NEW PROCESS CAPABILITY INDICES BASED ON SIX SIGMA STATISTICAL APPROACH FOR MEASURING THE PROCESS PERFORMANCE IN INDUSTRIES: A CASE STUDY IN ADEN'S OIL REFINERY YEMEN

by

FAISAL ALI MOHAMMED ALI
(1542111905)

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy (Statistics)

Institute of Engineering Mathematics
UNIVERSITI MALAYSIA PERLIS

2018

ACKNOWLEDGMENT

First of all, I would like to express my profound and sincere gratitude to Almighty Allah for granting me health, strength and giving me the opportunity to complete my thesis

Undertaking this PhD has been a truly life changing experience for me and it would not have been possible to do without the support that I received from many people. I would like to acknowledge people who so generously contributed to the work presented in this thesis.

First and foremost, my special thanks and profound gratitude goes to my enthusiastic and energetic supervisor Prof. Dr. Amran bin Ahmed for his outstanding and organized supervision throughout the journey to complete my thesis. He has taught me, both consciously and un-consciously, how good thesis, and analysis are done. I appreciate all his contributions of time, ideas, and kindness to make my PhD experience productive and stimulating. The joy and enthusiasm he has for his research was contagious and motivational for me, even during tough times in the PhD pursuit. I thank Prof. Dr Amran bin Ahmed for enlightening me with the necessary statistical knowledge to analyse my data in an efficient way. He has tremendous knowledge and experiences in this field. His kindness, enthusiasm and good works are unbeatable. My PhD journey with him has been an amazing and challenging experience and I thank him wholeheartedly, not only for his tremendous academic support, but also for his kindness, encouragements and friendliness.

I would like to take this opportunity to express my upmost appreciation to my beloved family for their constant support and motivations throughout my entire life especially my mother and my father. They are the backbone of my life and their presence in my life has made things easier, encouraged me to study hard and gave me the resilience and strength to carry on even when things went extremely hard. I would like to extend my deepest gratitude to my wife, and my daughters - Buthaina , Shatha and Shahd.

I would like to extend my appreciation to the Institute of Engineering Mathematics as a whole, staff and lecturers for providing the perfect research environment and for their kind assistant and friendly management. It was privilege knowing them and their kindness and assistance are well acknowledged. I thank the committee members, without whom this would not be possible, Prof. Dr. Ahmad Shukri Yahaya External Examiner and Dr. Safwati Ibrahim Internal Examiner.

Last but not least, I would like to thank my friends especially the good and close friends Brothers Adel Mohammed Al-Dhahebi and Majed Rafikullah.

Thank you so much!

Faisal Ali Mohammed

TABLE OF CONTENTS

LIST OF TABLES

NO. **PAGE**

LIST OF FIGURES

NO. **PAGE**

LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller (1979)
ARCH	AutoRegressive Conditional Heteroskedasticity
AR	Autoregressive model
ARL	Average Run Length
CDF	Commulative Distribution Function
CL	Centerline
CRL	Conforming run length
PDF	Probability Distribution Function
DMAIC	Design, Manage, Action,Implement, Control
DPMO	Defect Per Million Opportunities
DPO	Defect per Opportunity
DPU	Defect per Unit
EWMA	Exponentially weighted moving average
GDP	Gross Domestic Product
LM	Lagrange Multiplier
LSL	Lower Specification Limits
MPCIs	Multivariate Process Capability Indices
MVLUE	Minimum Variance linear Unbiased Estimator
NC	Non-Conformance
NCPPM	Nonconformance Part Per Million
PCA	Principal Component Analysis
PCIs	Process Capability Indices
PDCA	Plan, Do, Check, Action
PPM	Parts Per Million
RTY	Rolled Throughout Yield
S.D.	Standard Deviation
SSA	Six Sigma Academy
SS	Six Sigma
SPC	Statistical Process Control
SQC	Statistical Quality Control
SSQL	Six Sigma Quality Level
SSTY	Six Sigma Total of Yield

SSY	Six Sigma Yield
TL	Tolerance Limits
TQM	Total Quality Managment
USL	Upper Specification Limits
VAR	Vector Autoregression

