MODIFIED STATISTICAL PROCESS CONTROL FOR SHORT RUNS TEST AND MEASUREMENT PROCESS TO REDUCE FALSE ALARM

by

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LIST OF ABBREVIATIONS

ARL	Average Run Length
ATE	Automatic Test Equipment
CL	Center Line
CUSUM	Cumulative Sum
DMM	Digital Multimeter
DNOM	Deviation from Nominal
DOE	Design of Experiments
DUT	Device Under Test
ETE	Electronic Test Equipment
EWMA	Exponentially Weighted Moving Average
GUM	Guide to the Expression of Uncertainty in Measurement
LCL	Lower Control Limit
LSL	Lower Specification Limit
MCM	Monte Carlo Method
RL	Run Length
SDRL	Standard Deviation of Run Length
SOV	Stream of Variation
SPC	Statistical Process Control
SQC	Statistical Quality Control
T&M	Test and Measurement
TUR	Test Uncertainty Ratio
UCL	Upper Control Limit
USL	Upper Specification Limit
VGA	Vertical Gain Accuracy

LIST OF SYMBOLS

Q_i	input quantity of standard uncertainty
q_i	input estimate of standard uncertainty
s_i	sample standard deviation
c_i	sensitivity coefficient
u_{c}	combined standard uncertainty
k	coverage multiplier
U_M	expanded uncertainty for the class-M test station
T_m	measurement target for the *m*th test station
$\widehat{\sigma}_{u_M}$	estimate of the standard deviation of the measurement uncertainty
$\widehat{\sigma}_{x_m}$	estimate of the population standard deviation
S_{f_m}	S-factor for the *m*th test station
$\widehat{\sigma}_{p_m}$	estimate of the process standard deviation
$\overline{Z}_{im}$	*i*th response (standardized mean) on the *m*th test station
W_{im}	*i*th response (standardized range) on the *m*th test station
$\bar{x}_{im}$	*i*th response (mean) on the *m*th test station
R_{im}	*i*th response (range) on the *m*th test station
n	subgroup size
g	number of subgroups
$\overline{R}_m$	average range for the *m*th test station
A_2	control limit constants for various subgroup sizes
D_3	control limit constants for various subgroup sizes
D_4	control limit constants for various subgroup sizes

α	Type I error probability
σ	process variance
μ	process mean
x_1	measured values
$\bar{\bar{x}}$	average process mean
T_i	statistic based t-distribution
T_j	target value for the *j*th part
d_2	statistic constants for various subgroup sizes
d_3	statistic constants for various subgroup sizes
r_i	*i*th response of the range values
m_j	robust estimator of the median
$s_i^{(r)}$	robust standard deviation
ε_t	standard normal variable

PENGUBAHSUAIAN KAWALAN PROSES BERSTATISTIK UNTUK PROSES UJIAN DAN PENGUKURAN JANGKA PENDEK BAGI MENGURANGKAN PENGGERA PALSU

ABSTRAK

Ciri-ciri utama bagi proses ujian dan pengukuran (T&M) ialah proses pengeluaran secara singkat, merangkumi pelbagai kelompok produk dan ujian melalui beberapa stesen kerja. Carta kawalan Shewhart yang klasik, iaitu carta $\bar{x}$ dan carta R telah digunakan secara meluas dalam kawalan proses berstatistik (SPC). Proses pengeluaran yang beroperasi jangka pendek dalam T&M mengakibatkan ketidakcekapan carta kawalan ini di mana ianya tidak dapat menjamin had kawalan yang berkesan dengan data yang terhad. Ralat pengukuran ini akan meningkatkan risiko dalam keputusan penerimaan dan penolakan yang salah, secara tidak langsung mewujudkan masalah lain seperti proses pelarasan yang tidak perlu dan hilang keyakinan dalam SPC. Industri membenarkan pemasangan band kawalan seperti yang diamalkan dalam *Panduan Ekspresi Ketidakpastian Dalam Pengukuran* (GUM) untuk mengurangkan julat had penerimaan supaya ia dapat mengimbangkan ralat pengukuran secara tidak langsung. Kajian lalu yang menerangkan kaedah pemerhatian piawai amat disyorkan disebabkan keringkasannya dan kepraktisannya. Namun, ia telah menjadi satu kebimbangan kerana kaedah ini memerlukan data yang mencukupi untuk mengira had kawalan dan ia tidak mengatasi masalah ralat pengukuran. Berdasarkan premis ini, matlamat penyelidikan ini adalah bertujuan untuk membangunkan pengubahsuaian model SPC dengan mempertimbangkan ketidakpastian pengukuran dalam carta kawalan (carta $\overline{Z}$ dan carta W) yang diubahsuai bagi proses jangka pendek T&M dalam pelbagai stesen kerja. Pelaksanaan model ini

melibatkan dua fasa. Fasa I analisis restrospektif mengira parameter input, contohnya sisihan piawai ketidakpastian pengukuran, sasaran pengukuran, dan anggaran sisihan piawai populasi. Seterusnya, tetapan Band-5 and Faktor-S dicadangkan untuk membuat anggaran bagi sisihan piawai proses untuk memaksimakan peluang mengesan sebab tertentu dengan kadar penolakan palsu yang rendah. Akhirnya, pengubahsuaian carta $\overline{Z}$ dan carta W dijanakan dalam Fasa II dengan menggunakan kaedah pemerhatian piawai dengan sasaran pengukuran dan anggaran sisihan piawai proses. Ujian dijalankan berdasarkan peraturan Nelson untuk mentafsirkan carta kawalan. Untuk ujian pengesahan, tiga kes kajian, dilabelkan Kes I, Kes II dan Kes III telah dijalankan dengan perbezaan nisbah sisihan piawai dalam ketidakpastian pengukuran dan populasi untuk menunjukkan keberkesanan model yang dicadangkan. Sampel data daripada produk yang diuji pada stesen yang berlainan telah dikumpul selama setahun di kilang pembuatan T&M di Bayan Lepas, Pulau Pinang. Bagi Kes I dengan ralat pengukuran yang boleh diabaikan dan tidak menjejaskan sisihan piawai proses; keputusan menunjukkan bahawa tiada titik penggera palsu yang ditemui dalam semua kaedah. Dalam Kes II dengan ralat pengukuran yang mungkin mempengaruhi sisihan piawai proses secara nyata, dan keputusan menunjukkan bahawa model dengan tetapan Band-5 and Faktor-S mengurangkan kadar penggera palsu sebanyak 100% berbanding dengan kaedah Shewhart yang klasik, kecuali tetapan Band-5 yang mempunyai peralihan kecil yang berterusan (25% penggera palsu) telah dikesan secara palsu di stesen WH05. Dalam Kes III dengan ralat pengukuran yang lebih tinggi dan lebih ketaranya mempengaruhi sisihan piawai proses; keputusan menunjukkan bahawa kedua-dua kaedah yang dicadangkan memberi prestasi yang baik dalam pengubahsuian carta $\overline{Z}$ dan carta W, dengan mengurangkan kadar penggera palsu sebanyak 50% bagi stesen WH05, 0% bagi stesen WH06 dan 37.5% bagi stesen

