

**A MULTI-OBJECTIVES OPTIMIZATION MODEL FOR
THE JOINT DESIGN OF STATISTICAL PROCESS
CONTROL AND ENGINEERING PROCESS CONTROL**

BY

OMAR HAMOUD AHMED DEHWAH

A Thesis Presented to the

DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE


In

SYSTEMS ENGINEERING

December,2021

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN- 31261, SAUDI ARABIA
DEANSHIP OF GRADUATE STUDIES

This thesis, written by **OMAR HAMOUD AHMED DEHWAH** under the direction of his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN INDUSTRIAL AND SYSTEMS ENGINEERING**.



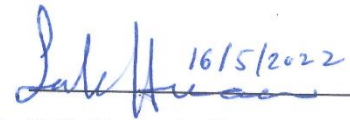
Dr. Anas Al-Sayed Al-Ghazi
Department Chairman



Dr. Suliman Saleh Al-Homidan
Dean of Graduate Studies

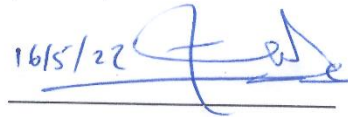
19-5-2022

Date



16/5/2022

Dr. Salih Osman Duffuaa
(Advisor)



16/5/22

Dr. Abdulwahed Abdulaziz Saif
(Member)



Dr. Anas Al-Sayed Al-Ghazi
(Member)



© OMAR HAMOUD AHMED DEHWAH

2021

ACKNOWLEDGMENTS

All praise, glory, thanks and gratitude be to almighty Allah, who bestowed me health, impetus, power and patience to accomplish this work.

The completion of this dissertation would not have been possible without the help and support of many people.

First and foremost, I would like to acknowledge my thesis advisor Dr. Salih Osman Duffuaa for his exceptional support, continuous guidance and expertise during this thesis work. I would like also to extend my thanks to the thesis committee members Dr. Abdulwahed Abdulaziz Saif and Dr. Anas Al-Sayed Al-Ghazi for their support, advice and motivation. Moreover, I would like to give a special thanks to Dr. Awsan Mohammed from Construction Engineering and Management Department for his continuous support, guidance and time, which helped me in achieving the result of this thesis. My sincere respect is also extended to my friends for their support and motivations

Last but not least, I would like to extend my appreciations and thanks for my beloved parents, brothers and sisters for their encouragement, support and cooperation.

TABLE OF CONTENTS

ACKNOWLEDGMENTS	II
TABLE OF CONTENTS	III
LIST OF TABLES	V
LIST OF FIGURES	VI
LIST OF ABBREVIATIONS	1
ABSTRACT.....	3
ملخص الرسالة.....	5
CHAPTER 1 INTRODUCTION.....	6
1.1 Introduction	6
1.2 Statistical process control	7
1.3 Engineering process control	7
1.4 Research objective	8
1.5 Thesis Organization.....	8
CHAPTER 2 LITERATURE REVIEW.....	9
CHAPTER 3 PROBLEM STATEMENT.....	25
3.1 Introduction	25
3.2 Problem Statement.....	25
CHAPTER 4 THE INTEGRATED MODEL.....	27
4.1 Introduction	27
4.2 The Proposed Model.....	27
4.2.1 Model Notation and Assumption	28
4.2.2 Multi-objective Model for The Design of the X-bar Control Chart	30
4.2.3 Adjustment or control limit (parameter D).....	35
4.3 Numerical Example (parameter D)	36
4.4 Results and Analysis.....	39

4.5 Sensitivity Analysis.....	46
CHAPTER 5 CONCLUSION AND FUTURE WORK.....	52
REFERENCES.....	54
VITAE.....	59

List of Tables

Table 4.1 Table of acronyms used for the model	28
Table 4.2 Weighted sum method results	40
Table 4.3 Domination check.....	41