LIST OF SYMBOLS

LCL	Lower Control Limit;
UCL	Upper Control Limit;
U	Upper specification limit for X ;
L	Lower specification limit for X ;
X	Any quality characteristic;
T	Target value for Characteristics X given by engineers;
μ	Process smean;
D	All tolerance between lower and upper specification limits, for X , given by engineering;
D_u	$U - T$ Part of interval tolerance between specification limits;
D_l	$T - L$ Part of interval tolerance between specification limits;
x_1	$\max\left(\frac{D_u}{\mathrm{D}}, \frac{D_l}{\mathrm{D}}\right)$;
x_2	$\min\left(\frac{D_u}{D}, \frac{D_l}{D}\right)$;
δ	$\lvert \mu - T \rvert = \text{Bias}(\mu - T) = \delta$. As variation coefficient;
δ'	$(\mu - T)/d$
d^*	$\min\left(\lvert U - \mu \rvert, \lvert \mu - L \rvert\right)$
λ	σ / d
d	$d = (U - L)/2$
n	Sample size
C_p	Bilateral unilateral process capability index;
Q	Uantification of specification $Q = (6\sigma/(U - L))*100\%$
C_{pk}	Bilateral specification process capability index ;
σ	Standard deviation of X ;
$\hat{\sigma}_{ss}$	$\hat{\sigma}_{ss} = \frac{d}{k}$;
$\hat{\sigma}_{LT}$	$= \sqrt{\frac{\sum_{i}^{n}\sum_{j}^{m}(X_{ij} - \overline{\overline{X}})^2}{(mn-1)}}$;
$\hat{\sigma}_R$	$= \frac{\overline{R}}{d_2(n)}$;
$\hat{\sigma}_s$	$= \frac{\overline{\mathrm{S}}}{C_4(n)}$, $S_i = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(x_{ij} - \overline{x}_i\right)^2}$;
$\hat{\sigma}_{si}$	$= \frac{S\,i}{C_4(V)}$, $V = \left(\sum_{i=1}^{m} n\right) - m + 1$;

$\hat{\sigma}_{wi}$	$=\frac{1}{\sum_{i=1}^{N} w_i} \cdot \sum_{i=1}^{N} \frac{w_i R_i}{d_2(n)}$, $w_i = \frac{[d_2(n_i)]^2}{1-[d_2(n_i)]^2}$;
$\hat{\sigma}_{hi}$	$=\frac{1}{\sum_{i=1}^{N} h_i} \sum_{i=1}^{N} \frac{h_i s_i}{C_4(n)}$, $h_i = \frac{[C_4(n_i)]^2}{1-[C_4(n_i)]^2}$;
C_4, d_2, d_3	Constants of the literat ure of control chart which are expressed as functions of the sample size (*n*);
Φ	Cumulative distribution function of the standard normal distribution;
Φ^{-1}	Inverse distribution function of the standard normal distribution;
ϕ	Probability density function ;
$\bar{X}^T$	Compute the sample mean vector $e_i'\bar{X}$
S	Sample covariance matrix;
C_{pm}	Taguchi capability index;
$k_c = L\sigma$	Quality level (level sigma process);
r	Sample correlation matrix;
d_i	$[(U-L)/2]'$;
T_i	Is the target value, $(T_1, T_2 .. T_v)'$;
μ_i	Overall mean of the quality characteristic generated from multiple rational subgroups; $(\mu_1, \mu_2 ... \mu_v) = e_i'\bar{X}$;
SSY	Six Sigma yield (univariate process yield);
S_{pk}	The process yield index for univariate normally distributed data;
SSS_{pk}	Six Sigma the process yield index for univariate normally distributed data;
SSC_{pk}	Six Sigma Process Capability index;
$SSQL_{pk}$	$\min\left(\frac{1-\delta'}{\lambda}+1.5, \frac{1+\delta'}{\lambda}+1.5\right)$ of Six Sigma level quality index;
$SSQL_{pl}$	$=\frac{1-\delta'}{\lambda}+1.5$;
$SSQL_{pu}$	$=\frac{1+\delta'}{\lambda}+1.5$;
$SSMS_{pk}$	Six Sigma rocess yield index for Multivariate normally distributed data;
$SSTY$	Six Sigma total yield (Overall Process Yield for Multivariate Characteristics);
$SSMS_{pk,PC}$	Six Sigma process yield index for Multivariate a normally distributed data

by Principle Component Analysis;

