included in the study did not offer Markov models, Petri-Net models, or neutral network courses in the software engineering programs. The CS programs included in the study only offered courses at the doctoral level of study in probabilistic modeling and optimization techniques. The IT degree programs included in the study did not include courses in optimization approaches at the bachelor's, master's, or doctoral level.

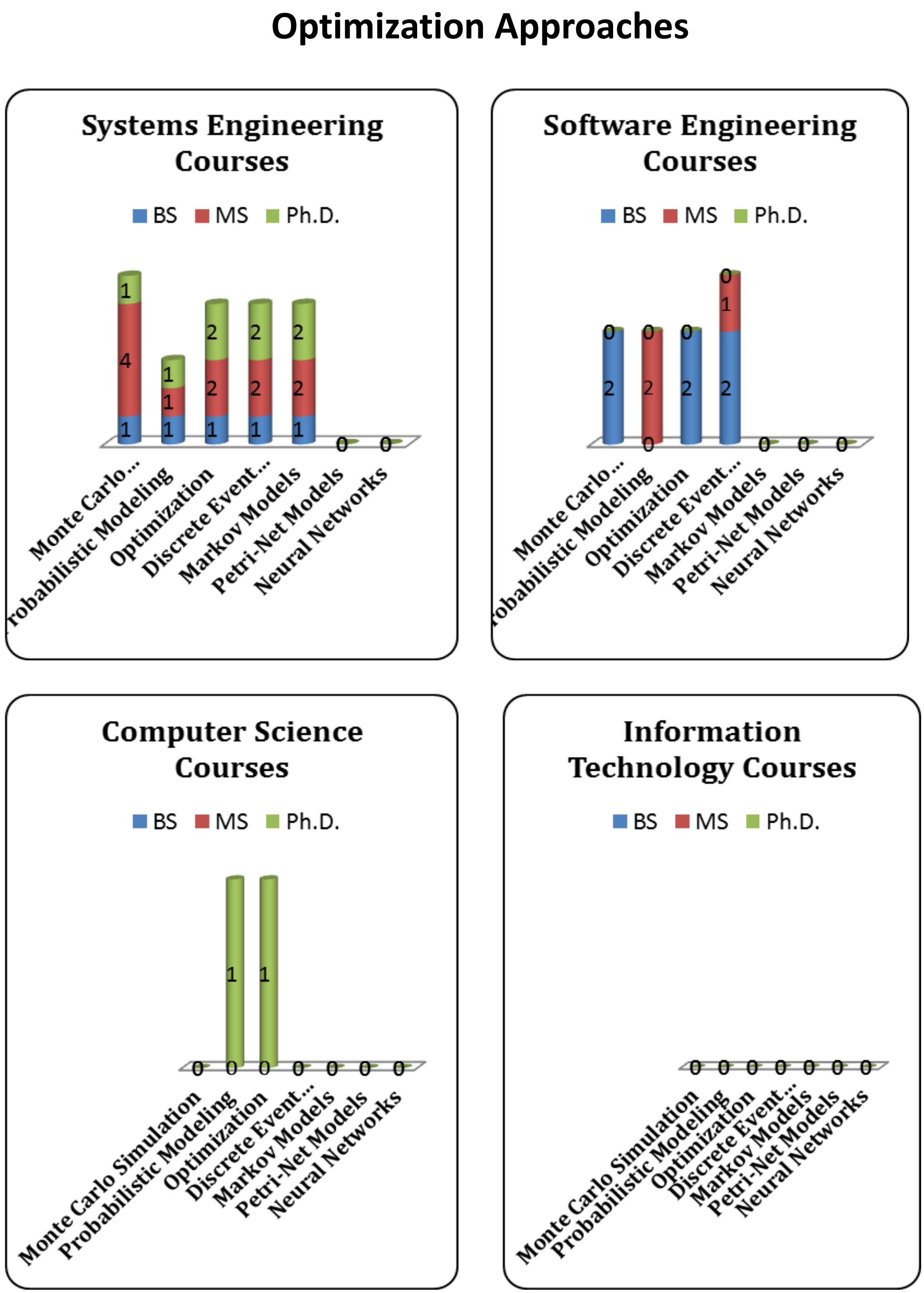
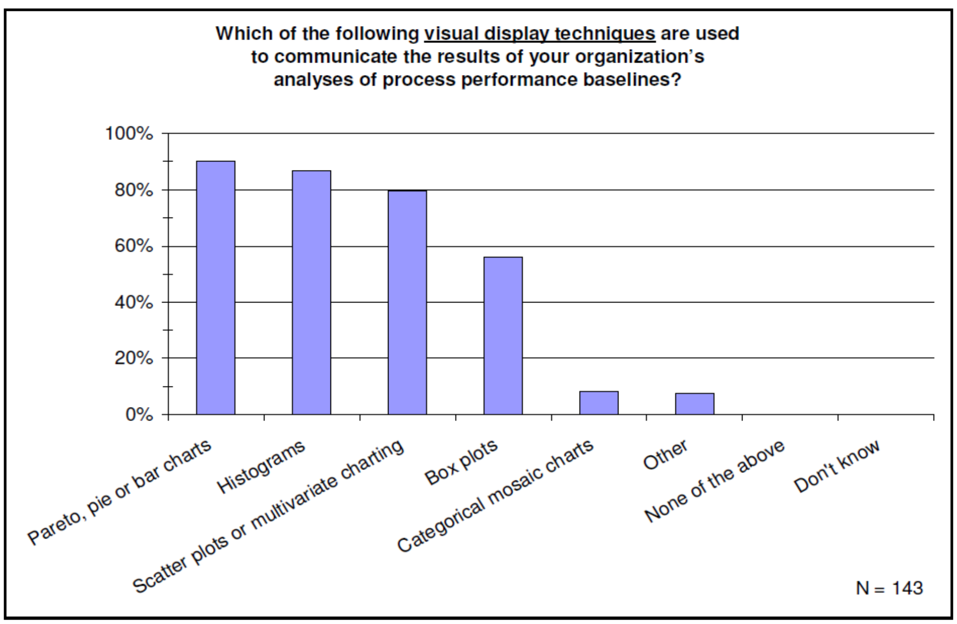


Figure 4.10: Optimization Approaches Taught in College Courses By Discipline

4.2.3 Visual Display Techniques Taught

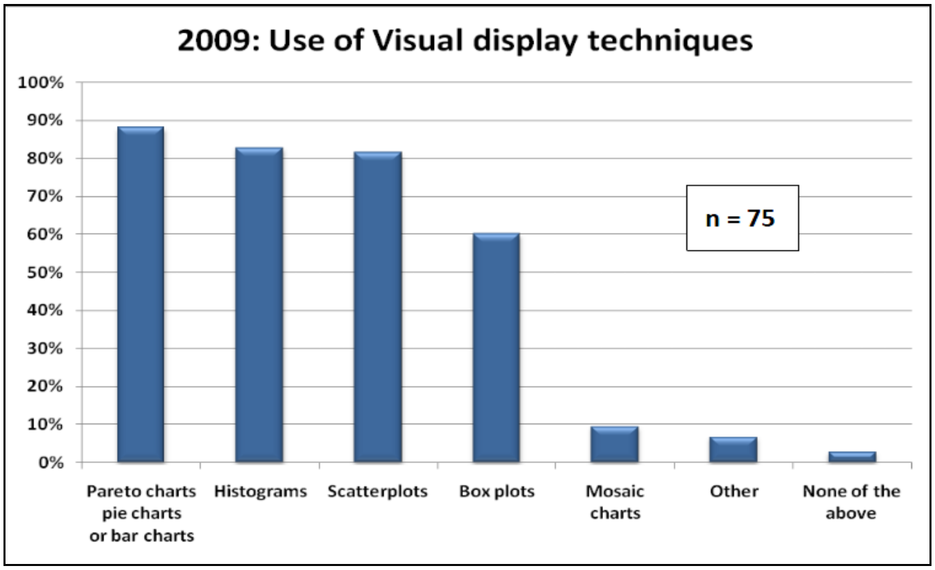
Table 4.4, in Section 4.2, contains a mapping of *visual display techniques* taught in SEI's high maturity measurement training courses to the gaps in courses taught in U.S. colleges that teach analytical techniques that can be applied to enable process improvement.

Figures 4.11 and 4.12, respectfully, show histograms of the 2008 and 2009 survey results conducted by the SEI of "visual display techniques" commonly used within organizations to visualize data. As illustrated in Figures 4.11 and 4.12, the Pareto and pie charts, along with histograms, are the most commonly used visualization techniques (Goldenson, McCurley, and Stoddard, 2009; McCurley and Goldenson, 2010) . The reported use of visual display techniques remained the same between the 2008 and 2009 survey results.



Source: CMU/SEI-2008-TR-024, (p.24)

Figure 4.11: Visual Display Techniques



Source: CMU/SEI-2010-TR-022, (p.30)

Figure 4.12: Process Performance Models Visual Display Techniques

The histogram in Figure 4.13 shows the "visual display techniques" taught in the SEI training courses that best align with the required or elective probability and statistics, SW/SE process improvement, or process improvement courses taught in U.S. colleges by discipline at the bachelor's, master's and doctoral level.

The research findings point out, as illustrated in Figure 4.13, that visual display techniques are taught in courses at the bachelor's and master's SE programs. Visual display techniques are taught in SW master's degree courses. Box plot techniques are included in the bachelor's level CS courses. Surprisingly, all visual display techniques identified are included in IT courses at the bachelor's, master's, and doctoral degree programs, based on the schools included in the study.

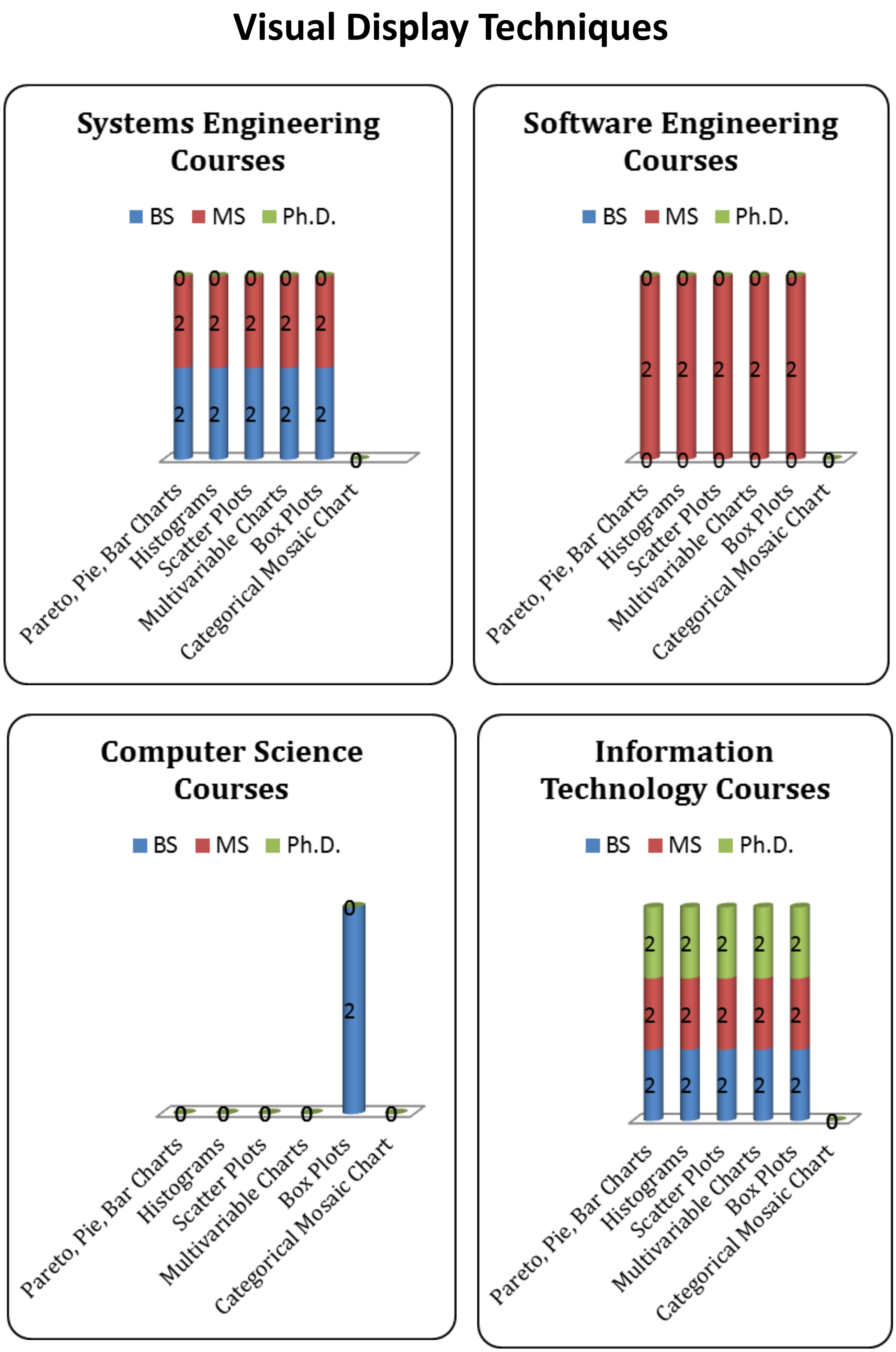


Figure 4.13: Visual Display Techniques Taught in College Courses By Discipline

4.2.4 Decision Techniques Taught

Table 4.4, in Section 4.2, contains a mapping of *decision techniques* taught in SEI's high maturity measurement training courses to the gaps in courses taught in U.S. colleges that teach analytical techniques that can be applied to enable process improvement.

Figure 4.14 shows a histogram of the 2009 survey results (Goldenson, McCurley and Stoddard, 2009) conducted by the SEI of "decision techniques" organizations use. As indicated by the survey results, a large number of organization use decision trees, weighted multi-criteria methods, and the wide band Delphi estimation technique.

The research findings point out, as illustrated in Figure 4.15, that decision techniques are taught in master's and doctoral courses in SE degree programs. Subjects such as analytical hierarchy process (AHP), real options, multi-criteria methods, and decision trees along with other decision methods are taught in SE degree programs. The research findings also point out that the decision tree method is taught in SW courses at the master's level, based on the sample results.