WH07. Kesimpulannya, penyelidikan ini telah mencadangkan dan menunjukkan bahawa pengubahsuaian model SPC dapat menangani isu-isu di bawah kajian yang disebabkan oleh proses pengeluaran jangka pendek dan ralat pengukuran. Model ini adalah praktikal untuk kilang pembuatan T&M bagi mengurangkan penggera palsu dan mengelakkan proses pelarasan yang tidak perlu.

MODIFIED STATISTICAL PROCESS CONTROL FOR SHORT RUNS TEST AND MEASUREMENT PROCESS TO REDUCE FALSE ALARM

ABSTRACT

The key characteristics of test and measurement (T&M) manufacturing are short production runs, multi-product families and testing at multi-stations. Classical Shewhart control charts, namely $\bar{x}$ chart and R chart have been widely used in statistical process control (SPC). Short production runs in T&M render these charts inefficacious as inherent meager data do not warrant meaningful control limits. Measurement errors increase the risks of false acceptance and rejection, thereby leading to consequences such as unnecessary process adjustment and loss of confidence in SPC. Industry practice allows the installation of Guard band, e.g., through *Guide to the Expression of Uncertainty in Measurement* (GUM) to reduce the width of acceptance limit, as an indirect way to compensate the measurement errors. Past related works which presented standardized observations technique is highly recommended due to its simplicity and practicality. However, the concern is that this technique requires sufficient data to calculate the control limits and it does not deal with the effect of measurement errors. Based on this premise, the research objective is to develop a modified SPC model by considering measurement uncertainty in modified control charts ($\overline{Z}$ chart and W chart) for short runs T&M process in multi-stations. The implementation of this model involves two phases. Phase I retrospective analysis computes the input parameters, such as the standard deviation of the measurement uncertainty, measurement target and estimate of the population standard deviation. Thereafter, Five-band setting and S–factor are proposed to estimate process standard deviation to maximize the the opportunity to detect assignable causes with low false-reject rate. Lastly, the modified $\overline{Z}$ chart and W chart are generated in Phase II using standardized observations technique that considers the measurement target and the estimated process standard deviations. Run tests based on Nelson's rules to interpret the control charts. In terms of validation, three case studies, labeled as Case I, Case II and Case III were conducted with different ratios of standard deviations in measurement uncertainty and population to demonstrate the effectiveness of the proposed model. A complete year's data samples were collected from products tested at multi-stations in a T&M manufacturing facility at Bayan Lepas, Penang. For Case I with the measurement error is negligible and does not affect the process standard deviation; the results indicate that there were no false alarm points found in all methods. In Case II with the measurement error may noticeably affect the process standard deviation, and the results show that the model with Five-band setting and S-factor reduced the false alarm rate by 100% in comparison to the classical Shewhart method, except for the Five-band setting which has a smaller sustained shift (25% false alarm) was falsely detected in station WH05. In Case III with the measurement error is relatively larger and appeared to be more significantly affecting the process standard deviation; the results reveal that both proposed methods performed well in modified $\overline{Z}$ and W charts, which reduced false alarm rate by 50% for station WH05, 0% for station WH06 and 37.5% for station WH07. As a conclusion, the research has proposed and demonstrated the modified SPC model can address the understudied issues caused by short production runs and measurement errors. The model is practical for T&M manufacturing to reduce false alarms and to prevent unnecessary process adjustment.

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CHAPTER ONE

INTRODUCTION

1.1 Background

Quality is increasingly a defining factor for a company's survival and success in today's competitive market. Such significance is particularly relevant to electronic test and measurement (T&M) manufacturing processes where advanced systems have to be developed to ensure products meeting customer and industry quality requirements. Statistical process control (SPC) is a normative quality control approach to monitor and statistically examine manufacturing processes. Three key characteristics of T&M manufacturing processes are short production runs, multi-product families and testing at multi-stations. These characteristics often entail insufficient data to construct meaningful control limits in traditional SPC charts. The inherent measurement error in processes is another critical concern. Therefore, these issues increase the complexity of real-time SPC in T&M manufacturing.

1.2 An Overview of Test and Measurement (T&M)

T&M equipment provides decisional information to verify whether the product's specifications and functionality are fulfilled. Measurement is defined as the process to experimentally obtain one or more quantity values that can be reasonably attributed to a quantity (JCGM 200:2012, 2012). The process transforms a physical variable into symbolic output using an instrument called electronic test equipment (ETE) (Webster, 1999). ETE can be either a basic setup of test instrument such as digital multimeter and oscilloscope, or complicated and automated system containing multiple test instruments. Automatic test equipment (ATE), a computer-controlled

ETE, has been widely used to replace manual measurement in many areas such as real-time monitoring. This is to ensure 100% conforming test, which is necessary to prevent non-conforming parts from reaching customers (Wadsworth et al., 2002). Accuracy in measurement is a critical consideration for the choice of ETE in an application. Other parameters are also considered such as sensitivity, linearity, and changes in reaction to ambient temperature (Morris & Langari, 2011).

T&M equipment market was expected to grow from USD 23.51 Billion by 2017 to USD 28.98 Billion by 2023 at a CAGR of 3.55% (MarketsandMarkets, 2017). The prediction is somewhat similar to the two individual studies by HNY Research (2018) and Technavio (2017) which forecasted a steady market grow within the same period. According to Business Wire (2017), the current top five leading vendors in the global T&M market are Anritsu, Bureau Veritas, Fortive, Keysight Technologies, and National Instruments. There are several impetuses for such growth. Firstly, huge market potential is in various end-use applications such as healthcare, IT and telecommunications, and automotive. These are attributed to the increasing technological advancement toward networking and communication, increased R&D spending, increased penetration of modular instrumentation, the development of 5G mobile network and rapid penetration of IoT devices (PRNewswire, 2017). Secondly, increased quality awareness, greater adoption of metrology in the manufacturing process, and safety and regulatory requirement have anticipated the repair and calibration market in North America and Europe to reach $3.98 billion by 2022 (Frost & Sullivan, 2018). Lastly, the aerospace and defense sectors are identified to be two of the primary factors driving the growth of T&M market in 2018 (Technavio, 2017). In these sectors, test equipment are much needed to verify the performance of command execution, communication network, surveillance application, and computer intelligence.