TS_{pk}	process yield index for Multivariate a normally distributed data;
$TS_{pk,PC}$	process yield index for Multivariate a normally distributed data by PCA;
TS_{pk,PC,B^*}	process yield index for Multivariate a normally distributed data by PCA;
a_i	$= d_i / \sqrt{2\sigma_i}\left((1-\delta')\phi(\frac{1-\delta_i'}{\lambda}) + (1+\delta_i')\phi(\frac{1+\delta_i'}{\lambda})\right)$;
b_i	$= \phi\left(\frac{1-\delta_i'}{\lambda}\right) - \phi\left(\frac{1+\delta_i'}{\lambda}\right)$;
σ_i	$(U_i + L_i)/d_i$;
δ_i'	$(\mu_i - T_i)/d_i$;
U_i'	Upper specification limit for X for Principal Component Analysis ;
L_i'	Lower specification limit for X for Principal Component Analysis ;
$\hat{\mu}_i$	$e_i'\bar{X}$;
$\hat{\sigma}_i^2$	λ_i ;
Σ	$= \begin{pmatrix} \sigma^2_{11} & \sigma^2_{12} & \cdots & \sigma^2_{1p} \\ \sigma^2_{21} & \sigma^2_{22} & \cdots & \sigma^2_{2p} \\ \sigma^2_{p1} & \sigma^2_{p2} & \cdots & \sigma^2_{pp} \end{pmatrix}$.

INDEKS KEUPAYAAN PROSES BARU BERDASARKAN PENDEKATAN BERSTATISTIK SIX SIGMA BAGI MENGUKUR PRESTASI PROSES DALAM INDUSTRI: SATU KAJIAN KES DI ADEN'S OIL REFINERY YEMEN.

ABSTRAK

Tujuan kajian ini adalah untuk mengukur dan menilai prestasi proses perindustrian melalui penggunaan Indeks keupayaan Proses (Process Capability Index - PCI) dan konsep Six Sigma (SS). Dengan ini, kajian ini mencadangkan empat kes yang berbeza untuk menganggar dan mengukur indeks hasil proses univariat SSS_{pk} berdasarkan indeks-indeks C_p, C_{pk}, S_{pk}, SSC_{pk} and $SSQL_{pk}$. Tambahan pula, kajian ini juga melanjutkan indeks hasil proses univariat SSS_{pk} yang diperolehi kepada indeks hasil umum multivariate yang dipanggil $SSMS_{pk}$ dan $SSMS_{pk.PC}$ berdasarkan Had Toleransi (TL) dan Analisis Komponen Utama (PCA), masing-masing untuk mengukur hasil proses keseluruhan proses-proses perindustrian. Keseluruhannya, kajian ini menyediakan pendekatan statistik berdasarkan konsep PCI dan SS untuk mengukur dan meningkatkan prestasi proses-proses univariat dan multivariate dalam industri. Untuk menunjukkan kebolehgunaan pendekatan yang dicadangkan, kajian ini membentangkan kajian kes industri untuk menilai prestasi proses penapisan minyak di Aden, Yaman. Sehubungan itu, data bagi tiga ciri penting untuk mengukur kualiti produk petroleum iaitu ketumpatan, nombor oktana dan tekanan wap dikumpul secara rawak dari kilang penapisan Aden. Penemuan kajian ini menunjukkan bahawa indeks yang dicadangkan $SSMS_{pk}$ dan $SSMS_{pk.PC}$ mengatasi indeks sedia ada $TS_{pk.PC}$, $S^T_{pk.PC}$ dan $TS_{pk,PC,B*}$. Hasil yang diperolehi untuk $SSMS_{pk}$ oleh model TL untuk kes A, B, C dan D masing-masing adalah 0.7114, 1.19, 0.525 dan 0.525. Keputusan yang diperolehi untuk $SSMS_{pk.PC}$ oleh model PCA ialah 0.367213. Sementara itu, keputusan hasil proses indikator $TS_{pk.PC}$, $S^T_{pk.PC}$ dan $TS_{pk,PC,B*}$ masing-masing adalah 0.154, 0.25 dan 0.28. Kajian ini mempunyai implikasi penting untuk pengamal perindustrian, penyelidik dan pakar kawalan kualiti yang berminat dalam penilaian prestasi proses. Akhir sekali, cadangan PCIs berdasarkan konsep SS ialah satu pendekatan yang menyakinkan dan boleh dilanjutkan dan/atau digunakan oleh industri dan pengamal-pengamal perindustrian yang lain untuk menilai prestasi proses dalam aspek ketepatan dan kawalan kualiti.