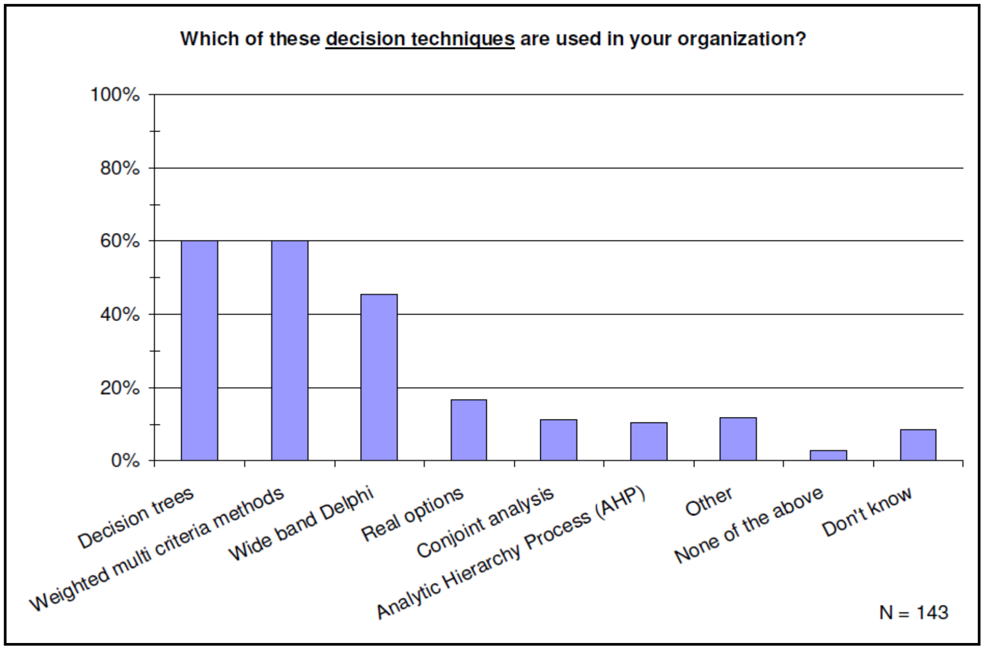


Figure 4.14: Decision Techniques Taught in College Courses By Discipline

Decision Techniques

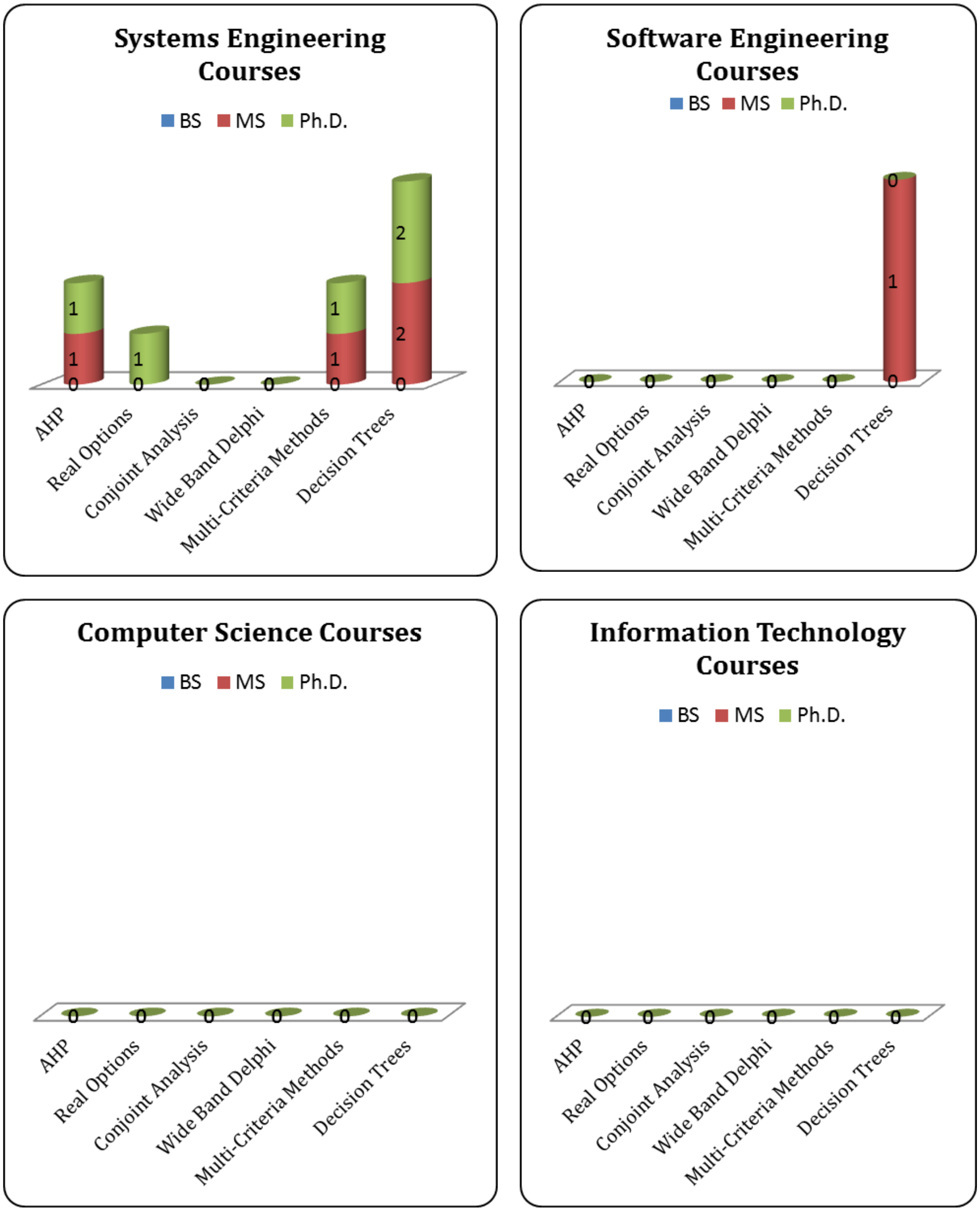


Figure 4.15: Visual Display Techniques Taught in College Courses By Discipline

4.3 Customer Satisfaction as a CMMI High Maturity Sub-Process

The purpose and intent of this portion of the research study consists of three components: (1) develop a customer satisfaction survey (CSS) for a company that develops case management software applications and analyze the results using statistical methods and techniques; (2) demonstrate the use of statistical and quantitative techniques to show how customer satisfaction indices (CSI) can meet the SEI CMMI requirements as a high maturity measurement; and (3) to develop a simulation model using the construct of the American Customer Satisfaction Index (ACSI) to predict the behavior of demonstrate the use of the ACSI score.

4.3.1 Customer Satisfaction Emphasis in the CMMI Model

The CMMI model places emphasis on meeting and satisfying customers' requirements and needs, and delivering quality products and services within cost and schedule parameters. The emphasis of customer satisfaction is intertwined within process areas (PAs) specific practices and introductory notes in the CMMI model as indicated in Table 4.6. References to CS appear in 8 PAs in CMMI-DEV, 11PAs in CMMI-SVC, and 8 PAs in CMMI-ACQ. The focus is on establishing customer satisfaction objectives, data collection, achieving and maintain a customer satisfaction rating at a certain value, assessing, resolving and improving issues / concerns related to customer satisfaction. It is surprising that customer satisfaction does not appear as a requirements development

(RD) process area in the CMMI-SVC or CMMI-ACQ models. Practitioners often have difficulty solidifying non-functional requirements.

Table 4.6: Customer Satisfaction Mapping in CMMI Models

Customer Satisfaction Mapping in CMMI Models				
Maturity Level	**Process Area**	**CMMI-Dev, V1.3**	**CMMI-SVC, v1.3**	**CMMI-ACQ, v1.3**
2	Acquisition Requirements Development (ARD)			X
3	Incident Resolution & Prevention (IRP)		X	
2	Measurement & Analysis (M&A)	X	X	
3	Organizational Process Focus (OPF)	X	X	X
4	Organizational Process Performance (OPP)	X	X	X
5	Organizational Performance Management (OPM)	X	X	X
2	Project Monitoring & Control (PMC)	X		X
4	Quantitative Work Management (QWM)		X	
4	Quantitative Project Management (QPM)	X		X
3	Requirements Development (RD)	X		
2	Service Delivery (SD)		X	
3	Service System Development (SSD)		X	
3	Strategic Service Management (STSM)		X	
2	Supplier Agreement Management (SAM)	X	X	
2	Work Monitoring & Control (WMC)		X	

4.3.2 American Customer Satisfaction Index (ACSI) Benchmark for Computer Software Development

The ACSI was established in 1994 by researchers at the National Quality Research Center, Stephen M. Ross School of Business at the University of Michigan. The ACSI is a cross-industry customer satisfaction benchmark measure (http://www.theacsi.org/customer-satisfaction-benchmarks) used to represent (Fornel et al., 1996) the quality of goods, products and services produced in the U.S. Companies use the ACSI scores as an evaluation to benchmark (IDeA Knowledge, 2006) and trend measure to compare themselves against other companies in the same industry. It is also used for reporting (internal and external), measurement of performance, and planning for performance improvement. The ACSI scores measure overall customer satisfaction and provide insight into the customer experience of the quality of products and services received. The ACSI (Angelova and Zekiri, 2011) uses a methodology and an equation that consists of the weighted average of three survey questions (Fornel et al., 1996; The ACSI Technical Staff, 2005; IDeA Knowledge, 2006)) to determine the overall customer satisfaction index. The questions are answered on a Likert Scale from 1 to 10 and converted to a customer satisfaction index score on a scale from 0 to 100.

The three survey questions in Table 4.7 are used to measure (Johnson et al., 2001) overall customer satisfaction. Customer satisfaction is a measure of perceived value. Customer expectation is a measure of prior experience of products or services obtain. Ideal performance is a measure customer loyalty or likelihood of repurchase.

According to the ACSI model the three survey questions combined provides a reliable customer satisfaction index score measure. The questions are as follows:

Table 4.7: Relevant Customer Satisfaction Questions

Customer Satisfaction Survey Questionnaire			
		Likert Scale: 1 to 10	
Questions	**Measurement**	**1**	**10**
What is your overall satisfaction with our product or service?	Customer Satisfaction	Very dissatisfied	Very satisfied
To what extent has our product or service met your expectations?	Customer Expectation	Met my expectations	Exceeds expectations
How well did our product or service compare with the ideal performance (or competitor with similar offering)?	Ideal Performance	Not ideal at all	Very ideal

On a quarterly basis, the ACSI reports all customer satisfaction benchmark index scores on a scale of 0 to 100 by industry, sector, and company. Over the last eight years (2006 – 2013), the ACSI industry benchmark score for *computer software development* companies ranged from 69 - 79. As an example, Microsoft has a 2013 ACSI benchmark score of 74 and all other software companies have an ACSI baseline score of 76.

The ACSI equation to calculate the index score is proprietary. The Department of Labor (Oates, 2013) uses an equation similar to the one below and a table of ACSI formula weights by state (See Appendix E) to calculate the customer satisfaction index score.

The equation below is used to calculate the overall customer satisfaction index score (OCSI). The means of the U.S. Department of Labor ACSI formula weights (e.g., customer satisfaction, expectancy, and ideal performance) listed in Attachment A for program year 2011, training and employment guidance letter number 12-12, dated January 7, 2013, will be used as the unconstrained weights in the equation to calculate the OCSI. The guidance letter provides a "Table of Weights for Use in Calculating State-Level American Customer Satisfaction Index (ACSI) Scores for Participant and Employer Satisfaction Surveys" (Oates, 2013).

Overall Customer Satisfaction Index Score Calculation

$$\text{OCSI} = \sum \left[\frac{(X_1 - 1)w_1 + (X_2 - 1)w_2 + (X_3 - 1)w_3}{9 \times 100}\right] \times 100 \qquad \textbf{(1)}$$

Whereas,

Average of Survey Satisfaction Score		Unconstrained Weights	
X_1	Overall Customer Satisfaction Score	W_1	0.3937
X_2	Met Expectancy Score	W_2	0.3282
X_3	Compare to Ideal Performance Score	W_3	0.2781

4.3.3 Software Development Organization Customer Satisfaction Survey Analysis Results

The researcher helped develop a customer satisfaction survey for a client that develops software applications. Because of confidentiality reasons and a non-disclosure agreement between the researcher and client, this research will not include the name of the organization nor the actual survey data. The researcher validated the modified empirical data contained in this research with the client. The OCSI score in Table 4.8 was calculated using the empirical data and the equation in Section 4.3.2. For comparisons, the calculated OCSI score using the empirical survey data will be compared to the simulated SOCSI (Simulated Overall Customer Satisfaction Index) score in a section that follows in this research.

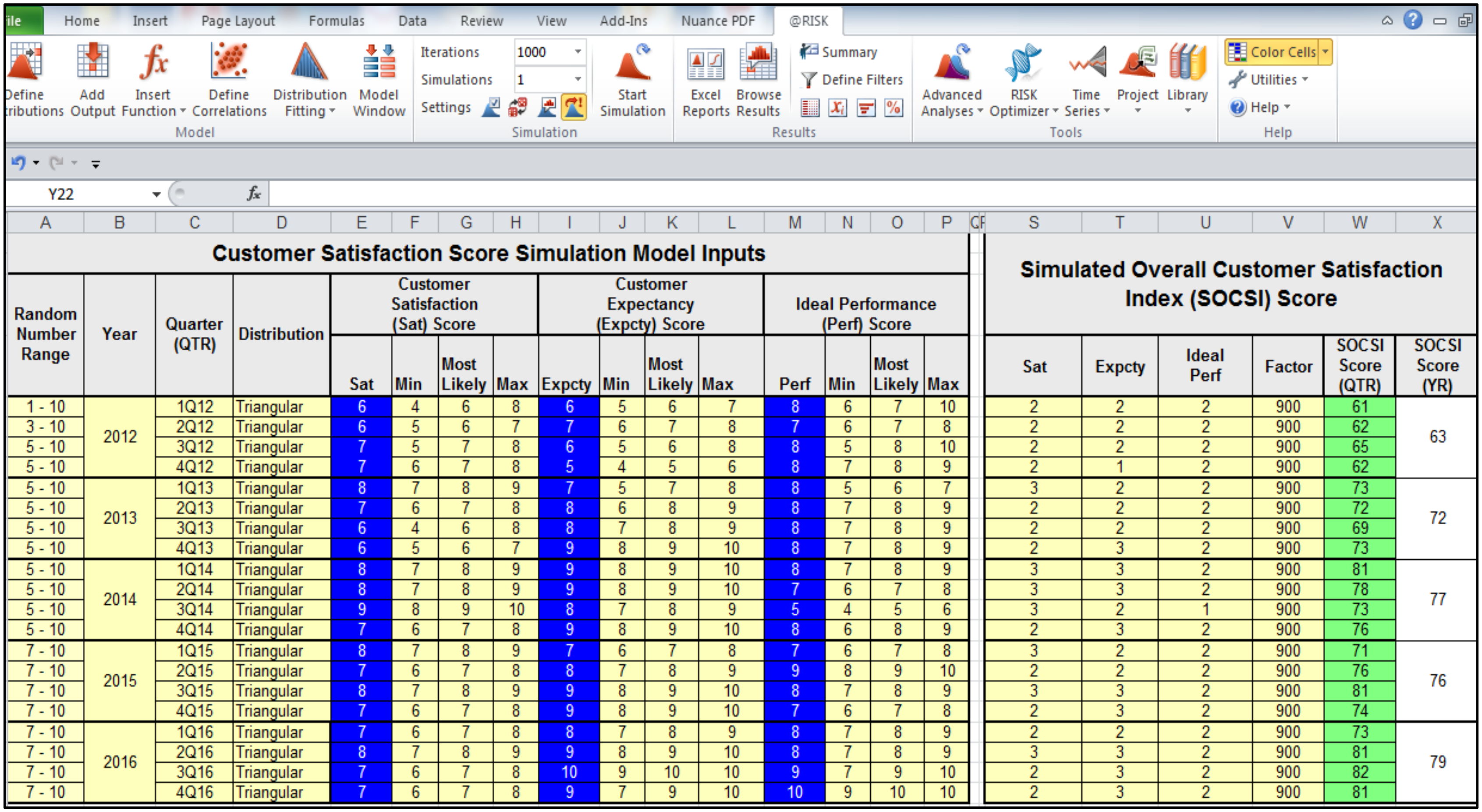
Table 4.8: Overall Customer Satisfaction Score Based on Empirical Data

Calculated Overall Customer Satisfaction Index(OCSI) Score (Based on Modified Empirical Survey Results)					
	Customer Satisfaction	Expectacy	Ideal Performance	Factor	OSCI Score
1&2Q12 Survey Data	5	7	6		**55**
Calculated OSCI Score	2	2	1	900	

4.3.4 Simulation Model of Overall Customer Satisfaction Index Scores

This section contains a *customer satisfaction* process-improvement simulation model developed by the research that can be used by an organization to establish a customer satisfaction baseline metric, and quality and process-performance objectives. The simulation model is used to examine risks, estimate or predict quarterly and annually simulated overall customer satisfaction index (SOCSI) scores over a 5 year projection.

The simulation model, Figure 4.16, was developed using expert judgment, a Microsoft Excel spreadsheet, OCSI score equation in Section 4.3.2, and the @Risk 6.2 add on spreadsheet tool by the Palisade Corporation that performs Monte Carlo and Latin Hypercube simulation sampling. The Latin Hypercube sampling method is more accurate and requires less iteration (Chonggang et al., 2005) than the traditional Monte Carlo sampling method. According to the Palisade Knowledge Base (www.kb.palisade.com) Latin Hypercube versus Monte Carlo sampling, "The Latin Hypercube method produces sample means that are much closer together for the same number of iterations. With the Latin Hypercube method, a smaller number of iterations will be sufficient to produce means within the desired confidence interval." In this research, the Mersenre Twister random generator, 1000 iterations, 1 simulation run with 60 inputs and 20 outputs were modeled using the Latin Hypercube sampling methods. The model uses the triangular distribution as the distribution to model the input values. The simulated output values (e.g., SOCSI scores) in the model are calculated using the equation in Section 4.3.2. The data displayed in Figure 4.16 are for modeling purposes and does not represent the simulated OCSI scores.



Random Number Range	Year	Quarter (QTR)	Distribution	Customer Satisfaction (Sat) Score: Sat	Min	Most Likely	Max	Customer Expectancy (Expcty) Score: Expcty	Min	Most Likely	Max	Ideal Performance (Perf) Score: Perf	Min	Most Likely	Max	Sat	Expcty	Ideal Perf	Factor	SOCSI Score (QTR)	SOCSI Score (YR)
1 - 10	2012	1Q12	Triangular	6	4	6	8	6	5	6	7	8	6	7	10	2	2	2	900	61	63
3 - 10		2Q12	Triangular	6	5	6	7	7	6	7	8	7	6	7	8	2	2	2	900	62	
5 - 10		3Q12	Triangular	7	5	7	8	6	5	6	8	8	5	8	10	2	2	2	900	65	
5 - 10		4Q12	Triangular	7	6	7	8	5	4	5	6	8	7	8	9	2	1	2	900	62	
5 - 10	2013	1Q13	Triangular	8	7	8	9	7	5	7	8	8	5	6	7	3	2	2	900	73	72
5 - 10		2Q13	Triangular	7	6	7	8	8	6	8	9	8	7	8	9	2	2	2	900	72	
5 - 10		3Q13	Triangular	6	4	6	8	8	7	8	9	8	7	8	9	2	2	2	900	69	
5 - 10		4Q13	Triangular	6	5	6	7	9	8	9	10	8	7	8	9	2	3	2	900	73	
5 - 10	2014	1Q14	Triangular	8	7	8	9	9	8	9	10	8	7	8	9	3	3	2	900	81	77
5 - 10		2Q14	Triangular	8	7	8	9	9	8	9	10	7	6	7	8	3	3	2	900	78	
5 - 10		3Q14	Triangular	9	8	9	10	8	7	8	9	5	4	5	6	3	2	1	900	73	
5 - 10		4Q14	Triangular	7	6	7	8	9	8	9	10	8	6	8	9	2	3	2	900	76	
7 - 10	2015	1Q15	Triangular	8	7	8	9	7	6	7	8	7	6	7	8	3	2	2	900	71	76
7 - 10		2Q15	Triangular	7	6	7	8	8	7	8	9	9	8	9	10	2	2	2	900	76	
7 - 10		3Q15	Triangular	8	7	8	9	9	8	9	10	8	7	8	9	3	3	2	900	81	
7 - 10		4Q15	Triangular	7	6	7	8	9	8	9	10	7	6	7	8	2	3	2	900	74	
7 - 10	2016	1Q16	Triangular	7	6	7	8	8	7	8	9	8	7	8	9	2	2	2	900	73	79
7 - 10		2Q16	Triangular	8	7	8	9	9	8	9	10	8	7	8	9	3	3	2	900	81	
7 - 10		3Q16	Triangular	7	6	7	8	10	9	10	10	9	7	9	10	2	3	2	900	82	
7 - 10		4Q16	Triangular	7	6	7	8	9	7	9	10	10	9	10	10	2	3	2	900	81	

Columns A–P: Customer Satisfaction Score Simulation Model Inputs. Columns S–X: Simulated Overall Customer Satisfaction Index (SOCSI) Score.