All ETEs are subjected to various degrees of error and measurement uncertainty. Furthermore, readings taken from an ETE may drift from their specified values over time (Cheatle, 2006). Therefore, the performance of the ETE should be monitored to decide on the right moment to perform periodical calibration. The calibration adjusts the output or indication of an ETE to concur with the reference measurement standard, within a specified accuracy (Kegel, 1996). Measurement errors are never be known exactly. In some instances, they may be estimated and tolerated or corrected for; or they may simply be acknowledged as being present. Regardless which treatment is given, its existence introduces a certain amount of measurement uncertainty (Castrup, 1995).

1.3 Quality Control in Test and Measurement (T&M)

Crosby (1979) defines quality as "*conformance to requirement*". Juran and Gryna (1988) define quality as "*fitness for purpose*". American Society of Quality (ASQ) defines quality in the early version of ISO9000 as "*the totality of features and characteristics of a product or service that bear on its ability to satisfy stated or implied needs*" (ISO8402:1986, 1986). Deming (1986) interprets Good quality as "*a predictable degree of uniformity and dependability at a low cost with a quality suited to the market*". In modern definition, quality is "*inversely proportional to variability*" (Montgomery, 2013). In essence, by reducing variability, quality improves, subsequently the production cost reduces.

In T&M industry, quality is defined as conformance to specification at the time of performance verification (Fasser & Brettner, 2003). ISO/IEC 17025 and

ANSI/NCSL Z540 are two primary standards governing the production of ETE. They provide the measurement service (calibration) with established laboratory set up (ISO/IEC 17025:2017, 2017; ANSI/NCSL Z540.3:2006, 2006). The compliance involves testing and laboratory calibration to operate a quality management system in line with ISO 9001 for their testing and calibration activities. Also, quality control and measurement system must be instituted and maintained to ascertain the qualities of products or services are within the stated error bounds (Morris, 1991). This includes evaluating main contributors to measurement uncertainty by the international guidelines, with full disclosure of such information on the calibration certificates. Quality assurance is a quality system with its purpose to assure that the overall quality control had been efficiently performed (Wadsworth et al., 2002).

1.4 Quality Control Methods

Statistical Quality Control (SQC) is arguably one of the most cost-effective ways to achieve quality standard (Chandra, 2001). The four primary SQC methods are acceptance sampling, statistical process control (SPC), process capability study and design of experiments (DOE) (Woodall & Montgomery, 1999; Reis et al., 2006). Acceptance sampling is one of the earliest quality monitoring techniques with product inspection and testing in conformance to specification. With the increased emphasis on SPC as an evidence of conformance to meet the quality requirement, the need for acceptance sampling had declined (Besterfiled, 2009). Process capability study quantifies the process variability to product requirement or specification. The main outputs of process capability study are process capability indices which provide a statistical measure of whether a production process is within the specification limits (Kane, 1986). DOE is a powerful tool capable to reduce the variability in processes and products rapidly (Fisher, 1935). DOE is an offline quality control tool nonetheless, frequently used during development activities and the early stages of production, rather than as a repetitive online monitoring (Montgomery, 2013).

SPC is a robust collection of problem-solving tools that can be applied to any process in achieving process stability and improving capability. Seven major SPC tools (Magnificent Seven) consist of a histogram or stem-and-leaf plot, check sheet, Pareto chart, cause and effect diagram, defect concentration diagram, scatter diagram and control charts (Madanhire & Mbohwa, 2016). Amongst them, the control charts are primary (Montgomery, 2013). Control charts serve three key functions (Shewhart, 1931; Wadsworth et al., 2002). First, it shows the amount and nature of variation of a specific time-series data collected over time; second, it indicates whether these data fall into statistical control limits and finally it enables pattern interpretation and early detection of changes in the process. The best point of control charts is its ability to detect fault or error quickly in the presence of disturbance. The disturbance includes shift (occurrence of a bias from process mean), drift (occurrence of a progressively decreasing or increasing trend), cyclical or periodical changes (Massart et al., 1998).

1.5 Problem Statement

SPC methods in T&M manufacturing processes are not as prevalent as in continuous process environment (high volume products in the long run). Due to the T&M industry context, the manufacturing processes are performed in short runs, with testing often occurs at multiple stations. This process is highly affected by measurement error.

Control chart requires sufficient subgroup data to estimate process parameters (μ and σ) and establish reliable control limits (Quesenberry, 1993). It is difficult to adopt classical SPC method in short runs due to inherent data deficiency (Khoo et al., 2005). This may result in a high false alarm rate (underestimation) or insensitive to detect process shifts (overestimation) (Gu et al., 2014). Another problem faced in short runs is that it entails a large number of charts for different product families and multiple stations. The mundane routines of plotting, monitoring and administration could be overwhelming.

Furthermore, All ETEs used in measurement processes are subjected to various measurement errors influenced by material, variations in ETEs, and environmental conditions. It increases the variations in the measurement processes and introduces a certain amount of measurement uncertainty. Costa and Castagliola (2011) underscore growing risk of false acceptance in SPC due to measurement error. This leads to consequences such as unnecessary process adjustment and loss of confidence in SPC. Therefore, to control manufacturing processes in T&M production based on measurement data, the implication of measurement uncertainty and short runs should be considered when implementing SPC for quality control.

1.6 Research Objectives

The aim of this research is to propose a modified SPC model to be integrated into T&M manufacturing system to monitor test stations and control quality of the product. Objectives of this research are as follows: -

i. To develop a modified SPC model primarily to maximize the chance of detecting true alarms (the assignable causes) with low false alarms (false-reject) rate.

ii. To demonstrate the effectiveness of the new model through actual implementation of several case studies in real industry.