List of Figures

Figure 4.1 Single process cycle.....	32
Figure 4.2 The proposed solution algorithm	38
Figure 4.3 Optimal points of the objectives function.....	42
Figure 4.4 Power vs. Income	43
Figure 4.5 Power vs. Taguchi Cost	44
Figure 4.6 Taguchi Cost vs. Income	45
Figure 4.7 Sigma vs. Power	47
Figure 4.8 In-plant cost vs. Taguchi-cost	48
Figure 4.9 Measurement cost vs. Taguchi-cost	49
Figure 4.10 Average time to find assignable cause vs. Income	50
Figure 4.11 Penalty cost vs. Income	51

LIST OF ABBREVIATIONS

SPC	:	Statistical Process Control
EPC	:	Engineering Process Control
ARL	:	Average Run Length
ATS	:	Average Time to Signal
MCDM	:	Multi Criteria Decision Making
VSI	:	Variable Sampling Intervals
APC	:	Automatic Process Control
AQC	:	Average Quality Cost
EHC	:	Expected Cost Per Hour
TQE	:	Taguchi's Quality Engineering
FSI	:	Fixed Sampling Interval
ANFIS	:	Adaptive Neural-Fuzzy Inference System
GA	:	Genetic Algorithm
DFA	:	Direct Fuzzy Approach
MEPC	:	Multivariate Engineering Process Control
MSPC	:	Multivariate Engineering Process Control

MGWMA	:	Multivariate Generally Weighted Moving Average
DEA	:	Data Envelopment Analysis
LRHC	:	Long-Run Hourly Cost
MOPSO	:	Multi-Objectives Particle Swarm Optimization Algorithm
ATS	:	Average Time to Signal
MODM	:	Multiple Objective Decision-Making Problem
PSO	:	Particle Swarm Optimization
MPD	:	The Managed Pressure Drilling
NSGA-II	:	Non-Dominated Sorting Genetic Algorithm-II
ESD	:	The Economic Statistical Design
AATS	:	Adjusted Average Time to Signal
MMSE	:	Minimum Mean Square Error
EWMA	:	The Exponentially Weighted Moving Average
MEWMA	:	Multivariate of EWMA
PID	:	Proportional Integral Derivative
MIMO	:	Multiple Inputs and Multiple Outputs
SMAP	:	Soil Moisture Active-Passive
MOGAESD	:	Multi-Objective Genetic Algorithm for Economic Statistical Design

ABSTRACT

Full Name : OMAR HAMOUD AHMED DEHWAH
Thesis Title : A MULTI-OBJECTIVES OPTIMIZATION MODEL FOR THE JOINT DESIGN OF SPC AND EPC
Major Field : INDUSTRIAL AND SYSTEMS ENGINEERING
Date of Degree : December 2021

Two different approaches have been identified that are used for process control, enhancement and improvement. These are statistical process control (SPC) and engineering process control (EPC). These methods were developed in isolation from each other and are widely utilized in various sectors. SPC targets to minimize changeability by examining and removing the assignable causes of deviation whereas EPC can attain the same objective by means of adjusting process variables to maintain the outputs of the process on target. Previous studies revealed that a joint design of SPC and EPC has not been addressed in a multi-objectives framework. Therefore, the purpose of the thesis is to design SPC and EPC jointly using multi-objectives optimization. In this thesis a statistical and economic criteria are utilized for the joint design of SPC and EPC. A novel process is designed that incorporates the merits of SPC and EPC. To demonstrate the benefit of the integration of the two approaches a numerical example has been presented and discussed. It has been observed that the integration of SPC and EPC leads to the earliest detection of assignable causes. Furthermore, in order to guarantee the results are valid sensitivity analysis has been conducted. In order to achieve the purpose of this thesis an efficient heuristic algorithm was utilized to solve the model and obtain the optimal results. This algorithm is based on an extensive search of the feasible region. At each iteration, the solution is obtained using BARON solver embedded in GAMS. The results show that the Taguchi cost objective is proportional to the

expected net income objective function. In addition, sensitivity analysis is conducted to identify the parameters that impact the model solution. The sensitivity analysis indicated the following important observations; i. When the value of sigma is increased the power of the chart reduces. ii. When the average time to find the assignable cause and penalty cost are increased, the expected net income objective function decreases.