Figure 4.16: Customer Satisfaction Score Simulation Model

4.3.5 Quantitatively Managed and Optimized Customer Satisfaction Index Scores

This section of the research contains the results from conducting a Monte Carlo simulation study, sensitivity analysis, and optimization study, using the model in Section 4.3.4, to establish process-performance baselines that can be used by an organization to help establish quality, process and business objectives and to determine whether or not they are realistic and can be aligned with the business strategy. The research demonstrates the use of SPC and advanced statistical and quantitative techniques to quantitatively manage and optimize a customer satisfaction sub-process for performance.

4.3.5.1 Simulated Baseline of Initial Overall Customer Satisfaction Index Scores

As mentioned in Section 4.3.4, the research presents a simulation model to model the predictive behavior of a customer satisfaction sub-process in order to establish a baseline.

A simulation study was conducted to establish the initial 1Q12 – 4Q13 customer satisfaction baseline data points. Random numbers between 1 and 10 were generated using Microsoft Excel to model the behavior of the customer satisfaction survey most likely value for each input, relying on expert judgment and opinion. The simulation model described in section 4.3.4 was used to model and predict the customer satisfaction outcomes (e.g., index scores for customer satisfaction, customer expectancy, and ideal performance). The triangular probability distribution was selected for this study because it is the most commonly used distribution for modeling expert opinion. The triangular distribution is defined by its three parameters or input values (e.g., minimum, most likely, and maximum). The random value (most likely), minimum and maximum values were entered into the model for each quarter.

Subsequently, a simulation of 1000 iterations was run to generate probability distribution graphs of possible output values, or range of results that characterizes the expected performance outcomes. Summary graphs and statistics of the output values are listed in Table 4.9. The mean value represent the SOCSI score baseline.

Table 4.9: 1Q12 – 4Q13 Baseline Simulated OCSI Scores

Baseline Simulation Output Results:
Overall Customer Satisfaction Index Score 1Q12 - 4Q13
(Iterations=1000)

Name	Graph	Min	Mean	Max	5%	95%
1Q12 - Simulated Overall Customer Satisfaction Index Score		48	61	74	53	68
2Q12 - Simulated Overall Customer Satisfaction Index Score		54	62	70	58	67
3Q12 - Simulated Overall Customer Satisfaction Index Score		52	65	78	56	73
4Q12 - Simulated Overall Customer Satisfaction Index Score		55	62	70	58	67
1Q13 - Simulated Overall Customer Satisfaction Index Score		63	73	82	68	78
2Q13 - Simulated Overall Customer Satisfaction Index Score		63	72	81	67	77
3Q13 - Simulated Overall Customer Satisfaction Index Score		58	69	82	62	76
4Q13 - Simulated Overall Customer Satisfaction Index Score		66	73	81	68	77

In order to establish a baseline, the initial data set was examined using descriptive statistics, normality test, and a fitted line plot. Descriptive statistics was used to calculate the 1Q12 through 4Q13 baseline SOCSI score $\bar{X}$ =67.13. A normality test was performed, Figure 4.17, to examine normality of the mean value data set. The data set is normal and has a p-value=0.127. Even though the data appears to be normal in Figure 4.17, there is evidence that a trend exists in the data set, Figure 4.18, and the process is not stable or quite mature at this point. An SPC control chart would not be recommended as the method to monitor the process at this point in time since this is a relatively short run intended to show maturity to a point where stability is reached. It is reasonable that there is a trend because there is learning and maturity being gained about the process. Control charts for trends exist but have not been included for the limited number of initial baseline data points. A fitted line plot, Figure 4.18, with a 95% prediction interval about the mean is a better method to use for now to monitor the initial baseline. The lower prediction interval range is between 52.00 and 64.59 and the upper prediction interval range is between 69.66 and 82.25. An initial SOCSI score baseline mean of 67.13 is established. After additional data points are collected and the process becomes stable the baseline will be re-established using an individual control chart Figure 4.18, also shows an R-squared value (variable variation) of 71.1% which indicates a high correlation of the observed data points.

The process is stable within the prediction intervals (e.g., does not have any special cause of variation) and is considered a quantitatively managed process (CMMI Product Team, 2006; CMMI Product Team, 2010). Quality and process performance is understood in statistical terms. Quantitative and quality objectives for the customer satisfaction process can be established, monitored, and managed.

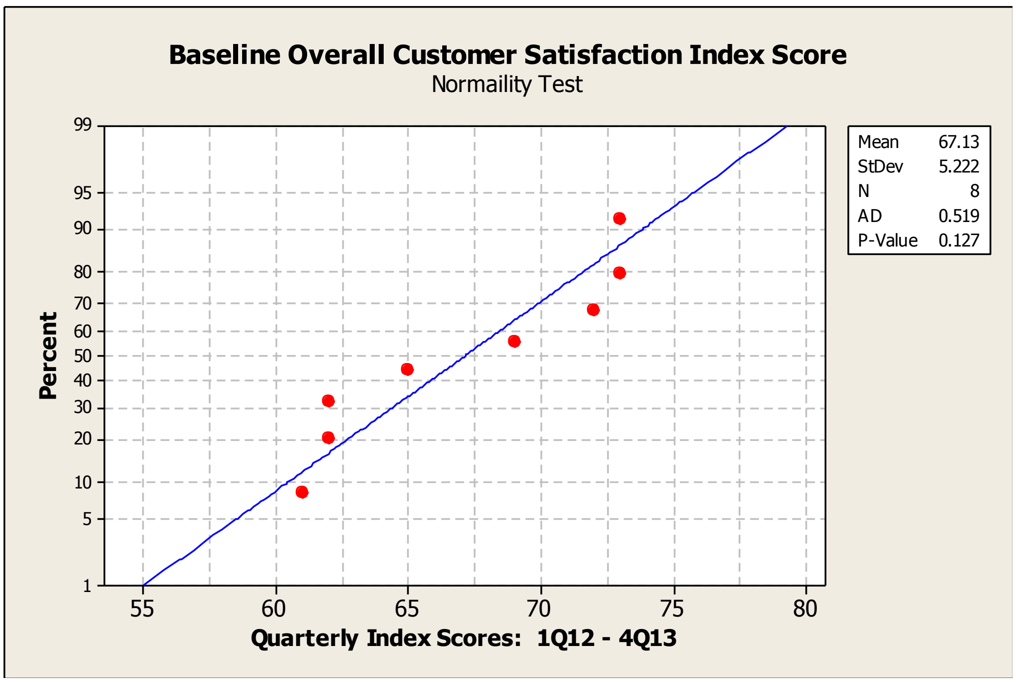


Figure 4.17: Baseline SOCSI Score Normaility Plot

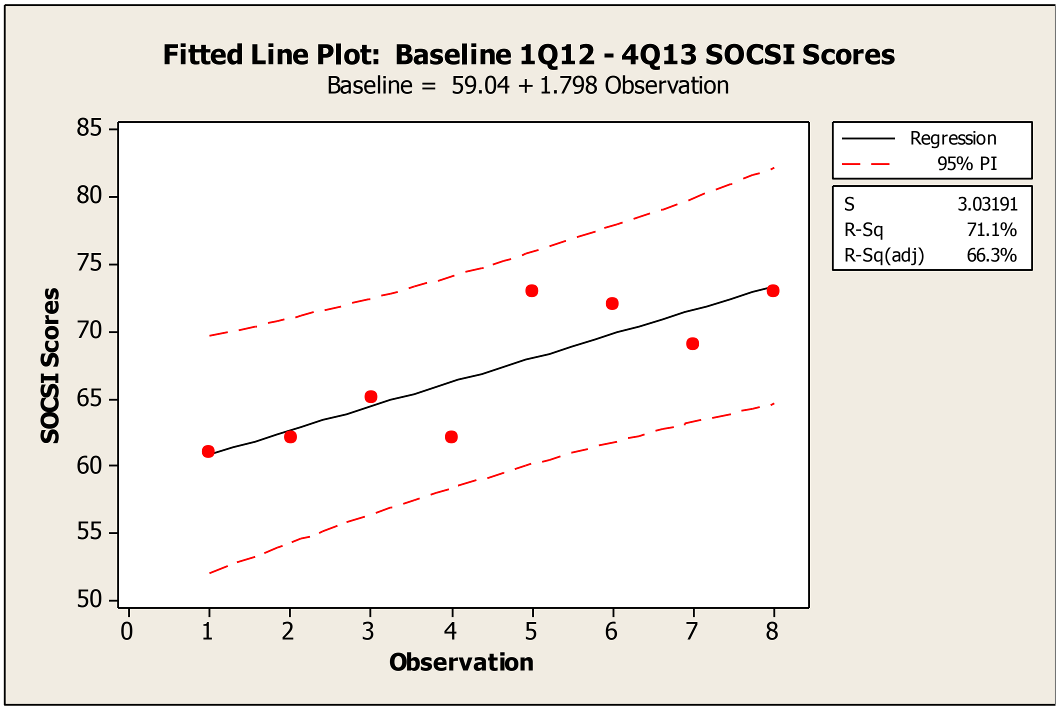


Figure 4.18: Fitted Line Plot, Baseline 1Q12 – 4Q13 SOCSI Scores

4.3.5.2 Re-Baseline Overall Customer Satisfaction Index Scores

In this section and section 4.3.5.5, the research provides a re-baseline demonstration of the SOCSI score index using simulated data and SPC charts. The baseline SOCSI scores for 1Q12-4Q14 are statistically stable. In this section, the simulated data points for 1Q15-4Q16 have been added to the data set. A quick review of the data set shows the SOCSI scores range between 61.00 and 82.00.

The data set was analyzed using a run chart, Figure 4.20, and a test for clustering was performed to detect special causes, trends, or anomalies. The test for clustering is non-significant at $\alpha = 0.05$ level. The p-value 0.089 for clustering is greater than the alpha

($\alpha = 0.05$). Therefore special causes are not inherent only common cause of process variation. The test also indicates that the data is in random order and the data points are ascending upwards which indicates a change in the process and a need to re-baseline the process.

According to the CMMI Product Team (2006, 2010), "An optimized process focuses on continually improving process performance through incremental and innovative process and technological improvements". The effects of deployed process improvements are measured and evaluated (CMMI Product Team, 2010) to assess the process performance objectives. In the CMMI models, version 1.2 (CMMI Product Team, 2006), the authors stated, "At Maturity level 5, organizations are concerned with addressing common causes of process variation and changing the process (to shift the mean of the process performance or reduce the inherent process variation and improve process performance.

In this example, the process shift occurred as a result from incremental changes in improvements to the survey instrument, survey questionnaire, and implementation of feedback obtained from customer satisfaction surveys. Figure 4.21, is a re-baseline of the SOCSI score for 1Q12-4Q16. The $\bar{X}$ =77.25 compare with the ACSI industry benchmark (see Section 4.3.6 Customer Satisfaction Index Score Dashboard for Industry Benchmarks).

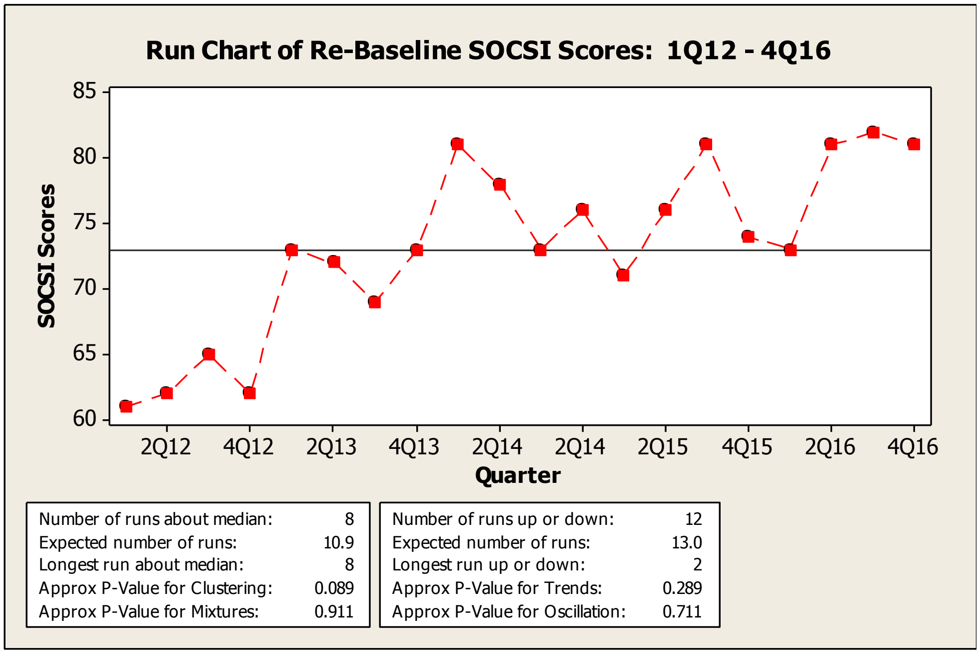


Figure 4.19: Run Chart Re-Baseline SOCSI Scores: 1Q12-416

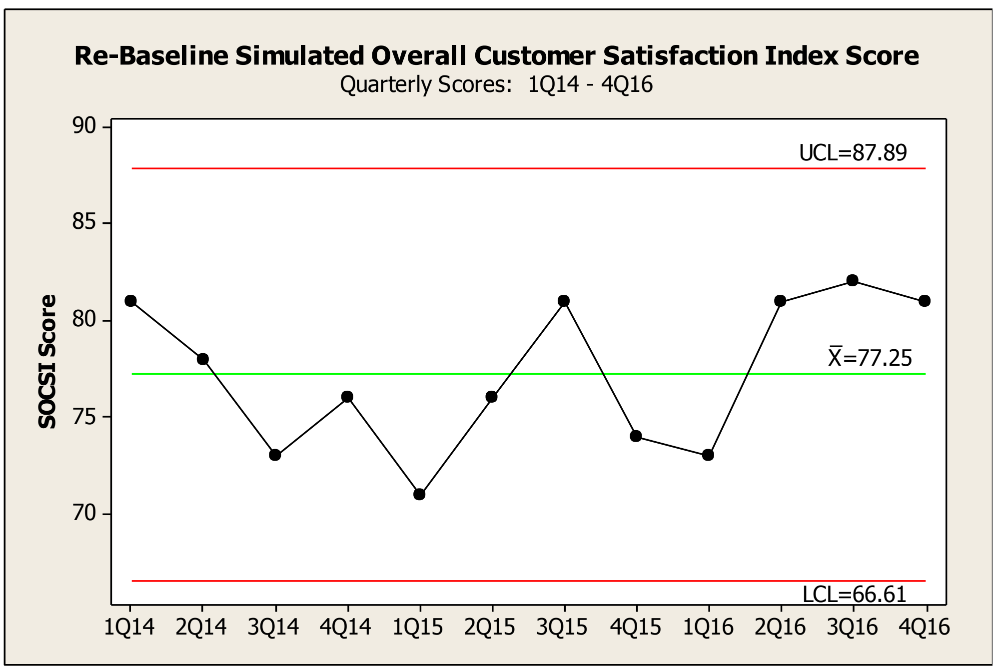


Figure 4.20: Re-Baseline SOCSI Score: 1Q12-4Q16

4.3.5.3 Optimized Overall Customer Satisfaction Index Score

This section of the research contains the results from performing an optimization study to evaluate the predictive outcomes of the 1Q14 – 4Q16 simulated OCSI scores.

As a reminder, the CMMI model uses the vernacular “optimize or optimizing” to characterize and evaluate the performance of a high Maturity Level (ML) 5 process. The CMMI model, v1.3, in the section titled, Understanding Maturity Levels, (The CMMI Product, 2010) uses the below excerpt to describe a ML 5 process.

> At maturity level 5, an organization continually improves its processes based on a quantitative understanding of its business objectives and performance needs. The organization uses a quantitative approach to understand the variation inherent in the process and the causes of process outcomes.
>
> Maturity level 5 focuses on continually improving process performance through incremental and innovative process and technological improvement. The organization’s quality and process performance objectives are established, continually revised to reflect changing business objectives and organizational performance, and used as criteria in managing process improvement. The effects of deployed process improvements are measured using statistical and other quantitative techniques and compared to quality and process performance objectives.