1.7 Research Scope

The proposed model focuses on maximizing the chance of detecting the true alarms (the assignable causes) with low false-reject rate in short production runs and process variations that cannot be effectively monitored due to effect of measurement error. The SPC model will focus on control chart techniques with univariate data subgroups (subgroup size more than one). A general assumption is that the process data (measured values) are independent and normally distributed. The data will be normalized via standardized observations technique before the process can be monitored. Guard band with measurement uncertainty will be articulated in the model design based on Guide to the Expression of Uncertainty in Measurement (GUM). Implementation of case studies is carried out in a single manufacturing premise due to stringent industry data disclosure policy and elusiveness of suitable cases elsewhere.

1.8 Significance of the Study

The study contributes towards knowledge development in SPC methods for short runs T&M process in multi-stations. Issues of short runs and measurement errors were addressed in this research. First, incorporation of measurement uncertainty from Guard band into control chart has created a new research path in quality control theories and practices.

Second, Five-band setting and S-factor were introduced to estimate process standard deviation. These were used for rescaling responses in the modified $\overline{Z}$ chart and W chart. These methods are also used to maximize the chance of detecting the assignable causes with comparatively low false-reject rate. Both methods are practical for T&M manufacturing process as the case studies have demonstrated the possibility to embed the system in automated quality control system in an efficient and effective manner.

Although many researchers have studied the effects of measurement errors in SPC, to the best of the author's knowledge, there is no known research on using Guard band or measurement uncertainty to alleviate the accompanying impacts of measurement errors for short runs process in multi-stations. Recent research on SPC short runs approach focuses mainly on estimation of the process parameters (μ and σ) using method such as student t-distribution to optimize the control chart performance. This research presents a new technique to estimate the process parameters to improve control chart in short runs process.

1.9 Thesis Organization

This thesis is organized into seven chapters. The arrangement of the contents largely conforms to the conventional thesis structure, in hope to provide the best readability of the research work. Firstly, this chapter introduces the background of test and measurement along with problem statement, research objectives and contributions. In Chapter 2, the literature relevant to the topics in this research is reviewed. Important concepts are synthesized and clarified. Following that, limitations and gaps in the previous studies are identified. Chapter 3 covers the research methodology of how the proposed model was developed. In Chapter 4, modified SPC model are proposed and implementation details are described. Chapter 5 consists of validation through three case studies involving different number of test stations in real industry and presents the results analysis and discussion. Lastly, Chapter 7 concludes this thesis and suggests possible directions for future research.

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview

A thorough literature review in short runs SPC and Guard band would be presented here. Content analysis method is used to identify and classify the quality control approaches found in the literature. The flow was structured in Figure 2.1. The complication of T&M industry in quality control was examined in Section 2.3. It is then followed by a discussion on the various quality control approaches found in literature. Short runs SPC approaches are focused next due to its prominence and prevalence in industries. The final section of this chapter centers on the critical findings of the literature review.

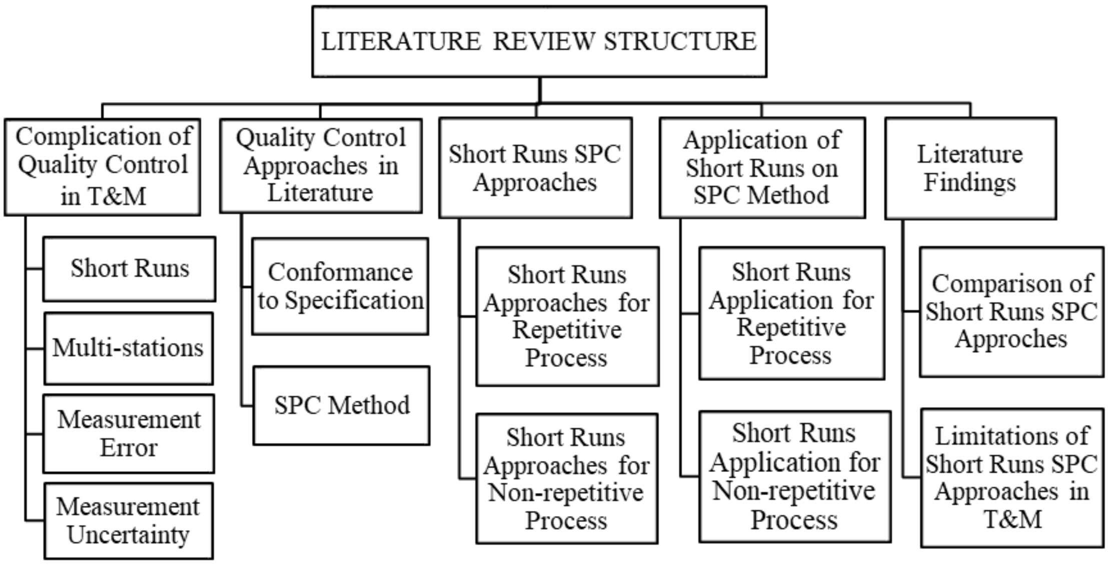

Figure 2.1: Literature review structure

2.2 Content Analysis

Literature is reviewed using content analysis in quality control, with attention on SPC and Guard band approaches. Content analysis is an observational research method, which systematically reviews the content of all forms of recorded communication (Kolbe & Brunette, 1991). It helps to ensure the quality of the work developed and to provide a suitable analysis of the decisions, procedures, and conclusions. Hachicha and Ghorbel (2012) presented the procedure for conducting content analysis is based on two steps. First, a definition of sources and procedures for the search of articles to be analyzed is determined; second, a definition of instrumental categories for the classification of the selected articles is made.

2.2.1 Literature Search Procedure

The selection of papers was carried out through an exhaustive search using ACM Digital Library, IEEE Xplore, JSTOR, ProQuest, Scopus, Science Direct, Springer, Taylor & Francis, and other online databases. The final updated set of papers for the review was compiled on January 2018.

Statistical Process Control or SPC are used as keywords in primary search, resulting more than five thousand papers appeared in these online databases. To search literatures related to particular subtopics, further refinements applied alternative keywords such as: “short runs”, “measurement error”, “control chart”, “standardized”, “nominal”, “self-starting”, “quality control”, “quality standard”, “multi-stations”, “test and measurement”, “conformance to specification”, “guard band”, “measurement variation”, and “measurement uncertainty”. Approximately two thousand papers were identified.

Papers were filtered out if it does not match all the criteria as below: -

i. The paper is written in English and was published in a peer-reviewed journal.

ii. The paper applies univariate Shewhart control chart. Multivariate techniques were not considered.

iii. The paper applies a SPC method addressing issues caused by short runs or measurement errors.