NEW PROCESS CAPABILITY INDICES BASED ON SIX SIGMA STATISTICAL APPROACH FOR MEASURING THE PROCESS PERFORMANCE IN INDUSTRIES: A CASE STUDY IN ADEN'S OIL REFINERY YEMEN

ABSTRACT

The purpose of this study is to measure and evaluate the process performance of the industrial processes through the use of Process Capability Indices (PCIs) and Six Sigma (SS) concept. In light of this, this study proposed four different cases to estimate and measure the univariate process yield index SSS_{pk} based on C_p, C_{pk}, S_{pk}, SSC_{pk} dan $SSQL_{pk}$ indices. Moreover, this study extends the proposed univariate process yield index SSS_{pk} to a multivariate generalized yield index called $SSMS_{pk}$ and $SSMS_{pk.PC}$ based on Tolerance Limits (TL) and Principal Component Analysis (PCA) respectively to measure the overall process yield of industrial processes. Overall, this study provided a statistical approach based on PCIs and SS concept to measure and improve process performance of the univariate and multivariate processes in industries. To demonstrate the applicability of the proposed approach, this study presents an industrial case study to assess the process performance of oil refinery in Aden, Yemen. Toward this end, the data for three essential quality characteristics of petroleum products namely density, octane number and vapor pressure were collected randomly from Aden refinery. The findings of this study indicated that the proposed indices $SSMS_{pk}$ and $SSMS_{pk.PC}$ outperformed the existing indices $TS_{pk.PC}$, $S^T_{pk.PC}$ and $TS_{pk,PC,B*}$. The obtained results for $SSMS_{pk}$ by TL model for A, B, C and D cases are 0.7114, 1.19, 0.525 and 0.525 respectively. The obtained results for $SSMS_{pk.PC}$ by PCA model is 0.367213. Meanwhile, the yield process results for $TS_{pk.PC}$, $S^T_{pk.PC}$ and $TS_{pk,PC,B*}$ indicators are 0.154, 0.25 and 0.28 respectively. This study has important implications for industrial practitioners, researchers and quality control experts interested in the evaluation of process performance. Finally, the proposed PCIs based on SS concept is a promising approach and thus can be extended and or utilized by other industries and practitioners to assess process performance in the aspect of precision and quality control.

CHAPTER 1 : INTRODUCTION

1.1 Introduction

This chapter is dedicated to the general context of this research. First, the theoretical background of the Statistical Quality Control (SQC), Capability Process Analysis (CPA), Six Sigma, Process Capability Indices (PCIs) based on Principal Component Analysis (PCA) and non-conforming is given. Afterwards, the research problem statements, research objectives, research scope and research framework are exposed. Finally, a brief summary of the research contributions as well as the organization of this thesis are presented.

1.2 Background

In today’s competitive and globalized markets, industries are obligated to produce high-quality and cost-effective products that consistently meet the consumers and engineering design specifications (Goswami & Dutta, 2013; Krolczyk et al., 2015 Felipe & Benedito, 2017). Subsequently, quality level and process capability have become indispensable attributes and key issues among producers to achieve competitive advantage particularly in the world of knowledgeable consumers (Leiva, Marchant, Saulo, Aslam, & Rojas, 2014; Krolczyk et al., 2015; Lupo, 2015). Over the years, manufacturers have consistently attempted to identify the sources of variations in order to develop control measures for eliminating or minimizing process variabilities whenever possible (Goodwin, 2015).

To address these challenges, various industries have utilized the concept of Statistical Quality Control (SQC) and statistical process control methods and strategies to improve the process performance of their manufactured products to ensure that the outputs of a process are within the specified limits of quality levels (Allam, Becker, Baudouin, Bigot, & Krumpipe, 2014; Felipe & Benedito, 2017; Goodwin, 2015; Srinivasan, Muthu, Devadasan, & Sugumaran, 2016). SQC is a set of statistical tools used by quality professionals to monitor and maintain the quality of products and services (Aboelmaged, 2010; Allam et al., 2014; Rao & Thejaswini, 2011; Srinivasan et al., 2016). The SQC principles are based on the theoretical probabilities as well as acquiring of data statistically (Wu, Pearn & Kotz, 2009). The concept of SQC was first pioneered by Walter A. Shewhart at Bell Laboratories in the early 1920s and found a wide consideration and acceptance particularly during the World War II as a statistical method for improving product quality. In light of this, the American Society for Quality Control was established in 1946 to promote and enlarge the use of quality improvement techniques for all types of products and services by providing a number of publications, technical conferences and training programs (Montgomery, 2009).