In earlier releases of the CMMI model, v1.2, (The CMMI Product Team, 2008), the emphasis on an optimizing process focuses on continually improving the range of process-performance through both incremental and innovative improvement, and managing common causes of variation inherent in the process.

To establish the data points for the 1Q14 – 4Q16 customer satisfaction optimization study, a simulation run of 1000 iterations was conducted. The same approach that was used to establish the baseline data points was used. Expert opinion and random numbers between 1 and 10 were used to establish the triangular distribution of the most likely values for customer satisfaction score, customer expectancy score, and the ideal performance score as an input in the simulation model for each quarter. Next, a simulation of 1000 iterations was run to generate probability distribution graphs of possible output values. The output values (means) were used as input values in the optimization model.

The optimization study was conducted using the Palisade; Risk Optimizer tool in @Risk 6.2 tool suite. The quarterly simulated output values (means) were used to define the risk optimization goal for each quarter in the model. Input cells in the model contain the most likely (i.e., the triangular distributions values). Simulation-optimization trails (1000 trails) were ran to evaluate the maximum and minimum impact on the mean SOCSI scores. The summary results of the maximum optimization trials are listed Tables 4.10 through 4.12.   The adjust cells in table contains the simulation input values of customer satisfaction survey scores from the three questions (e.g., Sat - Customer Satisfaction, Expcty – Customer Expectancy, and Perf – Ideal Performance). The tables contain summary data of the initial (trial 1) and optimized (trial 3) trial of each quarter for comparison.

Table 4.10: Summary of 2014 Optimization Results

Summary of 2014 Optimized Simulation Results										
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
1Q14	1	1000	81	81	3	74	91	8	9	8
	3	1000	85	85	3	75	92	9	10	9
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
2Q14	1	1000	78	78	3	70	86	8	9	7
	3	1000	82	82	3	71	89	9	10	8
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
3Q14	1	1000	73	73	3	65	80	9	8	5
	3	1000	77	77	3	66	83	10	9	6
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
4Q14	1	1000	76	76	3	67	85	7	9	8
	3	1000	80	80	4	68	88	8	10	9

Table 4.11: Summary of 2015 Optimization Results

Summary of 2015 Optimized Simulation Results										
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
1Q15	1	1000	71	71	3	63	80	8	7	7
	3	1000	75	75	3	65	82	9	8	8
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
2Q15	1	1000	76	76	3	69	84	7	8	9
	3	1000	80	80	3	71	87	8	9	10
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
3Q15	1	1000	81	81	3	74	89	8	9	8
	3	1000	85	85	3	75	92	9	10	9
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
4Q15	1	1000	74	74	3	66	82	7	9	7
	3	1000	78	78	3	67	85	8	10	8

Table 4.12: Summary of 2016 Optimization Results

Summary of 2016 Optimized Simulation Results										
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
1Q16	1	1000	73	73	3	66	81	7	8	8
	3	1000	77	77	3	67	84	8	9	9
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
2Q16	1	1000	81	81	3	74	90	8	9	8
	3	1000	85	85	3	75	92	9	10	9
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
3Q16	1	1000	82	82	3	73	88	7	10	9
	3	1000	84	84	3	73	91	8	10	10
	Trial	Iterations	Result	Goal Cell Statistics				Adjustable Cells		
				Mean	Std. Dev.	Min.	Max.	Sat	Expcty	Perf
4Q16	1	1000	81	81	3	71	90	7	9	10
	3	1000	84	84	3	72	91	8	10	10

4.3.5.4 Sensitivity Analysis of Optimized 1Q14 – 4Q16 SOCSI Scores

A sensitivity analysis was conducted on the 1Q14 – 4Q16 maximum optimized SOCSI scores to evaluate the inputs (e.g., customer satisfaction, expectation, and ideal performance, see Section 4.3.5.2) impact on the output (quarterly index score).

In the literature, Johnson et al. (2001) provide a discussion on the strengths and weaknesses of the ACSI model. The authors point out (Johnson et al., 2001b) that the ACSI model has several strengths. Johnson et al. (2001b) stated that, "… three measures of cumulative satisfaction (overall satisfaction, expectancy dis-confirmation, and comparison to an ideal) provide a reliable satisfaction index". Johnson et al. (2001), pointed out and argue, that, the ACSI model predicts that as both perceived value and perceived quality increase, so do customer satisfaction increase. As the impact of value increases relative to quality, price is a more important determinant of satisfaction. Some relationships involving the antecedents and consequence of satisfaction are conceptually and/or empirically weak. (Johnson, Anderson, & Fornell, 1995a; Johnson et al., 2001b) conducted a study and analysis using a three-stage least squares algorithm and correlation to assess the relationships between customer satisfaction, performance, and expectations. Johnson, Anderson, and Fornel (1995a) stated, "when satisfaction is modeled on as a function of performance and expectation, performance has a large and significant effect on satisfaction, while expectation has a smaller, although significant, effect on satisfaction for both the adaptive and rational models" and satisfaction is positively affected by both performance and expectations. Anderson and Sullivan (1993) conducted a study and surprisingly determined that expectation does not directly affect satisfaction, as is often suggested in the satisfaction literature. Frank and Entawa (2009) study found that Customer satisfaction is positively influenced by economic growth and negatively by current economic expectations, with half of the impact mediated by perceived value. Yurkyilimaz et al. (2013) conducted a study and found the relationship between customer expectation and customer satisfaction to be insignificant.

The sensitivity analysis optimized output results indicate that overall customer satisfaction output is mainly influenced by customer satisfaction, customer expectation, and ideal performance score, in that order. Table 4.13 shows a ranking order (in the columns from left to right) of the inputs on the output. The results of the output sensitivity analysis are displayed in the tornado charts: Figures 4.22 through 4.24. The longer bar on the top in the chart represents the input that has the most significant impact on the output. The ranking in the tornado chart is from highest to lowest impact on the output. The baseline optimized mean is also displayed in the chart. In this study, the customer satisfaction survey score has the most significant impact on overall customer satisfaction. In another notable point, a positive correlation exists between the inputs and output.

Table 4.13: Ranking of CSS Score Inputs on the Output

Summary: Ranking of Customer Satisfaction Inputs on Outputs (1Q14 - 4Q16)			
Input	**Rank 1**	**Rank 2**	**Rank 3**
Customer Satisfaction	10	2	0
Customer Expectancy	1	9	1
Ideal Performance	1	1	10

2014 Sensitivity Analysis of Overall Customer Satisfaction Index Scores

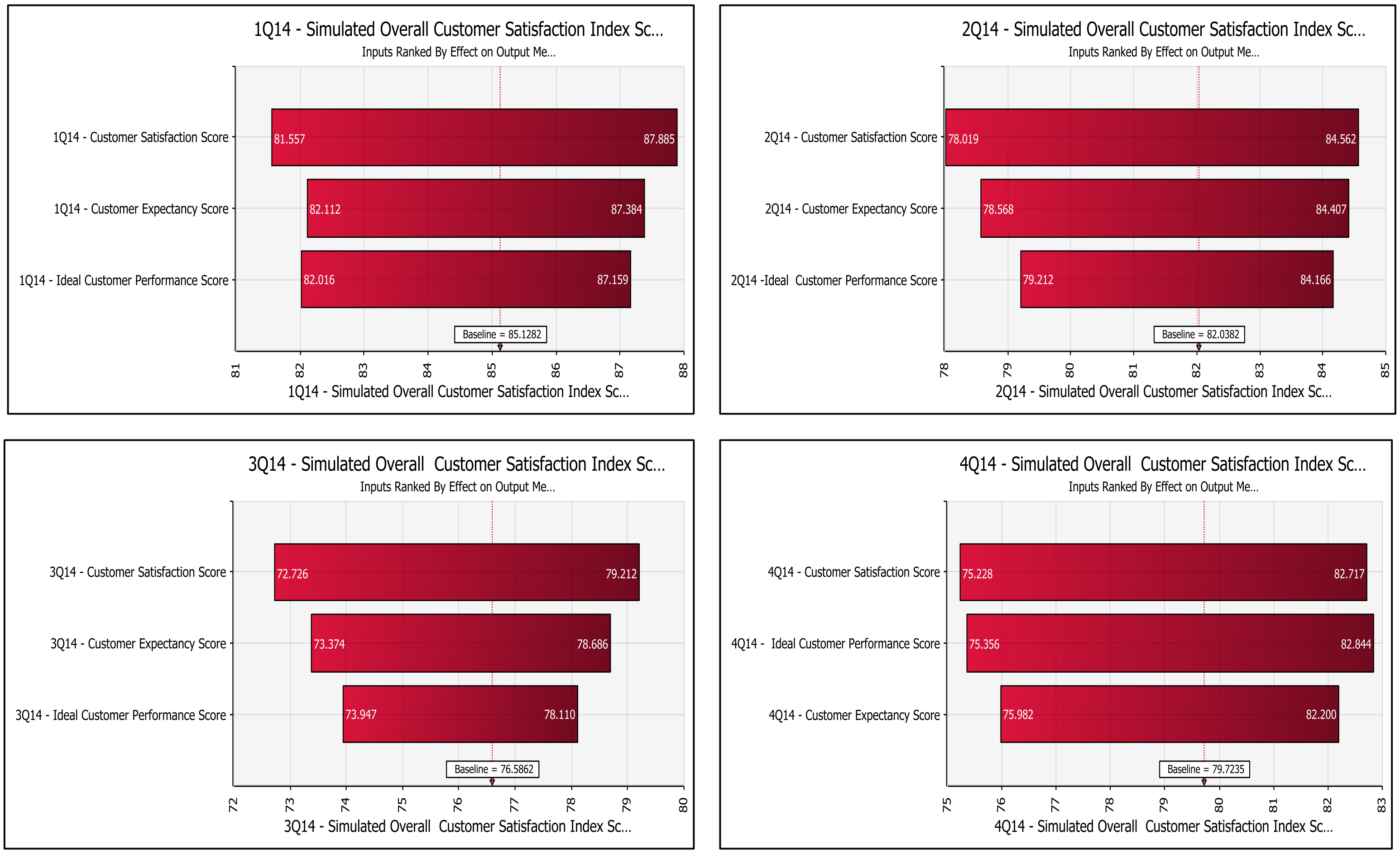


Figure 4.21: 2014 Sensitivity Analysis of the SOCSI Scores

2015 Sensitivity Analysis of Overall Customer Satisfaction Index Scores

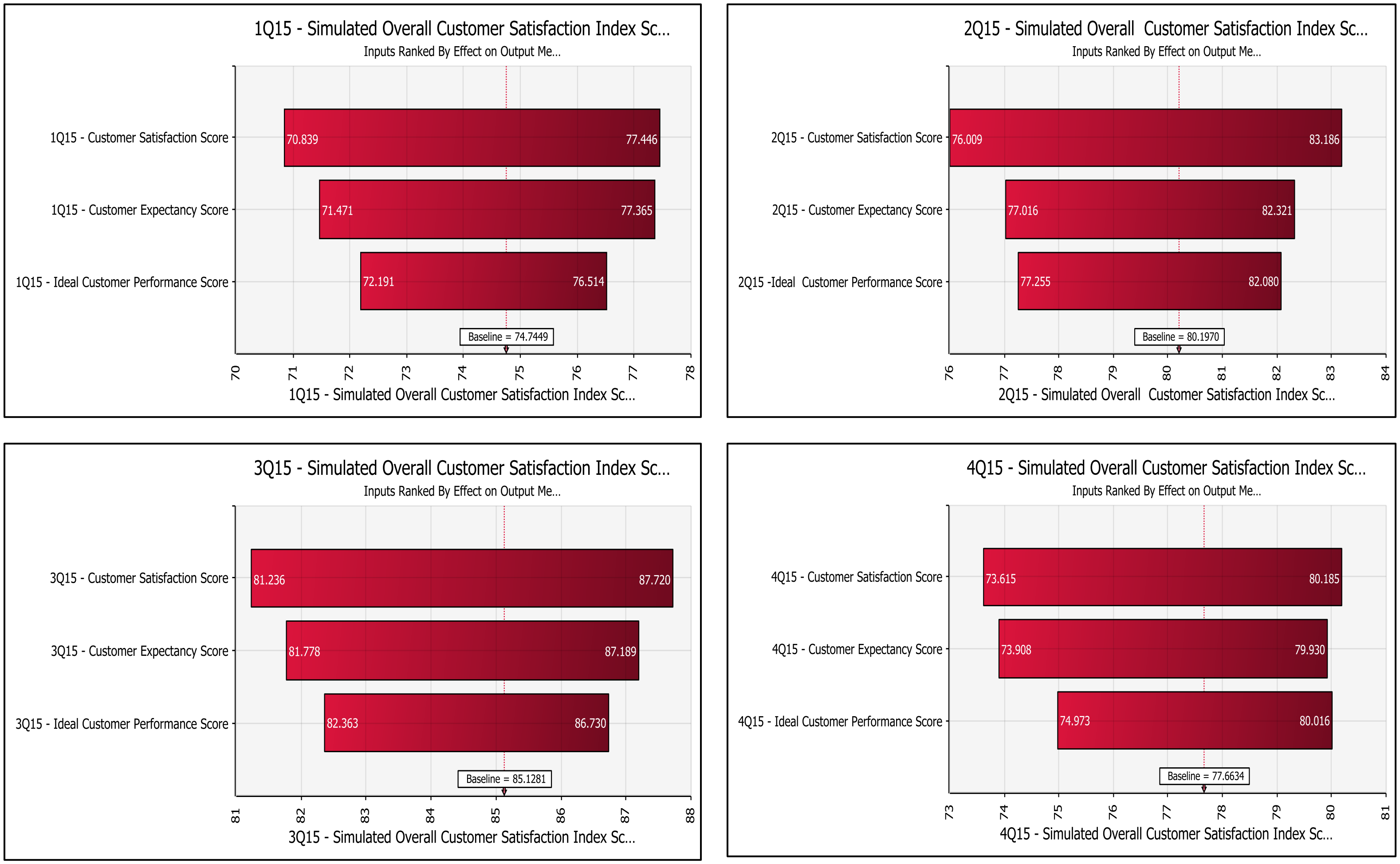


Figure 4.22: 2015 Sensitivity Analysis of the SOCSI Scores

2016 Sensitivity Analysis of Overall Customer Satisfaction Index Scores

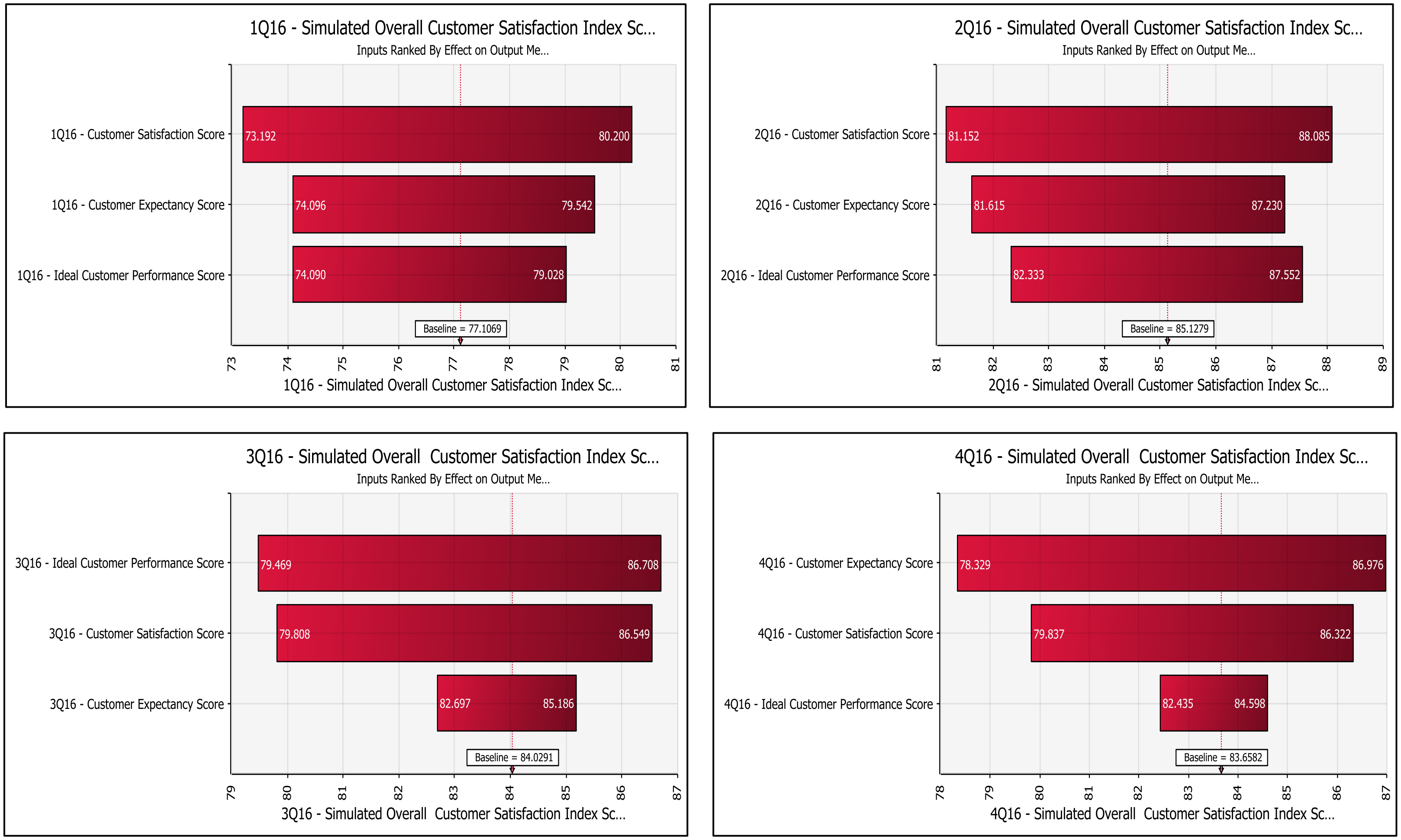
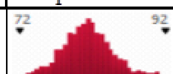
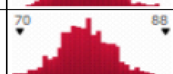
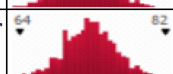
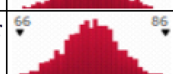
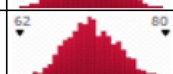
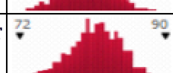
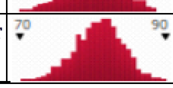


Figure 4.23: 2016 Sensitivity Analysis of the SOCSI Score

4.3.5.5 Statistical Process Control of Re-Baseline Simulated Overall Customer Satisfaction Index Score

This section of the research provides a demonstration of the use of individual SPC control charts to re-baseline the SOCSI score using Minitab 16 to analyze the before and after simulated process improvement in the customer satisfaction historical data set to see how the process mean and variability changes. The data set consists of the mean simulated baseline (1Q12 – 4Q13) and optimized minimum and maximum data points (1Q14 – 4Q16). The mean simulated data points for 1Q12 – 4Q13 are listed in Section 4.3.5.1, Table 4.9. The simulated optimized minimum and maximum mean data points for 1Q14 – 4Q16 are listed below in Table 4.14. Summary graphs and statistics of the output values are also listed in Table 4.14. The mean values in the table represent the initial SOCSI quarterly scores.