In addition, books, eBooks, Google Scholar, Wikipedia, and online training material are treated discreetly as alternative sources of information, mostly for the fundamental knowledge.

2.2.2 Classification Categories

Finally, about two hundred papers remain in the selection. Short runs SPC approaches are critically reviewed due to its prominence and prevalence in industries. The approaches are sorted according to the following categories:

i. Approach of quality control

ii. Techniques description and principles

iii. Application of the approach

iv. Performances criteria

v. Robustness in practical use

2.3 Complication of T&M Industry in Quality Control

Several product characteristics intrinsic to T&M industry make quality control particularly challenging. The products are relatively costly; demand unpredictable and with substantially strict regulatory compliance standards. Meanwhile, the manufacturing processes are short runs of high-mix low-volume and short product life cycles. Typically, a digital multimeter would have more than a hundred product varieties, which each having monthly order in the range of ten to hundred units. A common product life would be two years. Furthermore, products may be inspected at multiple test stations, and the measured values are profoundly affected by accuracy and precision of the designated ETE (Webster, 1999). These implications are explored in the following sections.

2.3.1 Short Runs

In quality control, short runs generically means a manufacturing situation in which product is produced in low volume (Del Castillo et al., 1996). Some invariably referred it as short production runs (Del Castillo & Montgomery, 1994) or short runs production (Khoo & Moslim, 2010). The term "short runs" would be used hereafter for sake of consistency. In a short runs environment, to establish reliable control limits is difficult due to inherent data deficiency (Khoo et al., 2005). Short runs may not reach a recommended baseline of 80 to 100 samples needed to secure meaningful control limits (Chen, 1997; Tsai et al., 2005; Montgomery, 2013).

Another major problem faced in short runs is the need to chart different processes for individual product families, entailing a considerably large number of charts. Even more charts are expected if different test stations are deployed. The onerous routines of plotting, monitoring and administration could be overwhelming. Furthermore, the control limits have to be constantly reviewed and revised. To address these matters, Khoo and Moslim (2010) provide two suggestions. First, startup control chart of which process parameters (μ and σ) initiated from a few units; second, plotting of all statistics on a standard scale, thus permitting different process variables to appear on a same control chart.

2.3.2 Multi-stations

Process control for multi-stations manufacturing processes is markedly challenging due to the variations caused by measurement error. Several studies have proposed a systematic approach using the stream of variation (SOV) model to overcome the limitations faced by SPC in multi-stations manufacturing processes (e.g. Jin & Shi, 1999; Camelio et al., 2003; Djurdjanovic & Ni, 2006; Zhang et al., 2007; Abellan-Nebot et al., 2011; Jiao & Djurdjanovic, 2011). The SOV model utilises a state-space representation to describe the critical control characteristics induced variations, their propagation along multiple operations and the accumulation of the control characteristics (Abellan-Nebot et al., 2011). The SOV model is beneficial in establishing a connection between the process level parameters and measured product quality (Djurdjanovic & Ni, 2006). However, the SOV models are mainly developed to lessen the dimensional variability in assembly and machining processes.

2.3.3 Measurement Error

Measurement error is the difference between the true value and the measured value of a quantity (Chakraborty & Khurshid, 2013). The measurement error comprises two components: random and systematic. Succinctly, the random error causes spreading in the measurement results, whereas the systematic error causes bias (Chandra, 2001). Several possible error sources are ETE accuracy, operates mistakes, environment factors, and random noises.

Measurement error is somewhat neglected in common SPC approaches (Wetherill & Brown, 1991), as both process variability and the error in the measurement system are being treated indifferently (Lanza et al., 2008; Chakraborty & Khurshid, 2013). In studying the effect of measurement error in chemical process control, Kanazuka (1986) noticed that the power of control limits in detecting the change diminishes when the measurement variance surpasses the process variance. In other words, the measurement error affects control factor limits and increases the Type I error (Tricker et al., 1998). Type I error is the probability that control chart indicates process is out of control but in reality the process is in-control (Cai et al., 2002). In this regards, Bennet (1954) employed a blanket process average instead of batch-dependent process average. Kanazuka (1986) proposed power graphs and larger sample sizes to recover the lost power.

Maleki et al. (2017) commented that most of researches investigated the effect of measurement errors on the SPC performance, while some recent ones have attempted to present remedial approaches to compensate the measurement errors. One of the most common remedial approaches to mitigate the effect of measurement error is the multiple measurements approach, which was first introduced by Linna and Woodall (2001). Recently, Mezouara et al. (2015), Becket and Paim (2017) proposed Guard band, which is another approach by considering the measurement uncertainty to compensate effect of measurement error. The Guard band approaches will be discussed in Subsection 2.4.1(a).

Linna and Woodall (2001) realized considerable statistical power by taking multiple measurements for individual items in a subgroup as long as the measurement error changes linearly with the assumed parameter. Khoo and Moslim (2010) suggested a start-up control chart from which process parameters initiated from a few units. Costa and Castagliola (2011) suggested that each sample should be measured at least four times to counteract the measurement error.

A larger sample size (Kanazuka, 1986) or repeated measurement on different ETEs (Linna & Woodall, 2001; Costa & Castagliola, 2011) could be done at the expense of time and cost. This approach could pose a challenge to T&M because the testing is relatively long and often demands various combinations of test parameters and settings. For example, an oscilloscope requires over 100 test parameters and settings and each run from 4 to 10 hours depending on a product’s bandwidth. Many of these strategies are deployed in a new category of SPC called short-run SPC, which is exclusively reviewed in the next section.

2.3.4 Measurement Uncertainty

Formally, the accuracy of the ETE denotes as one of the key instrument specifications. On this ground, the inherent accuracy of the measurement made with the ETE is foremost important. Accuracy measurement implies the existence of standards measurement and the evaluation of uncertainties in a measurement process (Kirkup & Frenkel, 2006). As shown in Figure 2.2, the measurement uncertainty provides calculated confidence level in the measured value that allows judgment on the significance of the measurement error for the measurement falling within a stated amount above or below the true value (Cheatle, 2006; Nielsen, 2017).