Statistical Process Control (SPC) has become an essential method for controlling and improving product quality in industrial sectors particularly since the emergence of process charts in the 1924s. SQC methods have been implemented vigorously in various industries and organizations to promote quality levels, improve process performance , reduce defects and variations of products and services (Allam et al., 2014; Felipe & Benedito, 2017; Srinivasan et al., 2016). Indeed, the role of SQC methods is significant in reducing process variability to produce products and services based on pre-specified limits (Srinivasan et al., 2016). Fridedrich (1777-1855) developed the concept of the natural curve as a standard for measuring variations. In addition, numerous methods have been developed to promote better quality control during manufacturing processes particularly the significant contributions made by Deming, Juran, Ishikawa, Montgomery and others (Juran, 1974; Montgomery, 2009; Zhang, 2016).

Process capability refers to the ability of a process to produce products that will consistently meet customer expectations and the design requirements (Felipe & Benedito, 2017; Krolczyk et al., 2015). More specifically, it is a scientific and a systematic procedure that uses control charts and capability indices to detect and eliminate the unnatural causes of variation until a state of statistical control is reached. According to Shahriari and Abdollahzadeh (2009) and Kotz and Lovelace (1998), the enemy of high process capability and perfect output is variation. The authors further stated that “since process variation can never be totally eliminated, the control of such variation is the key to achieve product quality”. Hence, in order to reach high process capability and perfect output, variation must be identified, controlled and eliminated (Goodwin, 2015).

Process Capability Analysis is a statistical technique used to determine how well a process meet a set of specification limits (Felipe & Benedito, 2017; Kargar, Mashinchi, & Parchami, 2014; Lupo, 2015; Montgomery, 2009). The procedure of capability analysis involves taking a sample data from a process to estimate the Defects Per Million Opportunities (DPMO), Process Capability Indices (PCIs) and Sigma Quality Estimates (Srinivasan et al., 2016). In fact, PCA provides numerical statistical measures including PCIs, Six Sigma, process expected loss and process yield to measure process capability, reduce variability and defects and consistently produce products and services that meet the pre-specified control limits (Chen, Yu, & Sheu, 2006). PCIs are powerful statistical tools utilized by industries to assess manufacturing process performance and to measure the variability of a process relative to its specification limits (Chakraborty & Chatterjee, 2016). In addition to providing numerical measures of whether or not a manufacturing process is capable of producing consistent products based on predetermined specification limits, PCIs are also convenient and an effective tools to facilitate communication among engineers (Allam et al., 2014; Pan, Li, & Shih, 2016; Parchami, Sadeghpour, Nourbakhsh, & Mashinchi, 2014; Pearn, Wu, & Chia, 2014; Pham, 2015; Srinivasan et al., 2016).

PCIs are essential indicators for evaluating process performance in industries through calculating process yield. Process yield refers to the capability of a process to produce consistent products and services according to pre-defined control limits. According to Tano and Vannman (2012) and Shi, Ma and Lin (2016), performance criteria are particularly evaluated by process yield index. Indeed, PCIs, C_p, C_{pk}, C_{pm} and S_{pk} are acknowledged as capability measures, quality assurance and capability analysis based on various criteria including consistency of process, the departure of a process from the target, process yield, and process loss (Chakraborty & Chatterjee, 2016). Besides that, the quality yield index of a process can be described as the conventional process yield minus the expected relative loss within the specifications. Thus, the quality index is a vital measure for evaluating process performance and process quality.

Since the 1980s, PCIs have gained significant consideration from both control engineers and researchers in industries and in the academic community (Anis, 2008; Chen, 2000; Chen et al., 2006; Kotz & Johnson, 2002, 1993; Wu et al., 2009). There are two types of PCIs which are, Univariate PCIs and Multivariate Process Capability Indices (MPCIs). The former measures the process performance of a single quality characteristic such as C_p, C_{pk}, C_{pm} and S_{pk}. Meanwhile, the latter deals with a process that has multiple quality characteristics such as MPCIs. Since various processes in industries involve multiple quality characteristics, MPCIs are the most widely applicable indicators. However, the selection of the correct MPCIs for a manufacturing process is always a challenge due to its mathematical complexity and different inferential ability (Srinivasan et al., 2016). Thus, in SQC the MPCIs remain an active research area whereby there are many unsolved issues and implications around their theoretical properties and practical applicability (Lupo, 2015).