Table 4.14: 1Q14 – 4Q16 Summary of Optimized SOCSI Scores

Optimized Simulation Output Results: Overall Customer Satisfaction Index Score: 1Q14 - 4Q16 (Iterations=1000)								
Name	Initial Simulation Scores						Optimized Simulation Score Means	
	Graph	Min	Mean	Max	5%	95%	Min	Max
1Q14 - Simulated Overall Customer Satisfaction Index Score		74	81	91	77	86	78	85
2Q14 - Simulated Overall Customer Satisfaction Index Score		70	78	86	74	83	75	82
3Q14 - Simulated Overall Customer Satisfaction Index Score		65	73	80	69	77	69	77
4Q14 - Simulated Overall Customer Satisfaction Index Score		67	76	85	71	81	71	80
1Q15 - Simulated Overall Customer Satisfaction Index Score		63	71	80	67	76	67	75
2Q15 - Simulated Overall Customer Satisfaction Index Score		69	76	84	72	81	73	80
3Q15 - Simulated Overall Customer Satisfaction Index Score		74	81	89	77	85	78	85
4Q15 - Simulated Overall Customer Satisfaction Index Score		66	74	82	69	78	70	78
1Q16 - Simulated Overall Customer Satisfaction Index Score		66	73	81	69	78	70	77
2Q16 - Simulated Overall Customer Satisfaction Index Score		74	81	90	77	86	78	85
3Q16 - Simulated Overall Customer Satisfaction Index Score		73	82	88	77	86	77	84
4Q16 - Simulated Overall Customer Satisfaction Index Score		71	81	90	76	86	76	84

The individual control chart in Figure 4.25 is a plot of the re-baseline optimized minimum historical data points (e.g., SOCSI quarterly scores 1Q12 – 4Q16). The control chart shows a shift in mean and control limits at point 78.00. The re-baseline optimized minimum quarterly customer satisfaction index mean shifted from $\bar{X}$=67.13 to $\bar{X}$=75.50, or 3-4 point departure from the simulated mean (i.e., SOCSI score) in an upward direction. This illustrates an improvement in the process (e.g., customer satisfaction survey scores).

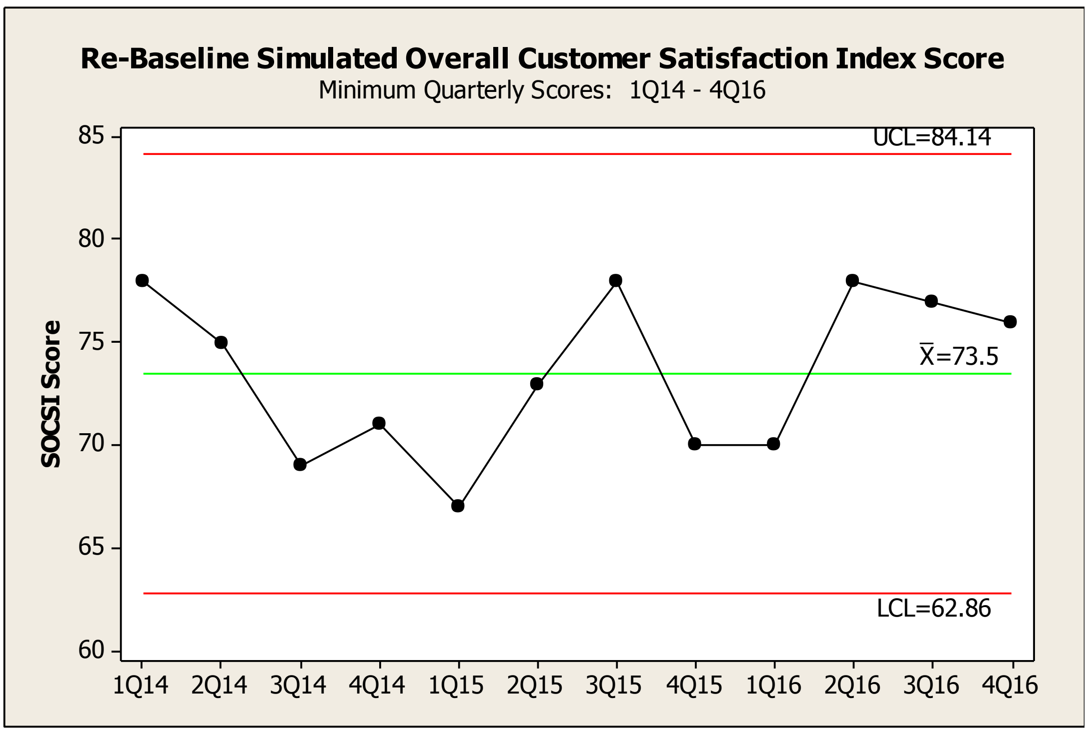


Figure 4.24: Re-Baseline Minimum SOCSI Scores

The individual control chart in Figure 4.26 is a plot of the re-baseline optimized maximum historical data points (e.g., SOCSI quarterly scores 1Q12 – 4Q16). The control chart shows a shift in mean and control limits at point 85. The re-baseline optimized maximum quarterly customer satisfaction index mean shows an upward shift from the simulated mean SOCSI score by 4 points. The re-baseline optimized maximum quarterly customer satisfaction index mean shifted from $\bar{X}$=67.16 to $\bar{X}$=8100. This illustrates an improvement in the process (i.e., customer satisfaction survey scores. See section 4.3.5.3, Tables 4.10 through 4.12).

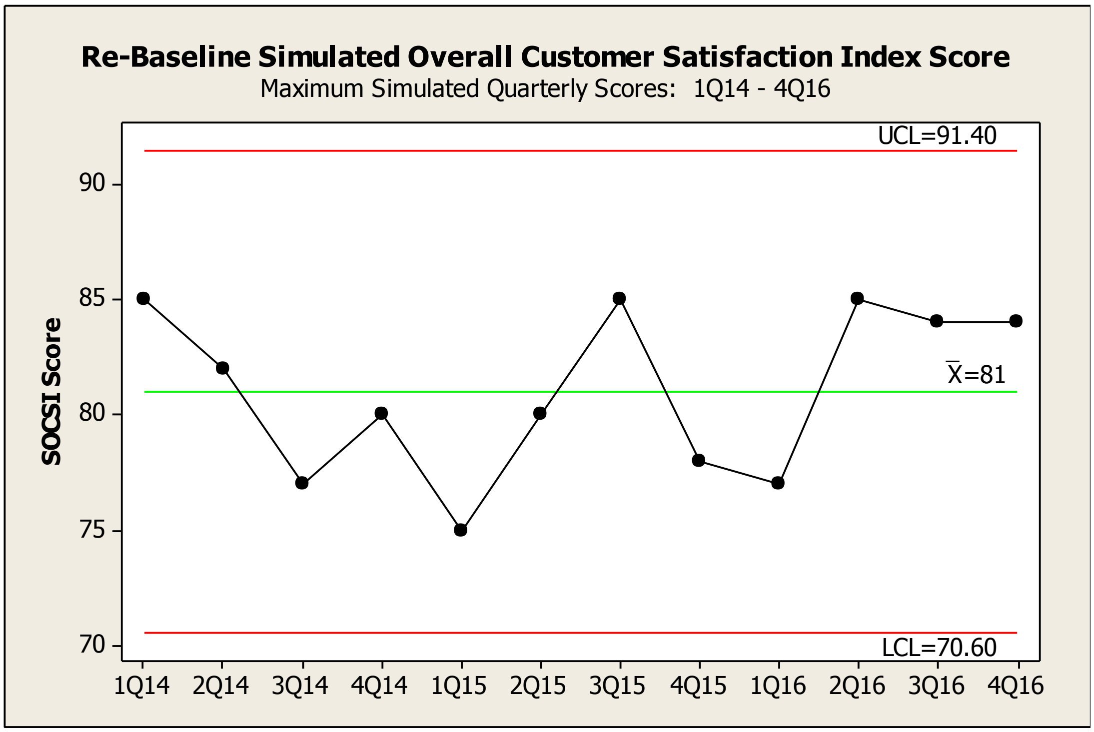


Figure 4.25: Re-Baseline Maximum SOCSI Scores

4.3.6 Customer Satisfaction Index Score Dashboard

This section of the research provides an overview and illustration of a dashboard designed and created by the researcher as a result of this study. The overall customer satisfaction index score dashboard has practical application in industry. The dashboard, Figure 4.27, displays insightful information in a tabular format and can be used by a customer-centric organization as a performance management tool to visually manage and monitor in real-time the business performance of their customer satisfaction business objectives intelligence. Everyone in an organization at all levels that interface with the customer should be able to access the dashboard.

Kaplan and Norton (1992) introduced the balanced scorecard as a performance management tool. Cash et al. (2012) pointed out that dashboards help establish and maintain continuous improvement based on real-time and current data, and improve coordination between different levels of people in an organization. Yigitbasioglu and Velcu (2012) noted several interesting findings during their review of dashboards in performance management. Yigitbasioglu and Velcu (2012) commented that although dashboards have been around since the early 1990's and became popular in 2001 (Few, 2006), "a handful of studies can be found in academic journals" and scientific literature has failed to keep pace with the developments of dashboards and provide little guidance for practitioners and researchers. Yigitbasioglu and Velcu (2012) also provided a discussion on the use of displaying information in a tabular format versus a graph. They concluded that tabular information is more superior for tasks that require extracting specific values and combining them to an overall. Graphs are more useful for information that requires identifying and understanding relationships and making comparisons.

The dashboard displays tabular OCSI information in a graphical user interface (GUI) for the purpose of comparison, business intelligence, trending and monitoring customer satisfaction business performance. The following information is displayed in the dashboard:

- Calculated empirical quarterly and annual OCSI scores based on survey data
- Simulated OCSI scores
- Industry benchmarks of ACSI historical computer software scores

Everyone in an organization that views the dashboard can perform quick comparisons of customer satisfaction index scores (e.g., empirical data, SOCSI, and 5 year benchmark scores).

Empirical Data				Simulated	Industry Benchmark ACSI Historical CSS Scores			
Year	Quarter (QTR)	OCSI Score (QTR)	OCSI Score (YR)	SOCSI Score (YR)	Year	Computer Software	All Other	Microsoft
2012	1Q12		14	63	2008	74	75	69
	2Q12	55						
	3Q12							
	4Q12							
2013	1Q13		0	72	2009	75	76	70
	2Q13							
	3Q13							
	4Q13							
2014	1Q14		0	81	2010	76	77	76
	2Q14							
	3Q14							
	4Q14							
2015	1Q15		0	80	2011	78	79	78
	2Q15							
	3Q15							
	4Q15							
2016	1Q16		0	83	2012	77	77	75
	2Q16							
	3Q16							
	4Q16							

Figure 4.26: Overall Customer Satisfaction Index Score Dashboard

5 SUMMARY, LIMITATIONS, AND FUTURE RESEARCH

5.1 Research Summary and Contributions

This section of the chapter briefly summarizes the research study contributions to the body of knowledge. The research was prompted by a need to conduct a study that focuses on preparing systems engineering and computing science students in disciplined methods to improve process-performance using quantitative and analytical techniques.

As a result of the research study, several contributions are made to the body of knowledge for systems engineering and computing science disciplines. Academicians, scholars, systems engineering and computing science process improvement practitioners, and researchers involved in customer satisfaction research, can study this report and gain useful insight. Members of the executive or senior leadership team will also find the results of this study useful because it provides discussion on process governance, an overview of the Capability Maturity Model Integration (CMMI) model foundation, and identifies programs from which to recruit engineers and scientists that have received academic training in quantitative and quality management methodologies and techniques.

The entire content of this research identifies gaps in the literature, adds to the literature, and provides results (see Section 4.1 through 4.2.4) that offer insight that identifies the lack of process improvement training and quantitative management courses taught in U.S. universities systems engineering and computing science degree programs. The research heightens awareness that academicians have conducted little research on applicable qualitative and quantitative analytical techniques that can be used to improve performance, or demonstrate high maturity as implied in the Capability Maturity Models (CMMIs) of the systems and software engineering processes. Few master's and doctoral dissertations have been published that focus on the use of applicable statistical, quantitative and optimization techniques to enable process improvement of the systems and software engineering processes and business processes, in general. Apparently, this is because the problems of applying the aforementioned techniques to improve the systems and software engineering process have not been perceived as being significant or addressed by the academic community. The need to address the gap identified in this study is an interdisciplinary problem that also needs the support of systems engineering and various computing disciplines in the academic community to help resolve. The research literature identifies notable academic research in the use of statistical modeling of the software and systems engineering process worth mentioning (see Section 2.8). As another notable observation, many of the degree programs included in this study did not offer a course or topic on the software and systems development lifecycle (SDLC), or software / systems engineering principles.

The research provides a comparison analysis in Section 4.2, which identifies the gaps that exist between what the SEI's has identified as "*healthy ingredients*" of a process performance model (e.g., statistical methods, optimization approaches, visual and decision techniques) and courses taught in the systems engineering and computing science disciplines in U.S. colleges and universities. This analysis also heightens the awareness of the need to offer process improvement, quantitative and quality management courses in systems engineering and the computing science discipline degree programs at all levels (i.e., bachelor, master's, and doctoral) of the degree program.

The research results clearly point out that there is a need to develop college courses that teach application of appropriate statistical, quantitative, and analytical skills to students in systems engineering and the computing disciplines. Even though some universities list courses in their catalogue, if not required as a core course, it can take several semesters before an elective course is offered. So it could be possible that graduates of those programs may not have been able to take these types of courses.

In industry, some of the common measurements organizations collect (Austin and Paulish, 1993; Goldenson, McCurley, and Stoddard, 2008; McCurley and Goldenson, 2010) of the software and systems engineering processes (see Section 2.4.3. SDLC models) typically include product quality and project performance metrics such as cost and schedule planning and delivery at completion, software lines of code / function-point estimation, defect density, requirements volatility, peer review inspections, test, etc. Customer satisfaction is considered a sub-process.

In section 4.3, the research provides a demonstration on the use of quantitative analysis, simulation and optimization techniques, and SPC control charts to establish baselines, evaluate trends, and monitor and predict future overall customer satisfaction performance using a dashboard. The approach, methodology, and analysis clearly illustrate how an organization can demonstrate customer satisfaction as a CMMI high maturity measurement. The research results contribute to the customer satisfaction and software and systems engineering literature. A mapping matrix was created that shows how customer satisfaction is intertwined within the CMMI models. Surprisingly, a rigorous review of the literature seems to uncover that until this study was conducted, did anyone create a simulation model using the American Customer Satisfaction Index score to analyze, optimize and predict future customer satisfaction performance. Sensitivity analyses were conducted to assess the significance of the inputs (i.e., customer satisfaction scores) on the overall customer satisfaction index score (i.e., outputs). More emphasis needs to be placed on customer satisfaction during elicitation of functional and non-functional requirements in the requirements development process.