Measurement uncertainty is computed to establish traceability for a reference (JCGM 100:2008, 2008). Two primary standards (ISO/IEC 17025:2017 and ANSI/NCSL Z540.3:2006) require instrument manufacturing engineers or laboratories to evaluate the measurement uncertainty and report Test Uncertainty Ratio (TUR), the ratio between specification and measurement uncertainty. False accept risk is the principal metric to evaluate the quality of a test or calibration process (Dobbert, 2008). ANSI/NCSL Z540.3:2006 addresses the requirements and responsibilities of the calibration system to establish 2% false accept risk and to control the accuracy with 4:1 TUR (Castrup, 2007). Macii et al. (2003) provided guidelines to determine TUR in the measurement process to reduce the decisional risks stemmed from measurement errors. In addition, measurement uncertainty shall always be considered for assessment of compliance with a specification (ILAC-G8:03/2009, 2009). The JCGM 100:2008 establishes general rules for evaluating and expressing measurement uncertainty.

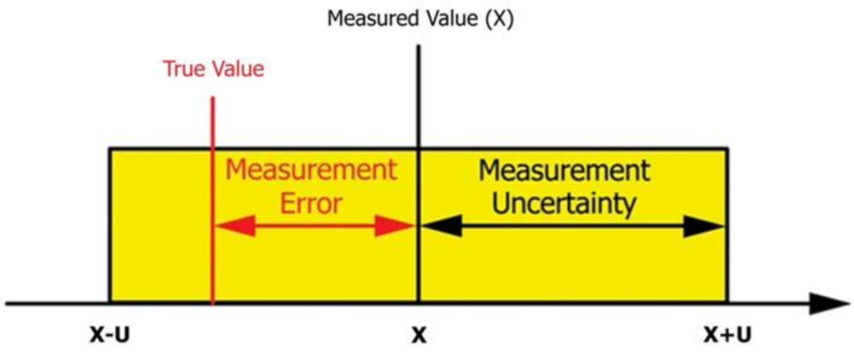

Figure 2.2: Measurement error and measurement uncertainty (Nielsen, 2017)

2.4 Quality Control Approaches in Literature

Figure 2.3 summarises approaches developed for quality control in T&M manufacturing. The two mainstreams are conformance to product specification using Guard band and SPC methods. These approaches will be explored in the next sections.

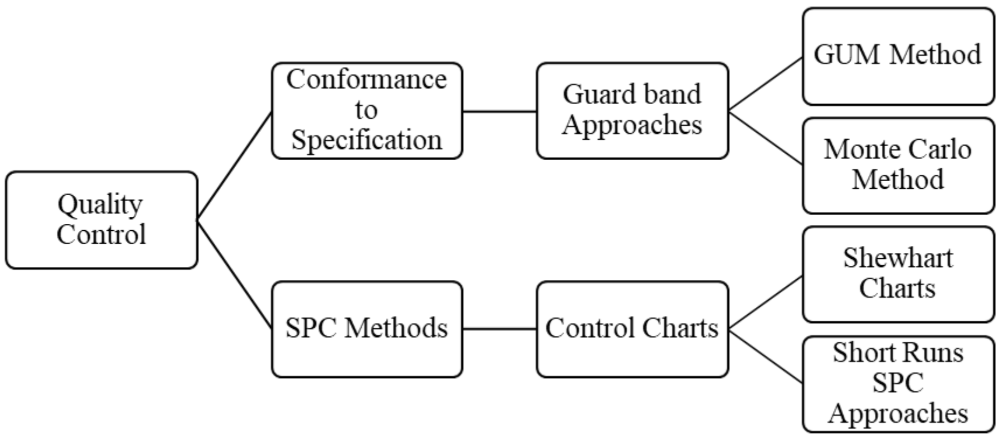

Figure 2.3: Quality control approaches

2.4.1 Conformance to Specification

Juran (1974) defines quality control as "*the regulatory process through which we measure actual quality performance, compare it with standards, and act on the difference*". The quality characteristics are therefore often evaluated relatively to specifications. As the fundamental of the concept are well established, measuring quality based on the conformance to the specification is prevalent amongst manufacturers (Fasser & Brettner, 2003). As shown in Figure 2.4, both lower specification limit (LSL) and upper specification limit (USL) represent acceptable products limits where output measurement could tolerate.

The product quality is assessed by measuring a particular parameter that indicates predefined product characteristics. In other words, a product is deemed to be of good quality if the measurement is within its specification limits and of bad quality if is not.

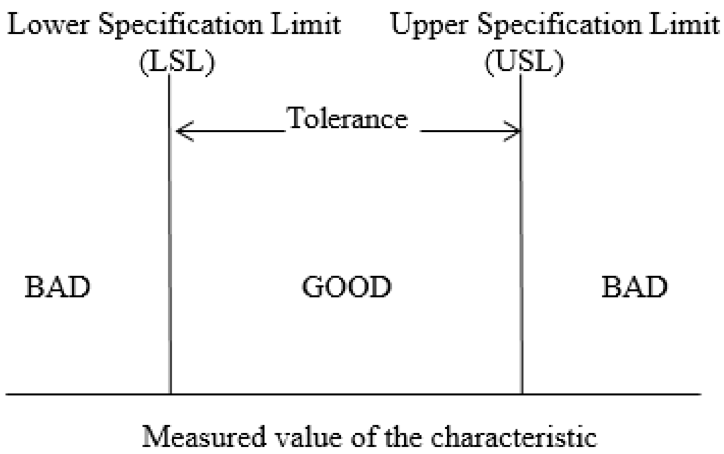

Figure 2.4: The traditional way of assessing quality (Fasser & Brettner, 2003)

2.4.1(a) Guard Band Approaches

In T&M processes, measurement error could be the main concerning issue. The most immediate approach to control the measurement errors is to select a more precise ETE to reduce the measurement variability (Mottonen et al., 2008). However, implementing option along this line could also suggest a significantly more expensive ETE. Thus, a tradeoff is needed between the precision level and associated cost factors. Mezouara et al. (2015) proposed Guard band to reduce the width of acceptance limit (as shown in Figure 2.5). Industry practice allows the installation of Guard band, e.g., through Guide to the Expression of Uncertainty in Measurement (GUM), published by ISO in 1993 (JCGM 100:2008, 2008), as an indirect way to compensate the measurement error.