In the last 20 years, several quality engineers and statisticians have studied PCIs to improve both process potential and process performance (Felipe & Benedito, 2017). A number of researchers further employed PCIs in the process of quality planning to select process alternatives with appropriate process capability during the initial planning stage of the product development cycle (Montgomery, 2009; Parchami et al., 2014). In spite of the large volume of work done on PCIs, the majority of the literature within this area primarily focuses on univariate PCIs to assess process capability of a single quality characteristic (Felipe & Benedito, 2017; Dharmasena & Zeephongsekul, 2014; Pham, 2015; Srinivasan et al., 2016). Meanwhile, the literature indicates a paucity in terms of the number of studies on MPCIs for assessing process capability of processes with several quality characteristics. Furthermore, the recent advances in engineering specifications and technology have made it compulsory for quality professionals to seek consistent improvement for MPCIs (Chakraborty & Chatterjee, 2016). Hence, there is a need to ascertain capability by examining multiple characteristics simultaneously while taking into consideration the idea of Six Sigma.

One of the fundamental statistical capability process control tools is Six Sigma technique which is used to ensure that a process is capable of producing high-quality products based on pre-specified limits by eliminating defects and reducing process variability (Aboelmaged, 2010; Allam et al., 2014; Allen, 2006; Gupta, 2015; Nourelfath, Aldowaisan, & Hassan, 2016; Rao & Thejaswini, 2011; Srinivasan et al., 2016). Over the years, Six Sigma has received tremendous attention from various researchers and quality specialists in various fields particularly those who are working in industries and manufacturing companies (Aboelmaged, 2010; Allen, 2006; Muralidharan, 2015). For example, the majority of global companies including Motorola, Toyota, GE, IBM and LG have utilized Six Sigma initiatives and concept in their production processes. In fact, Six Sigma was first introduced for Motorola Company by Bill Smith and Mikel J Harry in 1986. Since then Six Sigma has become a way for Motorola to express its quality goal of 3.4 Defects Per Million Opportunities (DPMO), where a defect opportunity is a process failure that is critical to the customer. Motorola see this goal so that process variability is ± 6S.D, from the mean. This means 99.99966% process yield in the long term, and the non-conformities in PPM are only 3.4. Six Sigma results in only 3.4 DPMO when tolerating the process mean to shift by as much as 1.5σ off the process target. Thus, the widely accepted definition of a Six Sigma process is one that only produces 3.4 DPMO (Nourelfath et al., 2016; Shi et al., 2016; Tano & Vannman, 2012).

Recently, Six Sigma concept has been introduced to improve the quality and to reduce defects of production processes in industries (Nourelfath et al., 2016). The term Six Sigma has been derived from the process capability indices. In fact, Gupta, (2015) has indicated that the Six Sigma roots are originated from the process capability. In spite of the importance of Six Sigma as a process capability statistical tool in controlling and monitoring the process performance, it has not been implemented as a statistical process capability tool for improving process performance in oil refinery processes, particularly in Yemen. In fact, previous studies on oil refinery process have focused on using statistical quality control charts mainly $\overline{X}$, $\overline{R}$ and $\overline{X}_S$ charts and tools of Ishikawa (Alkubaisi, 2013; Bhanpurkar, Bangar, Goyal, & Agrawal, 2012; He, Lin, Li, Sui, & Xu, 2015; Kannan, & Murugan, 2012). Besides, existing PCIs based on Six Sigma indicators have not been developed sufficiently particularly MPCIs and thus the existing PCIs provide only a range of quality levels rather than a specific quality level value (Bothe, 2002; Chen et al., 2016). Moreover, existing PCIs based on Six Sigma do not consider the shift of the process mean from the target by 1.5 sigma (Bothe, 2002).

This study focuses on the univariate and multivariate process performance indices based on Six Sigma concept. In this case, the univariate process performance indices C_p, C_{pk} and S_{pk} are extended to SSC_{pk}, $SSQL_{pk}$ and SSS_{pk} for measuring capability, sigma level and yield process respectively. Besides, this study proposes four different ways to measure the univariate process yield SSS_{pk} based on C_p, C_{pk}, S_{pk}, SSC_{pk} and $SSQL_{pk}$ indices. In addition, the univariate yield index SSS_{pk} is extended to a multivariate generalized yield index called $SSMS_{pk}$ to measure overall process yield. Besides, this study aims to analyze different and probable configurations