The dashboard has practical application to any organization that benchmarks their customer satisfaction business performance objective against the American Customer Satisfaction Index (ACSI). Organizations should find that the research results in Section 4.3 are useful and perhaps they will consider adopting the simulation model and dashboard.

Knowledge of "how to apply the applicable quantitative and statistical techniques" to manage the software and systems engineering processes is becoming increasingly important (McCray and Santos, 2009).

5.2 Research Limitations

The limitations of this study are discussed in the paragraphs that follow.

5.2.1. Process Improvement Gap Analysis Study Limitations

For comparison, there was a lack of prior research studies and literature conducted on the gaps that exist in developing the body of knowledge and quantitative skills taught in systems engineering and the computing science disciplines in quality management and process improvement courses.

The Peterson's online database of U.S. colleges and universities was used as a source to identify and retrieve the names and total number of U.S. colleges and universities to include in the study. In addition, the INCOSE (International Council of Systems Engineering) list of systems engineering schools was used. In order not to bias which schools to include or exclude from the study, as a decision criteria, the school's overall enrollment size and the difficulty of admission were used. The following overall student minimum and maximum enrollment sizes were used as decision criteria to select the universities. For universities that offered degree programs in CS enrollment size between 2,801 and 31,589 students, SW enrollment size between 1,832 and 21,646 students, and IT enrollment size between 3,291 and 42,910 students. Enrollment size and difficulty of admission were not used as decision criteria for universities that offered SE degree programs. Universities with enrollment size lower than the minimum and higher than the aforementioned maximum were excluded from the study. The university's admissions difficulty are listed in Table 3.1 and characterized in Peterson's database admissions selectivity criteria as *very difficult, moderately difficult, minimally difficult, and non-competitive.*

The number of colleges and universities included in the study are listed in Table 5.1 (also see Section 3.3.1, Table 3.1 and Table 3.2) below. The number of colleges and universities excluded from the study are included in Table 5.1, as well. Several of the excluded systems engineering degree programs did not have a systems engineering focus. The focus was in manufacturing engineering, industrial engineering, and systems control theory.

Table 5.1: Number of Colleges & Universities Not Included In the Study

Degree Program	**Number of U.S. College & University Degree Programs Peterson's Search Results: 2009**	**Process Improvement Gap Analysis Study**	
		Number Included	**Number Not Included**
Software Engineering	64	40	24
Systems Engineering	79	43	36
Computer Science	89	40	49
Information Technology	176	49	127

This study was unique because, in general, it heightened awareness and validated the gap that exists between industry and academia.

5.2.2. Customer Satisfaction Survey Study Limitations

In 2012, during an advisory board council meeting in a company that design and produce business software applications, in which the researcher was a member on, the senior management team, identified a need to obtain insight from their customers on the perceived value, expectation, quality issues, and loyalty. The advisory board members recommended that a case study and customer satisfaction survey be administered to obtain the voice of the customer and perceived values. This was the first time the company administered and collected customer satisfaction survey data. The empirical survey data were collected for one time period only (i.e., one quarter). The company did not have any historical customer satisfaction survey data that could have also been used for benchmarking or to compare to the simulated data set. . A larger subset of empirical data points would have been available to compare against the simulated data points.

The team members assigned to the project were not familiar with designing a survey questionnaire and analyzing the data. The researcher provided the team with the assistance needed to design the customer satisfaction survey questionnaire, provide clarity to questions of uncertainly, and help interpret the survey data. All the survey respondents did not complete and return the online survey. Some of the respondents that took the survey did not answer all of the questions on the survey questionnaire. Due to the confidentiality agreement that was put in place between the researcher and the company, responses to open-ended questions cannot be included in the research findings. More open-ended questions should have been included in the survey questionnaire design as suggested by the researcher to obtain additional insight into the voice of the customer.

5.3 Recommendations for Future Research

This section of the dissertation provides recommendations for possible continued research as a result of the findings of this effort.

The CMMI model has been adopted as an international process improvement model framework. Further research could involve conducting a similar mixed-method exploratory or comparative study (e.g., gap analysis) to obtain insight into the gaps that exists in the body of knowledge of process improvement, quality management, and quantitative techniques taught to students in systems engineering and the computing science discipline degree programs in non-U.S. colleges and universities degree programs. The study should focus on identifying required and elective courses that provide students with foundational knowledge and quantitative skills that can be applied to analyze software and systems engineering processes for performance. The research findings can be compared with the results in Section 4.2 and 4.3 of this study.

The information contained in Table 5.2, below, can be used by the researcher as a starting point. The table contains a summary of the number of high maturity Levels 4 and 5 CMMI appraisals by a country that exists in the published appraisal results (https://sas.cmmiinstitute.com/pars/) database as of December 2013. The March 2013 maturity profile report prepared by Keller and Mack (2013) contain more information on the number of total SCAMPI appraisals conducted (e.g., ML1 through ML5) by country. The table also contains a preliminary mapping of the countries that have a systems engineering (SE) degree program in their colleges and universities. The letter “Y” in the table denotes "yes" that the countries have SE degree programs in their colleges and universities. The table does not denote the number of colleges and universities in the country that offers a SE degree program; however, it indicates that some countries do not have universities that offer SE degree programs. At a quick glance, the table points out that India and China, followed by the U.S., have the largest number of CMMI high maturity level appraisals. China and India are amongst the 2013 fastest growing world economies.

Table 5.2: CMMI High Maturity Level 4 & 5 Appraisals by Country

Total Number of CMMI High Maturity Appraisals by Country as of December 2013

	High Maturity Level (ML)			SE Degree		Maturity Level (ML)			SE Degree
Country	ML 4	ML 5	* Total Appraisals		Country	ML 4	ML 5	* Total Appraisals	
Argentina	0	7	7	Y	Peru	0	2	2	Y
Australia	0	2	2	Y	Philippines	1	5	6	Y
Brazil	1	11	12	Y	Portugal	0	3	3	Y
Canada	1	5	6	Y	Russia	0	4	4	Y
Chile	0	5	5		Saudi Arabia	2	3	5	
China	66	68	134	Y	Singapore	2	1	3	Y
Columbia	3	7	10	Y	Spain	3	12	15	
Egypt	0	2	2		Sri Lanka	0	1	1	Y
France	0	1	1	Y	Switzerland	0	1	1	Y
Hong Kong	0	4	4	Y	Taiwan	5	1	6	
India	5	144	149	Y	Thailand	0	4	4	Y
Israel	0	5	5	Y	Turkey	0	3	3	Y
Italy	0	1	1		United Arab Emirates	0	2	2	
Japan	9	13	22	Y	United Kingdom	1	7	8	Y
Korea, Republic of	14	9	23		United States	8	71	79	Y
Malaysia	0	3	3	Y	Uruguay	0	3	3	
Mexico	4	11	15		Viet Nam	1	4	5	
Pakistan	0	1	1	Y					

Note: * This is a subset of the total number of appraisals by country located in the published appraisal results (PARS) database.

Another study could perhaps involve developing and administering a survey to the high maturity appraised organizations to gain insight into the type of academic and professional training the process improvement practitioners received (e.g., quality management methodologies and statistical, analytical, optimization and quantitative analysis techniques, etc.).

A follow on study to this research could involve administering a survey to students that graduated from colleges and universities listed in this study systems engineering and computing science degree program to obtain their perspective on the importance of learning and developing foundational knowledge and quantitative skills that can be applied to analyze software and systems engineering processes for performance and improvement.

As another research suggestion, future study could focus on the development of a compendium of quantitative, statistical, analytical, visualization, and decision science methods and techniques that are applicable for turning software and systems engineering enterprise business process data into insightful information. Appendix F contains a list of recommended topics that could be included in the compendium and an interdisciplinary software and systems engineering process performance improvement basic and advanced level course. Perhaps the course should include an overview of process improvement models and measurement methods, applicable statistical process control charts, probability and statistics theory, exploratory data analysis techniques, regression and variance analysis, advanced multivariate techniques, quantitative management and optimization approaches, decision analysis techniques, and the analysis of non-normal data. What was not described in Table 5.1, but is covered in the published appraisal results database, is that the database contains more appraisals at ML3 and below than those at higher maturity appraisals. If process improvement practitioners or metrics coordinators in lower level appraised maturity organizations knew how to apply the appropriate analytical techniques and what metrics to collect and monitor, then more organizations would be appraised at a higher maturity level.

The results of the gap analysis study was presented and well accepted at the SEI Measurement and Analysis Working Group Meeting (McCray, 2010b), and at the 14th Annual International Conference on Industrial Engineering, Theory, Applications, and Practice (McCray and Santos, 2009). The future plan will involve implementing the communication plan in Table 5.3 in order to help increase awareness of the need to develop college courses that teach application of applicable statistical, quantitative, analytical, and process improvement skills to students in systems engineering and the computing disciplines. The communication plan listed the academic community and professional practice target audience. The channels of communications will involve sending out email messages, conducting telephone conversations / conferences, presenting the findings at seminars, workshops, and conferences when feasible.

Table 5.3: Gap Analysis Communication Plan

Communication Plan: Gaps In Process Improvement Courses Taught				
Academic Community	**Software Engineering**	**Systems Engineering**	**Computer Science**	**Information Technology**
Deans / Program Directors (Schools in the Study)	X	X	X	X
Applied Science Accreditation Commission (ASAC)				X
Computing Accreditation Commission (CAC)			X	
Engineering Accreditation Commission (EAC)	X	X		
Middle States Commission on Higher Education (MSCHE)	X	X	X	X
New England Association of Schools and Colleges Commission on Institutions of Higher Education (NESC/CIHE)	X	X	X	X
North Central Association of Colleges and Schools The Higher Learning Commission (NC/HLC)	X	X	X	X
Northwest Commission on Colleges and Universities (NWCCU)	X	X		X
Southern Association of Colleges and Schools Commission on Colleges (SACSCOC)	X	X	X	X
WASC Senior College and University Commission (WASC)	X	X	X	X
Professional Practice				
International Council on Systems Engineering (INCOSE)		X		
IEEE Computer Society	X		X	X
Association of Information Technology Processionals (AITP)				X
Software Engineering Institute (SEI), Measurement and Analysis Working Group	X	X		

Continued research using the approaches, methodologies, and the simulation model created as a result of this research study can be expanded upon to evaluate, and predict future outcomes of customer satisfaction survey data in other industries or business sectors. Future research should involve the use of a larger set of historical empirical data to compare against the simulated data points.

In addition, as another recommendation for further research, customer satisfaction researchers or companies that use the ACSI score as a benchmark can use the simulation and optimization modeling approach described earlier in Section 4.3 to model their customer satisfaction data to predict future outcomes, establish a baseline, and obtain a better understanding of the input impacts on the output using sensitivity analysis. The researcher's analysis can be compared to the research findings in this study.

Appendix A. U.S.A. Software Engineering Schools Included In the Study

Software Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Champlain College, Burlington, VT	SWE 2xx - Software Engineering Process	Degree not offered	Degree not offered	No	NEASC/CIHE
Auburn University, Auburn, AL	STAT 3600 Probability and Statistics (M) COMP 5700 Software Process (M) COMP 5710 Software Quality Assurance	COMP 6700 Software Process COMP 6710 Software Quality Assurance	COMP 6700 Software Process COMP 6710 Software Quality Assurance	EAC	SACSCOC
Penn State Erie, The Behrend College	STAT 301Statistical Analysis I	Degree not offered	Degree not offered	EAC	MSCHE

Software Engineering Degree Programs				Accreditation	
University	Bachelor's	Master's	Doctoral	ABET (Program)	CHEA (Regional)
Monmouth University	SE403: Software Process Improvement MA319: Probability and Statistics I	SE580 The Software Engineering Process	Degree not offered	EAC	MSCHE
University of Wisconsin–Platteville	SE 3730 Software Quality MATH 4030 Statistical Methods w/Apps	Degree not offered	Degree not offered	EAC	NCA/HLC
South Dakota State University	No applicable courses offered	No applicable courses offered	Degree not offered	No	NCA/HLC
Carroll University, Waukesha, WI	MATH 312 Theory of Probability & Statistics	No applicable courses	Degree not offered	No	NCA/HLC
Southern Polytechnic State University	MATH 2260 Probability & Statistics I SWE 3643 Software Testing & Quality Assurance	SWE 6763 Software Metrics and Quality Management	Degree not offered	EAC	SACSCOC

Software Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Clarkson University, Postdam, NY	MA383 Applied Statistics **MA381 Probability	Degree not offered	Degree not offered	EAC	MSCHE
Milwaukee School of Engineering	MA-262 Probability and Statistics SE-280 Software Engineering Process SE-4831 Software Quality Assurance	Degree not offered	Degree not offered	EAC	NCA/HLC
Rose-Hulman Institute of Technology	MA 381Introduction to Probability with Statistical Applications	Degree not offered	Degree not offered	EAC	NCA/HLC
Fairfield University	MA 351 Probability and Statistics I	No applicable courses offered	Degree not offered	EAC	NEASC/CIHE
University of Michigan, Dearborn	IMSE317 Prob & Stat	No applicable course	Degree not offered	EAC	NCA/HLC
The University of Texas at Arlington	IE 3301 Engineering Probability CSE 4322-001 Software Project Management	CSE 5325-001 Software Engineering 2: Management, Maintenance, & Quality Assurance	Degree not offered	EAC	SACSCOC

Software Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Liberty University	ENGS 363 Software Testing and Quality Assurance	Degree not offered	Degree not offered	No	SACSCOC
Robert Morris University	ENGR2080-A Engineering Statistics	Degree not offered	Degree not offered	N	MSCHE
George Mason University	Degree not offered	**SWE 630 Software Engineering Economics	**SWE 630 Software Engineering Economics	No	SACSCOC
National University	Degree not offered	SEN 635 - Software Testing Strategies and Metrics SEN 660 - Software Quality Engineering	Degree not offered	No	WASC
Embry-Riddle Aeronautical University	Degree not offered	**SE 580 Software Process Definition and Modeling **SE 585 Metrics and Statistical Methods for Software Engineering **SE 625 Software Quality Engineering and Assurance	Degree not offered	EAC	SACSCOC

Software Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
DePaul University	Degree not offered	SE 368 Software Measurement & Project Estimation SE 468 Software Measurement/Project Estimation SE 427 Software Quality Management	Degree not offered	No	NCA/HLC
Southern Methodist University	Degree not offered	No applicable course	EMIS 7310 Probability & Stats for Engs EMIS 737 Design of Experiment	No	SACSCOC
Drexel University	Degree not offered	No applicable course	Degree not offered	EAC	MSCHE
Stevens Institute of Technology	Degree not offered	No applicable course	Degree not offered	No	MSCHE
University of Southern California	Degree not offered	No applicable course	Degree not offered	No	WASC
Brandeis University	Degree not offered	No applicable course	Degree not offered	No	NEASC/CIHE

Software Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Villanova University	Degree not offered	No applicable course	Degree not offered	No	MSCHE
Mercer University	Degree not offered	No applicable course	Degree not offered	No	SACSCOC
Air Force institute of Technology	Degree not offered	No applicable course	Degree not offered	No	NCA/HLC
Naval Postgraduate School	Degree not offered	No applicable course	Degree not offered	No	WASC
University of Alabama, Huntsville	Degree not offered	No applicable course	Degree not offered	No	SACSCOC
Seattle University	Degree not offered	CSSE 536 Software Project Management	Degree not offered	No	NWCCU

Software Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Arizona State University	Degree not offered	CSE 566 Software Project, Process and Quality Management **IEE 572 Design of Experiment **CSE 561 Modeling & Simulation Theory & Application **IEE 578 Regression Analysis **IEE 581 Six Sigma Methodology	Degree not offered	No	NCA/HLC
California State University, Sacramento	Degree not offered	CSC 231 Software Engineering Metrics	Degree not offered	No	WASC
California State University, Fullerton	Degree not offered	CPSC 547 - Software Measurement	Degree not offered	No	WASC
Carnegie Mellon, Silicon Valley	Degree not offered	**17-635 Software Measurement **17-690 Seminar in Software Process	Degree not offered	No	MSCHE

Software Engineering Degree Programs				Accreditation	
University	Bachelor's	Master's	Doctoral	ABET (Program)	CHEA (Regional)
University of Management and Technology	Cst 187. Software Quality Assurance	No applicable courses offered Cst 285 SQA has a test focus	Degree not offered	No	DETC
Florida Institute of Technology	CSE 4621Software Metrics and Modeling	CSE 2400 Applied Statistics SWE 5621 Software Metrics and Modeling	Degreed not offered	EAC	SACSCOC
Michigan Technological University	CS4712: Software Quality Assurance	Degree not offered	Degree not offered	No	NCA/HLC
The University of Texas at Dallas	CS/SE 3341 Probability and Statistics in Computer Science and Software Engineering SE 3354 Software Engineering	Courses not applicable	Courses not applicable	EAC	SACSCOC

Software Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Rochester Institute of Technology	1016-314 Engineering & Statistics 4010-450 Software Process & Product Quality 4010-456 Software Process & Project Management	4011-740 Empirical Software Engineering 4011-750 Software Modeling **4011-760 Software Quality Engineering	Degree not offered	EAC	MSCHE