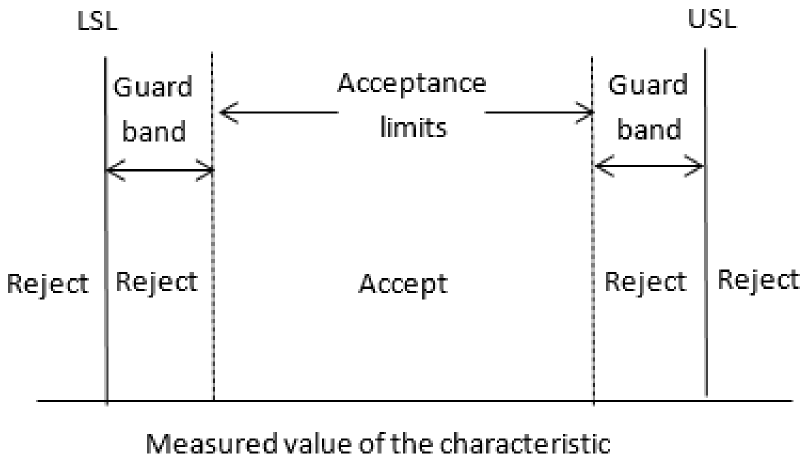

Figure 2.5: Assessing quality with Guard band (Mezouara et al., 2015)

The acceptable risk in Guard band setting is tied in with the presence of measurement error. Two common approaches are adopted to evaluate the uncertainty of the measurement, namely Guide to the Expression of Uncertainty in Measurement (GUM) and Monte Carlo method (MCM). GUM approves the use of both partial derivatives (Type A and Type B) and MCM bases on the general concept of propagating probability density function (Sediva & Havlikova, 2013). GUM and MCM have been used rather extensively and effectively for many years. They are more easily interpreted rather than Markov chain Monte Carlo method (a more recent Bayesian approach) (Forbes, 2012). The integrations of these approaches into Guard band are explained below.

i. Guard Band proposed in GUM

In GUM, measurement uncertainties are standard deviations of probability distributions, interpreted by Type A and Type B evaluations (Bich et al., 2006). Underpinned these two evaluations are Bayesian probability theory which offers a unique, self-consistent method for quantitative reasoning on incomplete sets of information (Kacker & Jones, 2003). Further details about Type A and Type B evaluations will be discussed in Chapter 4. The measurement uncertainties from these evaluations can be aggregated mathematically through Summation in Quadrature (Bell, 2001) to form combined standard uncertainty. GUM requires a high level of confidence (referred as coverage probability) associated with measurement uncertainty (UKAS, 2007). Thus, the combined standard uncertainty needs to be multiplied by a coverage multiplier (k) to become the expanded uncertainty, which in turn provides the tolerance for a measurement. In general, the value of the k will be in the range 2 to 3 based on the level of confidence required (JCGM 100:2008, 2008). The measurement uncertainty must be characterized by a Gaussian distribution (or a scaled and shifted t-distribution) (Bich et al., 2006).

ii. Guard Band generated through Monte Carlo Method (MCM)

MCM is operated through experimental simulations instead of mathematical models (Silva Hack & Caten, 2012). MCM performs random sampling from the probability distribution of the input quantities and provides a probability density function for the output quantity (Cox & Siebert, 2006). It accommodates complicated distributions of input quantities such as U-shaped, asymmetric distribution. The main shortcoming of MCM is a large quantity of random numbers generator and the appropriate simulation software is needed (Sediva & Havlikova, 2013).

iii. Applying Guard Band in T&M Processes

In T&M processes, Guard band is applied for managing false accept risk that the acceptance limits are more stringent than the specification limits (Dobbert, 2008). A common practice is to set the Guard band to a value equals to the 95% confidence level expanded uncertainty of the measurement process (ILAC-G8:03/2009, 2009). ISO/IEC 17025:2017 compliance requires a reading and its tolerance both fall within the specification limits, as in the case of first readings in Figure 2.6. Noncompliance with the specification happens when the measured value exceeds the specification limit (discounted with the expanded uncertainty), as in the case of the fourth reading (reported as "Failed" in Figure 2.6). As long as its bounds of the expanded uncertainty overlap the specification limit, as in the cases of the second and third readings (Figure 2.6), the state of compliance or non-compliance of a measured value cannot be determined. This is hence reported as "Undetermined", and prompts for further study on the absolute quality compliance. Expanded uncertainty acts as a Guard band to reduce the width of acceptance limit.

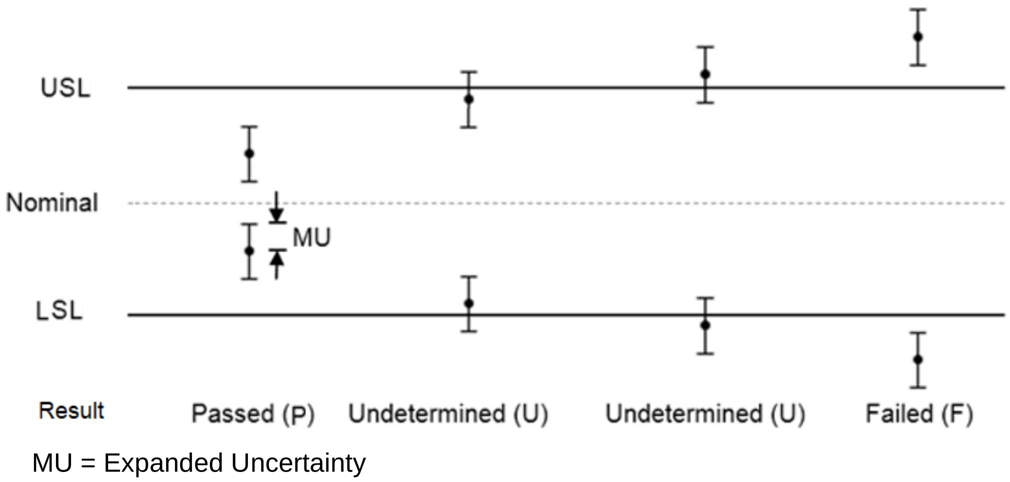

Figure 2.6: Specification compliance (ILAC-G8:03/2009, 2009)

iv. *Industry Applications of Guard B*and

The economic aspects of Guard band have been studied by several researchers (Deaver, 1995; Kim et al., 2007; Mezouara et al.,2015; Pou & Leblond, 2015) to ensure the acceptable risk in the product conformity. Deaver (1995) proposed using Guard band when maintaining 4:1 TUR of fails to prevent unjustified false rejection rate. Dobbert (2008) presented a Guard band strategy for managing false accept risk without requiring statistic knowledge to obtain the standard deviation for the a priori probability distribution. The false reject risk for the managed risk Guard band is significantly lower than expanded uncertainty Guard band.