SUMMARY STATISTICS		Bachelor	Master	Doctoral	Total
Total Number of Degree Prgm Assessed		**21**	**31**	**3**	55
Required course (i.e. Process Imprv, Software Quality		5	6	0	
Elective course offered		0		0	
Gap - no applicable course		1	16	1	
Other courses with foundational knowledge		15	9	2	

Legend:
Black - Course included in curricula
**Course electives

Number of Universities:
Initial Review N=64; Correlated with 2007 study of 26 MS degree programs conducted by Stevens Institute.
Study Size N=40
Source: Peterson's List of U.S. Colleges and Universities

Appendix B. U.S.A. Systems Engineering Universities Included In the Study

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Johns Hopkins University, Baltimore, MD, US	Degree not offered	625 . 403 - Statistical Methods and Data Analysis (inference stats) **645 . 756 - Metrics, Modeling and Simulation for Systems Engineering (course no longer offered)	Degree not offered	No	MSCHE
United States Naval Academy, Annapolis, MD, US	System Modeling and Simulation (ES301)	Degree not offered	Degree not offered	EAC	MSCHE
California Institute of Technology Industrial Relations Center, Pasadena, CA, US	Degree not offered - certificate program only	Degree not offered - certificate program only	Degree not offered - certificate program only	No	WASC

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Boston University, Boston, MA, US	Degree not offered	EK 500 Probability with Statistical Applications SE/EC 524 Optimization Theory and Methods **EC 505 Stochastic Processes **SE/ME 714 Advanced Stochastic Modeling and Simulation SE/EC/ME 733 Discrete Event and Hybrid Systems	EK 500 Probability with Statistical Applications SE/EC 524 Optimization Theory and Methods **EC 505 Stochastic Processes **SE/ME 714 Advanced Stochastic Modeling and Simulation SE/EC/ME 733 Discrete Event and Hybrid Systems	No	NEASC/CIHE
Southern Methodist University, Dallas, TX, US	Degree not offered	**EMIS 7364 Statistical Quality Control **EMIS 7300 Systems Analysis	Degree not offered	No	SACSCOC
George Washington University, Washington, DC, US	ApSc 115 - Engineering Analysis III (Probability & Statistics) ApSc 116 - Engineering Analysis IV (advanced	**EMSE 273 Discrete Systems Simulation	**EMSE 273 Discrete Systems Simulation	No	MSCHE

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
	probability& statistics EMSE 173 - Discrete Systems Simulation EMSE 182 - Quality Control and Acceptance Sampling Stat - Upper Level Elective in Stats				
Colorado State University - Pueblo, Pueblo, CO, US	Degree not offered	EN 520 Simulation Experiments	No applicable courses offered	No	NCA/HLC
University of Maryland, Baltimore County (UMBC), Baltimore, MD, US	Degree not offered	ENEE 662: System Modeling, Simulation, and Analysis [3] **CMSC 645: Advanced Software Engineering	Degree not offered	No	MSCHE

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
University of Pennsylvania, Philadelphia, PA, US	Degree not offered	ENM 503 Introduction to Probability & Statistics ESE 603 Simulation Modeling & Analysis **ESE 530 Elements of Probability Theory	Degree not offered	EAC	MSCHE
Old Dominion University, Norfolk, VA, US	Degree not offered	**ENMA 614 Quality System Design **ENMA 717 Parametric Cost Estimating **ENMA 710 Modeling and Analysis of Systems	**ENMA 614 Quality System Design **ENMA 717 Parametric Cost Estimating **ENMA 710 Modeling and Analysis of Systems	No	SACSCOC
University of Maryland, College Park, MD, US	Degree not offered	ENSE 627 System Quality and Robustness Analysis **BMGT 835 Simulation of Discrete-Event Systems	Degree not offered	No	MSCHE
Massachusetts Institute of Technology, Cambridge, MA, US	Degree not offered	ESD Statistical Methods in Engineering Design **ESD Statistical Reasoning and Data Modeling **ESD Eng. And Statistics & Prob.	Degree not offered	No	NEASC/CIHE

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
University of Central Florida, Orlando, FL, US	Degree not offered	ESI 5219 Engineering Statistics **ESI 5531 Discrete Systems Simulation **ESI 6225 Quality Design and Control **ESI 5227 Total Quality Improvement ESI 6217. Statistical Aspects of Digital Simulation		No	SACSCOC
University of Texas at Arlington, Arlington, TX, US	Degree not offered	IE 5351. INTRODUCTION TO SYSTEMS ENGINEERING AND ANALYSIS IE 5318. ADVANCED ENGINEERING STATISTICS **IE 5322. SIMULATION AND OPTIMIZATION **IE 5320. ENTERPRISE ENGINEERING METHODS	Degree not offered	No	SACSCOC
University of Minnesota, Minneapolis, MN, US	Degree not offered	IE 5553 Simulation **IE 4521. Statistics, Quality, and Reliability **IE 5545 Decision Analysis **IE 5522 Quality engineering and Reliability	Degree not offered	No	NCA/HLC

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Arizona State University, Tempe, AZ, US	Degree not offered	IEE 545 - Simulating Stochastic Systems IEE 572 - Design of Experiments **(M)CSE 566 - Software Project, Process and Quality Management **(M)CSE 591 - Modeling and Simulation Theory and Application	Degree not offered	No	NCA/HLC
University of Alabama, Huntsville, Huntsville, AL, US	Degree not offered	ISE 526 Design and Analysis of Experiments ISE 690 Statistical Methods for Engineers	ISE 637 Systems Analysis and Modeling **ISE 723 Engineering Economic Analysis ISE 526 Design and Analysis of Experiments ISE 690 Statistical Methods for Engineers ISE 790 Advanced Statistical Applications	No	SACSCOC
Virginia Polytechnic & State University, Blacksburg,	Degree not offered	**ISE 5454 Simulation I **ISE 5474 Statistical Theory of Quality Control **ISE 6494 Advanced Simulations	Degree not offered	No	SACSCOC

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Colorado State University, Fort Collins, CO, US	Degree not offered	MECH 513 – Simulation Fundamentals	Degree not offered	No	NCA/HLC
Embry-Riddle Aeronautical University, Daytona Beach, FL, US	Degree not offered	**MSE 540 Simulation & Software Engineering	Degree not offered	No	SACSCOC
California State University - Fullerton, Fullerton, CA, US	Degree not offered	**MSEE with Option in SE** EGEE 585 Optimization Techniques in Systems Engineering **EGEE 587 Operational Analysis Techniques in Systems Engineering**	Degree not offered	No	WASC
Colorado Technical University, Colorado Springs, CO, US	Degree not offered	No applicable core courses offered **CS805 Experimental Design **CS812 Quantitative Analysis **CS671 Software Systems Engineering Process	Degree not offered	No	NCA/HLC
Rensselaer Polytechnic Institute, Troy, NY	No applicable courses offered	No applicable courses offered	Degree not offered	No	MSCHE

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
University of Houston, Houston, TX, US	Degree not offered	No applicable courses offered	Degree not offered	No	SACSCOC
Cornell University, Ithaca, NY, US	Degree not offered	No applicable courses offered	Degree not offered	No	MSCHE
Worcester Polytechnic Institute, Worcester, MA, US	Degree not offered	No applicable courses offered	Degree not offered	No	NEASC/CIHE
Naval Postgraduate School, Monterey, CA,	Degree not offered	No applicable courses offered	Degree not offered	EAC	WASC
Walden University, Baltimore, MD, US	Degree not offered	NSYS 6140 Systems Optimization and Analysis **NMTH 6701 Probability and Statistics for Scientists and Scientists and Engineer **NSEN 6061 Software Measurement	Degree not offered	No	NCA/HLC

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Southern Polytechnic State University, Marietta, GA, US	SyE2600 Applications of Probability SyE3600 Statistics with Applications **SyE3650 Process Engineering & Improvement** SyE3850 Design of Experiments SyE4500 System Modeling & Simulation	QA 6610 Statistics **QA 6611 Advanced Statistical Applications **SyE 6035 Modeling and Simulation	Degree not offered	No	SACSCOC
University of Florida, Gainesville, FL, US	Degree not offered	See comment	Degree not offered	EAC	SACSCOC
Loyola Marymount University, Los Angeles, CA, US	Degree not offered	**SELP 500 Quality** SELP 660 Lean Methods	Degree not offered	No	WASC

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
National University, LaJolla, CA, US	Degree not offered	**SEN 635 - Software Testing Strategies and Metrics **ENM 604 - Quality Management Specialization in Lean Six Sigma **SEN 660 Software Quality Engineering Green and Black Belt Courses	Degree not offered	No	WASC
University of Houston - Clear Lake, Houston, TX, US	Degree not offered	SENG 5233 Systems Engineering Analysis & Modeling **SENG 5332: Decision Analysis for Systems Engineering	Degree not offered	No	SACSCOC

Systems Engineering Degree Programs				Accreditation	
University	Bachelor's	Master's	Doctoral	ABET (Program)	CHEA (Regional)
University of Arizona, Tucson, AZ, US	SIE 265 Engineering Management I SIE 305 Introduction to Engineering Probability and Statistics SIE 321 Probabilistic Models in Operations Research SIE 330R Engineering Experiment Design **SIE 406 Quality Engineering **SIE 430 Engineering Statistics SIE 431 Simulation Modeling and Analysis	**SIE 506 Quality Engineering **SIE 522 Engineering Decision Making Under Uncertainty **SIE 606 Advanced Quality Engineering	Degree not offered	EAC	NCA/HLC

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Missouri University of Science and Technology, Rolla, MO, US	Degree not offered	**STAT 443 Nonparametric Statistical Methods **STAT 444 Design & Analysis of Experiment **STAT 445 Multivariate Statistical Methods **Emgt 356 Industrial Systems Simulation	**STAT 443 Nonparametric Statistical Methods **STAT 444 Design & Analysis of Experiment **STAT 445 Multivariate Statistical Methods **Emgt 356 Industrial Systems Simulation	No	NCA/HLC
Penn State University at Great Valley, Malvern, PA, US	Degree not offered	STAT 500 Applied Statistics	Degree not offered	No	MSCHE

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Air Force Institute of Technology, Dayton, OH, US	Degree not offered	STAT 583 Introduction to Probability and Statistics or, **STAT 527 Intro to Probability **STAT 537 Intro to Statistics **MECH 620 System Optimization **OPER 540 Stochastic Modeling and Analysis I	STAT 583 Introduction to Probability and Statistics **STAT 527 Intro to Probability **STAT 537 Intro to Statistics **MECH 620 System Optimization **OPER 540 Stochastic Modeling and Analysis I	EAC	NCA/HLC
University of Arkansas at Little Rock, Little Rock, AR, US	SYEN 3316 Discrete Event Systems Modeling and Simulation	SYEN 7314 Multicriteria Decision and Risk Analysis		EAC	NCA/HLC
Florida Institute of Technology, Melbourne, FL, US	Degree not offered	**SYS 5385 System Life Cycle Cost Estimation	Degree not offered	No	SACSCOC

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
University of Virginia, Charlottesville, VA, US	**APMA 312 Statistics** SYS 362 Discrete Event Simulations APMA 310 Probability SYS 421 Linear Statistical Models	SYS 621 Linear Statistical Models **STAT 510 Statistics	**SYS 763 Response Surface Methods**	EAC	SACSCOC
Stevens Institute of Technology, Hoboken, NJ, US	Degree not offered	**SYS 501 Probability and Statistics for Systems Engineering **SYS 595 Design of Experiments and Optimization **SYS 611 Modeling and Simulation (Module version is SDOE 611) **SYS 660 Decision and Risk Analysis (Module version is SDOE 660)	**SYS 501 Probability and Statistics for Systems Engineering **SYS 595 Design of Experiments and Optimization **SYS 611 Modeling and Simulation (Module version is SDOE 611) **SYS 660 Decision and Risk Analysis (Module version is SDOE 660)	No	MSCHE

Systems Engineering Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Portland State University, Portland, OR, US	Degree not offered	**SYSC 529/629: Business Process Modeling & Simulation** or, SYSC 527 Discrete Systems Simulation	Degree not offered	No	NWCCU
George Mason University, Fairfax, VA, US	SYST 330 Systems Methods (3:3:0) SYST 335/OR 335 Discrete Systems Modeling and Simulation (3:3:0)	SYST 611 System Methodology and Modeling **SYST 664 Bayesian Inference and Decision Analysis **SYST 620 Discrete Event Systems **SYST 677 Statistical Process Control	SYST 677 Statistical Process Control OR 635 Discrete System Simulation	EAC	SACSCOC

SUMMARY STATISTICS	Bachelor	Master	Doctoral	Total
Total Number of Degree Prgm Assessed	**9**	**41**	**10**	**60**
Required course (i.e. Process Imprv, Software Qualit		7	1	
Elective course offered	1			
Gap - no applicable course	1	6	2	
Other courses with foundational knowledge	7	28	7	

Source: INCOSE homepage and Peterson's 2009 List of Colleges and Universities

Legend:
Black - Course included in curricula
**Course electives

Number of Universities
Initial Review N=79
Study Size N=43

Appendix C. U.S.A Computer Science Universities Included In the Study

Computer Science Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
University of Michigan	Stats 412/426 Probability & Statistics	Degree not offered	Degree not offered	CAC	NCA/HLC
American University	STAT Basic Statistics	No applicable course offered	Degree not offered	No	MSCHE
Penn State Erie, The Behrend College	STAT 301	Degree not offered	Degree not offered	No	MSCHE
State University of New York College at Oneonta	STAT 261 Probability Models & Statistic	Degree not offered	Degree not offered	No	MSCHE
Missouri University of Science and Technology	STAT 215 Engineering Stats	No applicable course offered	No applicable course offered	CAC	NCA/HLC
Florida International University	STA 3033 Intro to Probability and Statistics for CS	No applicable course offered	No applicable course offered	CAC	SACSCOC
University of Tulsa	No applicable course	Stat Course	Stat Course	No	NCA/HLC
University of California, Irvine	No applicable course	No applicable course offered	No applicable course offered	CAC	NCA/HLC
Boston University	No applicable course	No applicable course offered	No applicable course offered	No	NEASC/CHE

Computer Science Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
University of California, Santa Barbara	No applicable course	No applicable course offered	No applicable course offered	CAC	WASC
The University of North Carolina at Chapel Hill	No applicable course	No applicable course offered	**STAT 435 Introduction to Probability	No	SACSCOC
University of California, Riverside	No applicable course	No applicable course offered	No applicable course offered	CAC	WASC
University of California, Santa Cruz	No applicable course	No applicable course offered	No applicable course offered	No	WASC
The George Washington University	No applicable course	No applicable course offered	No applicable course offered	CAC	MSCHE
Fordham University	No applicable course	No applicable course offered	Degree not offered	No	MSCHE
Rensselaer Polytechnic Institute	No applicable course	No applicable course offered	No applicable course offered	No	MSCHE
Chapman University	No applicable course	No applicable course offered	Degree not offered	No	WASC
Worcester Polytechnic Institute	No applicable course	No applicable course offered	No applicable course offered	CAC	NEASC/CHE

Computer Science Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
University of Puerto Rico, Río Piedras	No applicable course	Degree not offered	Degree not offered	CAC	MSCHE
State University of New York College at Geneseo	No applicable course	Degree not offered	Degree not offered	No	MSCHE
University of Rochester	No applicable course	Degree not offered	Degree not offered	No	MSCHE
University of San Diego	No applicable course	Degree not offered	Degree not offered	No	WASC
Providence College	No applicable course	Degree not offered	Degree not offered	No	NEASC/CHE
Oberlin College	No applicable course	Degree not offered	Degree not offered	No	NCA/HLC
Furman University	**MTH-340 Probability	Degree not offered	Degree not offered	No	SACSCOC
Boston College	MTH 426 Probability	Degree not offered	Degree not offered	No	NEASC/CHE

Computer Science Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
University of Miami	MTH 224 Intro to Probability & Statistics **MTH 525 Intro to Mathematical Statistics	No applicable course offered	No applicable course offered	No	SACSCOC
Pepperdine University	MATH 510 Probability & Statistic I	Degree not offered	Degree not offered	No	WASC
University of Illinois at Urbana–Champaign	Math 463 /Stat 400 Statistics and Probability I	Degree not offered	Degree not offered	CAC	NCA/HLC
Case Western Reserve University	MATH 380 Intro to Probability, or **STAT 312 Basic Stat for Engineers	Degree not offered	Degree not offered	CAC	NCA/HLC
University of Wisconsin–Madison	Math 331 Intro to Probability & Statistics	No applicable course offered	**726 Nonlinear Optimization I	No	NCA/HLC

Computer Science Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
State University of New York at Binghamton	Math 327 Probability w/Statistical Methods, or **ISE Probabilistic Systems I	No applicable course offered	No applicable course offered	CAC	MSCHE
Northeastern University	MATH 3081 Probability & Statistics	No applicable course offered	No applicable course offered	No	NEASC/CHE
Marist College	MATH 130 Introductory Statics	No applicable course offered	Degree not offered	No	MSCHE
Villanova University	MAT 4310 Statistical Methods	No applicable course offered	Degree not offered	CAC	MSCHE
The Richard Stockton College of New Jersey	CSIS 1206 Statistics **CSIS 3327 Probability & Applied Stats	Degree not offered	Degree not offered	No	MSCHE
University of California, San Diego	CSE 103 Probability & Statistics	No applicable course offered	No applicable course offered	No	WASC
University of California, Berkeley	CS 169 Software Engineering	Degree not offered	Degree not offered	CAC	WASC

Computer Science Degree Programs				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Stony Brook University, State University of New York	AMS 310 Survey of Probability & Statistics	No applicable course offered	Degree not offered	CAC	MSCHE
Vanderbilt University	216/217 Statistics/Probability	No applicable course offered	No applicable course offered	No	SACSCOC

SUMMARY STATISTICS		Bachelor	Master	Doctoral	Total
Total Number of Degree Prgm Assessed		**40**	**24**	**18**	82
Required course (i.e. Process Improvement, Software Quality)					
Elective course offered					
Gap - no applicable course		18	22	14	
Other courses with foundational knowledge		22	2	4	

Legend:
Black - Course included in curricula
**Course electives

Source: Peterson's List of U.S. Colleges and Universities

Number of Universities:
Initial Review N=89

Study Size
N=40

Appendix D. U.S.A. Information Technology Universities Included In the Study

Information Technology Degree Program				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
North Carolina State University, Raleigh, NC	Call the school	Degree not offered	Degree not offered	No	SACSCOC
San Jose State University, San Jose, CA				No	WASC
Temple University, Philadelphia, PA	Math 2031 Probability & Statistics	No applicable courses offered	STAT 8003 Statistical Methods I	No	MSCHE
DePaul University, Chicago, IL	IT 223 Data Analysis	CSC Data Analysis and Regression	IT223 data Analysis.	No	NCA/HLC
Indiana University–Purdue University Indianapolis, Indianapolis, IN	*CIT 22000 Quantitative Analysis	TECH 50700 Measurement and Evaluation in Industry and Technology TECH 50800 Quality and Productivity in Industry and Technology	Degree not offered	ASAC	NCA/HLC

Information Technology Degree Program				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Brigham Young University, Provo, UT	*STAT 332 : Quality Improvement for Industry	Stat 510 Intro to Stat for Grad Students	Degree not offered	ASAC	NWCCU
Central Michigan University, Mount Pleasant, MI	STA 282 Introduction to Statistics, or STA 382 Elementary Statistics Analysis	STA 282 Introduction to Statistics	Degree not offered	No	NCA/HLC
Northern Kentucky University, Highland Heights, KY	No applicable courses offered	No applicable courses offered	Degree not offered	No	SACSCOC
National University, La Jolla, CA	No applicable courses offered	No applicable courses offered	Degree not offered	No	WASC
Southern Polytechnic State University, Marietta, GA	**MATH 2260 Probability & Statistics IET 2227 Industrial Statistics	No applicable courses offered	Degree not offered	ASAC	SACSCOC

Information Technology Degree Program				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
Winston-Salem State University, Winston-Salem, NC	MAT 2336 Elementary Statistics	No applicable courses offered	Degree not offered	ASAC	SACSCOC
New Jersey Institute of Technology, Newark, NJ	No applicable courses offered	No applicable courses	Degree not offered	No	MSCHE
California State University, Dominguez Hills, Carson, CA	Degree Not offered	No applicable courses	Degree not offered	No	WASC
Kutztown University of Pennsylvania, Kutztown, PA	MAT 140 Applied Stat Methods	No applicable course	Degree not offered	No	MSCHE
Illinois State University, Normal, IL	Degree Not offered	No applicable course	Degree not offered	No	NCA/HLC
University of Massachusetts Boston, Boston MA	IT 111 Managerial Statistics	MSIS 630 Statistical Analysis for Managers	Degree not offered	No	NEASC/CIHE

Information Technology Degree Program				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
University of Missouri–Kansas City, MO	STAT 235 Statistics	Degree not offered	Degree not offered	ASAC	NCA/HLC
Montclair State University, Upper Montclair, NJ	SAT 401 Applied Statistics for Sciences	Degree not offered	Degree not offered	No	MSCHE
University of Central Florida, Orlando	No applicable courses offered	Degree not offered	Degree not offered	No	SACSCOC
Florida International University, Miami, FL	No applicable courses offered	Degree not offered	Degree not offered	No	SACSCOC
Western Kentucky University, Bowling Green, KY	No applicable courses offered	Degree not offered	Degree not offered	No	SACSCOC
New Mexico State University, Las Cruces, ,NM	No applicable courses offered	Degree not offered	Degree not offered	No	NCA/HLC
Youngstown State University, Youngstown, OH	No applicable courses offered	Degree not offered	Degree not offered	No	NCA/HLC

Information Technology Degree Program				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
American Public University System, Charles Town, WV	No applicable courses offered	Degree not offered	Degree not offered	No	NCA/HLC
University of Wisconsin–Whitewater, WI	No applicable courses offered	Degree not offered	Degree not offered	No	NCA/HLC
University of Phoenix–Southern California Campus, Fountain Valley, CA	No applicable courses offered	Degree not offered	Degree not offered	No	NCA/HLC
Indiana State University, Terre Haute, IN	No applicable courses offered	Degree not offered	Degree not offered	No	NCA/HLC
Marquette University, Milwaukee, WI	No applicable courses offered	Degree not offered	Degree not offered	No	NCA/HLC
Slippery Rock University of Pennsylvania, Slippery Rock, PA	No applicable courses offered	Degree not offered	Degree not offered	ASAC	MSCHE
Armstrong Atlantic State University, Savannah, GA	No applicable courses offered	Degree not offered	Degree not offered	No	SACSCOC

Information Technology Degree Program				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
The University of North Carolina at Pembroke, Pembroke, NC	No applicable courses offered	Degree not offered	Degree not offered	No	SACSCOC
Bellevue University, Bellevue, NE	No applicable courses offered	Degree not offered	Degree not offered	No	NCA/HLC
Monroe College, Bronx, NY	No applicable courses offered	Degree not offered	Degree not offered	No	MSCHE
Plymouth State University, Plymouth, NH	No applicable courses offered	Degree not offered	Degree not offered	No	NEASC/CIHE
University of Phoenix–Phoenix Campus, Phoenix, AZ	No applicable courses offered	Degree not offered	Degree not offered	No	NCA/HLC
Point Park University, Pittsburgh, PA	No applicable courses offered	Degree not offered	Degree not offered	No	MSCHE
University of Phoenix–Sacramento Valley Campus, Sacramento, CA	No applicable courses offered	Degree not offered	Degree not offered	No	NCA/HLC

Information Technology Degree Program				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
University of New Hampshire, Durham, NH	MATH 439, Statistical Discovery for Everyone	Degree not offered	Degree not offered	ASAC	NEASC/CIHE
Abilene Christian University, Abilene, TX	MATH 377 Statistical Methods I	Degree not offered	Degree not offered	No	SACSCOC
Franklin University, Columbus, OH	MATH 215 Statistical Concepts	Degree not offered	Degree not offered	No	NCA/HLC
Marist College, Poughkeepsie, NY	MATH 130 Intro to Statistics I	Degree not offered	Degree not offered	No	MSCHE
California State University, Chico, CA	MATH 105 Statistics	Degree not offered	Degree not offered	No	WASC
University of Denver, Denver, CO	MATC 1200 Statistics STAT 1300 Statistics	Degree not offered	Degree not offered	No	NCA/HLC
San Diego State University, San Diego, CA	IDS 301. Statistical Analysis for Business	Degree not offered	Degree not offered	No	WASC
Fairleigh Dickinson University, Metropolitan Campus, Teaneck, NJ	EGTG4221 Statistics & Reliability for IT	Degree not offered	Degree not offered	No	MSCHE

Information Technology Degree Program				Accreditation	
University	**Bachelor's**	**Master's**	**Doctoral**	**ABET (Program)**	**CHEA (Regional)**
California State University, Los Angeles, CA	ECON 209 Applied Business and Economic Statistics	Degree not offered	Degree not offered	No	WASC
University of Houston, Huston, TX	TMTH 3360 Applied Tech Statistics	63024 Contemporary Quality Assessment in Project Management	Degree not offered	No	SACSCOC
Rochester Institute of Technology, Rochester, NY SW - Richard Meagher	No applicable courses offered	**4002-820 Economics of Software Development	Degree not offered	ASAC	MSCHE
East Carolina University	Degree Not offered	Degree not offered	Degree not offered	No	SACSCOC

SUMMARY STATISTICS	Bachelor	Master	Doctoral	Total
Total Number of Degree Programs Assessed	**47**	**18**	**4**	69
Required course (i.e. Process Improvement, Software Quality)	2	0		
Gap - no applicable course	26	11	2	
Programs that offer courses that build on foundational knowledge	19	7	2	

Legend:
Black - Course included in the curricula
* Course listed in the catalogue
**Course electives
Source: INCOSE homepage and Peterson's 2009 List of Colleges and Universities

Number of Universities:
Initial Review N=70 (40% of 173)
Study Size N=49

Appendix E. Weights for Calculating ACSI Scores by State

U.S. Department of Labor Table of Weights for Use in Calculating State Level ACSI Scores by State

American Customer Satisfaction Index (ACSI)
Formula Weights for Program Year 2011

State	Satisfaction (SATIS)	Confirm (CONFIRM)	Ideal (IDEAL)
Alabama	0.3932	0.3246	0.2822
Alaska	0.3507	0.3545	0.2948
Arizona	0.4032	0.3186	0.2781
Arkansas	0.3919	0.3232	0.2849
California	0.3905	0.3317	0.2778
Colorado	0.4053	0.3203	0.2745
Connecticut	0.3853	0.3298	0.2849
Delaware	0.3866	0.3330	0.2804
DC	0.3750	0.3319	0.2931
Florida	0.3906	0.3282	0.2812
Georgia	0.4011	0.3265	0.2724
Hawaii	0.4048	0.3190	0.2761
Idaho	0.3797	0.3524	0.2679
Illinois	0.3857	0.3302	0.2841
Indiana	0.4081	0.3161	0.2758
Iowa	0.3899	0.3235	0.2866
Kansas	0.4002	0.3314	0.2684
Kentucky	0.3862	0.3307	0.2831
Louisiana	0.3940	0.3241	0.2819
Maine	0.3952	0.3233	0.2815
Maryland	0.3762	0.3302	0.2936
Massachusetts	0.3879	0.3315	0.2806
Michigan	0.3913	0.3272	0.2815
Minnesota	0.3931	0.3278	0.2791
Mississippi	0.3957	0.3307	0.2736
Missouri	0.3979	0.3276	0.2745
Montana	0.4007	0.3215	0.2778

State	Satisfaction (SATIS)	Confirm (CONFIRM)	Ideal (IDEAL)
Nebraska	0.3913	0.3352	0.2735
Nevada	0.3995	0.3198	0.2807
New Hampshire	0.3937	0.3284	0.2779
New Jersey	0.3834	0.3269	0.2896
New Mexico	0.4178	0.3224	0.2598
New York	0.3913	0.3338	0.2749
North Carolina	0.4012	0.3225	0.2763
North Dakota	0.3991	0.3131	0.2877
Ohio	0.3940	0.3294	0.2766
Oklahoma	0.3945	0.3294	0.2761
Oregon	0.3997	0.3246	0.2758
Pennsylvania	0.3939	0.3282	0.2779
Rhode Island	0.4118	0.3399	0.2483
South Carolina	0.4054	0.3151	0.2795
South Dakota	0.4017	0.3155	0.2828
Tennessee	0.4018	0.3180	0.2802
Texas	0.4016	0.3232	0.2752
Utah	0.4013	0.3198	0.2789
Vermont	0.3864	0.3678	0.2457
Virginia	0.3996	0.3284	0.2720
Washington	0.3944	0.3227	0.2829
West Virginia	0.3881	0.3281	0.2838
Wisconsin	0.3950	0.3236	0.2813
Wyoming	0.3730	0.3526	0.2744
Aggregate	***0.4127***	***0.3688***	***0.3229***

Source: Training and Employment Guidance Letter No. 12-12, dated January 7, 2013.

Appendix F. List of Process Performance Topics

Recommended List of Topics for Software and Systems Engineering Process Performance Improvement Course		
Quantitative Analysis Techniques and Methodologies	**Foundational Concepts**	**Advanced Concepts**
Overview of Process Improvement Models and Measurement Methods		
International Organization for Standardization (ISO) Process Improvement Models	X	X
Information Technology Infrastructure Library (ITIL)	X	X
Capability Maturity Model Integration (CMMI) Model Frameworks	X	X
CMMI High Maturity Process Areas	X	X
Process Governance, Architecture, and Process Procedure	X	X
Process and Product Quality Assurance		X
Peer Review Process	X	X
Process Mapping and Process Flow Charts	X	X
SIPOC Diagram (Suppliers, Inputs, Process, Outputs ,Customers)	X	X
How to Establish Process Performance Baselines		X
Software / Systems Engineering Lifecycle Models	X	X
Software / Systems Engineering Leading and Lagging Measurement Indicators	X	X
Statistical Thinking	X	X
Measurement Scales and Data Types	X	
Univariate, Bivariate, and Multivariate Data Analysis	X	X
Enumerative Study versus Analytic Study	X	X
Goal-Question-Metric	X	X
Understanding Central Limit Theorem	X	
Understanding Central Limit Theorem and Non-Normality		X
Process Mapping and Process Flow Charts	X	X
SIPOC Diagram (Suppliers, Inputs, Process, Outputs ,Customers)	X	X

Recommended List of Topics for Software and Systems Engineering Process Performance Improvement Course		
Quantitative Analysis Techniques and Methodologies	**Foundational Concepts**	**Advanced Concepts**
Statistical Process Control (SPC) Charts		
Variable Control Charts	X	
Attribute Control Charts	X	X
Short Run Control Charts		X
Individual Control Chart	X	X
Exponential Weighted Moving Average Chart (EWMA)		X
Multivariate SPC Charts		X
Hotelling T^2		X
Understand Western Electric Rules for Symmetric and Non-Symmetric Data Distributions	X	X
Statistical Methods		
Affinity analysis		X
Capability analysis	X	X
Cause and Effect Diagram	X	
Checklists	X	
Control Plan	X	X
Failure Mode and Effect Analysis (FMEA)	X	X
Hypothesis Testing	X	X
Ishikawa Diagram	X	
Kaizen	X	
Mistake-Proofing	X	
Pareto Chart	X	
Queuing Theory		X
Spreadsheet Modeling and Analysis		X
Exploratory Data Analysis Techniques		
Bar, Pie, Run Charts, and Patterns	X	X
Normality Test	X	X
Box Plot, Dot Plot, Interval Plot, Scatter Plot, Histogram, and Stem-and-Leaf Chart	X	X
Radar chart	X	X

Recommended List of Topics for Software and Systems Engineering Process Performance Improvement Course		
Quantitative Analysis Techniques and Methodologies	**Foundational Concepts**	**Advanced Concepts**
Probability and Statistics Theory		
Point Estimation	X	X
Hypothesis Testing	X	X
Analysis of Variance (ANOVA)	X	X
Analysis of Means	X	X
Distribution Theory	X	X
Regression Analysis		
General Linear Regression	X	X
Fitted Line Plots	X	X
Prediction and Confidence Intervals (Ellipses, Bands, and Limits)	X	X
Logistic Regression		X
Principal Component Analysis		X
Scatter Diagrams	X	X
Correlation Analysis	X	X
Variance Analysis		
Analysis of Variance (ANOVA)	X	X
Analysis of Covariance (ANCOVA)		X
Multivariate Analysis of Variance (MANNOVA)	X	X
Nonlinear Regression		X
Bayesian Methods		X
Multivariate Techniques		
Canonical Correlation Analysis		X
Multiple Regression		X
Conjoint Analysis		X
Multivariate Analysis of Variance		X
Design of Experiment		
Response surface design	X	X
Taguchi Methods		X

Recommended List of Topics for Software and Systems Engineering Process Performance Improvement Course		
Quantitative Analysis Techniques and Methodologies	**Foundational Concepts**	**Advanced Concepts**
Optimization Approaches		
Probability Modeling		X
Monte Carlo Simulation	X	X
Discrete Event Simulation	X	X
Analyzing Outliers		
SPC charts	X	X
Univariate, Bivariate, and Multivariate Data Sets	X	X
Variation and Capability Analysis	X	X
Variation Reduction and Optimization		X
Non-Normal Data Analysis		
Analyzing Non-Normal Data	X	X
Transformation Techniques	X	X
Autocorrelation (Correlogram)		X
Average Run Length (ARL)	X	X
Non-Parametric Statistics		X
Decision Techniques		
Analytic Hierarchy Process (AHP)	X	X
Conjoint Analysis		X
Wideband Delphi	X	
Multivoting	X	
Nominal Group Technique	X	
Decision Making Under Uncertainty	X	X
Risk Analysis	X	X
Pairwise Comparison	X	
Sensitivity Analysis		X
Utility Function	X	X
Decision Trees		X

Recommended List of Topics for Software and Systems Engineering Process Performance Improvement Course		
Quantitative Analysis Techniques and Methodologies	**Foundational Concepts**	**Advanced Concepts**
Software Measurements		
Source Lines of Code (SLOC)	X	X
Function Point Estimation	X	X
Capability Growth Models		X
Project Management Metrics	X	X
Prediction Modeling of Software and Systems Engineering Process	X	X

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