Kim et al. (2007) and Mezouara et al. (2015) proposed models for the economic design of measurement systems by incorporating the concepts of measurement precision and Guard band to minimize the impacts of measurement errors. In Kim et al. (2007), the sensitivity analysis of an optical scanning device examined the effects of process parameters, such as false acceptance risk, rejection costs, and the expected total cost. In Mezouara et al. (2015), different economic aspects (at the cost of an increased risk of false rejection) of measurement errors were weighted in when selecting the precision level and determining the width of the Guard band with an acceptable customer risk. The results of indirect tensile tests of stiffness modulus showed that Guard banding ensures the good product would be accepted 99.23% with customer risk of 0.71%.

The practice of Guard band can also be analyzed in terms of costs, impact and optimized measurement uncertainty. Pendrill (2014) introduced optimized measurement uncertainty in conformity assessment that deals with qualitative observations and economic risk. The optimized measurement uncertainty includes economic assessments of test and measurement with the costs of incorrect decision-making.

ISO/IEC GUIDE 98-4 (2012) requires a metrologist to control the process by considering the customer and supplier risks. Pou and Leblond (2015) proposed Guard band to control of customer and supplier risks by analyzing the obtained experimental data using Bayesian approach and taking into account the measurement uncertainty. The method minimizes the weighted sum of two risks when the capability of the process of measurement cannot be held. On the other hand, Becket and Paim (2017) reviewed the acceptance criteria defined in reference manual of measurement systems analysis (MSA and VDA 5). Acceptance criteria have established an approval between customer and supplier for measuring system and measurement process. Based on the evaluations performed, they recommended including bias into the tolerance limits (the implement of Guard band). The bias is treated as a source of measurement uncertainty.

In summary, Guard band is an established practice in production testing. However, Guard band increases chances for a conforming product to be erroneously classified as failed in testing (Williams & Hakins, 1993). Guard band lacks of function extension, such as integrating of Shewhart control charts to screen for assignable causes and to detect early quality deterioration in the process (Hossain et al., 1996).

2.4.2 Statistical Process Control (SPC) Methods

Statistical process control (SPC) using control charts, is one of the prevailing tools in quality control to monitor the variation in a process and ensure that the process is in a state of control (Srinivasu et al., 2011). Control chart was pioneered by Shewhart in the early 1920s (Shewhart, 1931). Classical control chart applications involve two distinct phases, Phase I and Phase II (Woodall & Montgomery 1999; Montgomery, 2013). Phase I is a retrospective analysis that constructs trail control limits with historical data to determine if the process is stable or vice versa. In Phase II, control chart is used to monitor new process outcomes.

It may note in the passing that Shewhart control charts are often being compared with cumulative sum (CUSUM) chart (Page, 1954) and exponentially weighted moving average (EWMA) (Roberts, 1959) due to their function compatibility in detecting small shifts in measured values. Both methods require certain level of statistics skill and knowledge, therefore are comparatively less favored in manufacturing area.

Control charts can be either univariate or multivariate. Univariate control chart is a single measurement characteristic to be monitored. Whereas, multivariate control chart measures multiple characteristics, monitoring two or more related measurement characteristics in a manufacturing process (Hachicha & Ghorbel, 2012). Practical implementation in the microelectronics industry is almost exclusively done by using univariate control charts although several multivariate approaches have been proposed (e.g., Khoo & Quah, 2002; Kalgonda & Kulkarni, 2004; Jaupi et al., 2013). With this reason, literature review will focus on techniques in univariate Shewhart $\bar{x}$ chart and R chart.

2.4.2(a) Shewhart $\bar{x}$ Chart and R Chart

Shewhart control charts have been widely accepted in manufacturing processes to stabilize and monitor the mean of different processes when the response can be measured (Montgomery, 2013). Response is a statistic (e.g., mean, range) of measurements characteristic grouped by subgroup size (*n*) for the sample data taken from the measured value. The basic Shewhart control charts are $\bar{X}$ chart for controlling the process average and the R chart (or S chart) for controlling the process variability. They detect process shifts in the mean and variance (Haridy et al., 2016). Shewhart control charts plot a sequence of process measurements with the upper and lower control limits as shown in Figure 2.7. A response falling outside the control limits indicates the presence of a special cause (assignable cause) hence triggers containment and corrective actions (Madanhire & Mbohwa, 2016).

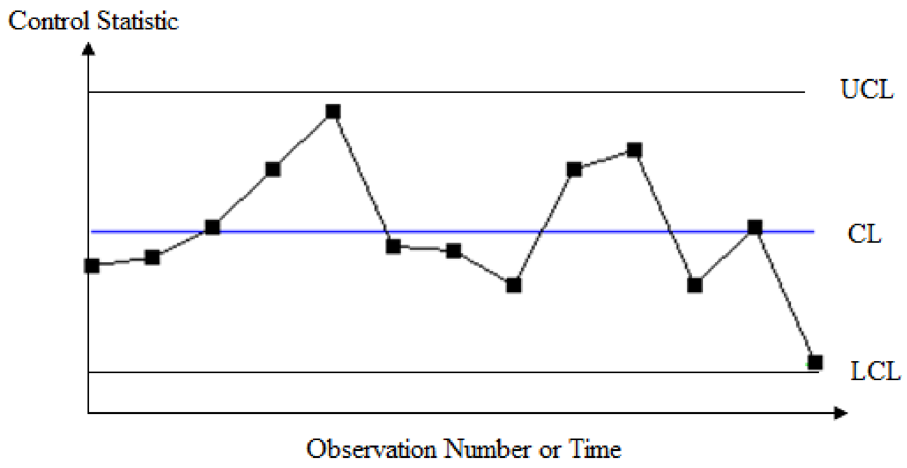

Figure 2.7: Shewhart control chart (Montgomery, 2013)

The control limits are usually set at ±3 standard deviations from central line, which produces a Type I error (false alarm) of a α = 0.0027 if the underlying distribution is normal (Montgomery, 2013; Cascos & López-Díaz, 2018). The center line (CL), upper control limit (UCL) and lower control limit (LCL) for the $\bar{x}$ chart are computed by:

$$CL_{\bar{x}} = \bar{\bar{x}} \tag{2.1}$$

$$UCL_{\bar{x}} = \bar{\bar{x}} + 3\sigma_{\bar{x}}$$

$$LCL_{\bar{x}} = \bar{\bar{x}} - 3\sigma_{\bar{x}}$$

and R chart's are computed by:

$$CL_R = \bar{R} \tag{2.2}$$