ملخص الرسالة

إسم الطالب : عمر حمود أحمد دحوة

عنوان الرسالة : نموذج لتحسين عدة أهداف لتصميم مشترك بين التحكم بالعمليات الإحصائية والهندسية

التخصص : هندسة النظم الصناعية

تاريخ الدرجة العلمية : جمادى الاولى 1443 هـ

تم تحديد طريقتين مختلفتين تستخدمان للتحكم في العمليات وتحسينها. الطريقتان هما التحكم الإحصائي في العمليات والتحكم الهندسي في العمليات. تم تطوير هذه الأساليب بمعزل عن بعضها البعض وتستخدم هذه الأساليب على نطاق واسع في مختلف القطاعات. تهدف طريقة التحكم الإحصائي الى تقليل قابلية التغيير من خلال فحص وإزالة أسباب الانحراف القابلة للتخصيص بينما يمكن لطريقة التحكم في العملية الهندسية تحقيق نفس الهدف عن طريق التعامل مع متغيرات العملية للحفاظ على مخرجات العملية للوصول إلى نتيجة مقاربة للهدف. دلت مراجعة الدراسات السابقة أن التصميم المشترك للطريقتين المستخدمة للتحكم بالعمليات سواء كانت في العملية الإحصائية أو في العملية الهندسية لم يتم تناوله في إطار متعدد الأهداف. لذلك ، فإن الغرض من الأطروحة هو تصميم الطريقتان بشكل مشترك باستخدام نموذج متعدد الأهداف. وشملت الأهداف معايير إحصائية وإقتصادية. تم تصميم عملية جديدة تتضمن ميزة SPC و EPC لتقليل التباين والانحراف. لتوضيح ذلك، تم عرض مثال رقمي ومناقشته. ولوحظ أن تكامل الطريقتين يؤدي إلى الاكتشاف المبكر للأسباب القابلة للتخصيص، علاوة على ذلك، تم إجراء تحليل للحساسية من أجل ضمان الاحتفاظ بالنتائج في مواقف مختلفة لأسباب قابلة للإحالة ووسط العديد من وحدات التحكم في العمليات الهندسية. ومن أجل تحقيق هذا الغرض، تم استخدام خوارزمية إرشادية فعالة لتحليل النموذج والحصول على النتائج المثلى. تعتمد هذه الخوارزمية على بحث شامل عن الحلول الممكنة. في كل تكرار، يتم الحصول على الحل باستخدام طريقة بارون للحلول عن طريق برنامج جامز (Gams). أظهرت النتائج أن هدف تكلفة تاغوشي يتناسب مع دالة هدف صافي الدخل المتوقع. بالإضافة إلى ذلك، تم إجراء تحليل الحساسية لتحديد العوامل التي تؤثر على حل النموذج. أوضح تحليل الحساسية إلى الملاحظات الهامة التالية؛ أولاً عندما تزداد قيمة سيجما تقل قوة الرسم البياني. وثانياً عندما يزيد متوسط الوقت للعثور على التكلفة القابلة للتخصيص وتكلفة الجزاء ، تنخفض دالة هدف صافي الدخل المتوقع.

CHAPTER 1

INTRODUCTION

1.1 Introduction

In the area of enhancing productivity for industrial processes, Statistical process control (SPC) is known to be amongst the top efficient first-rate innovative procedures that applies exclusive statistical techniques. SPC can be described as the use of statistical methods or tools to manage processes. SPC tools and tactics can assist in monitoring process behavior, discover troubles in interior systems, and find proper solutions for production issues. SPC primarily employs statistical control charts for separating the assignable and common sources of variation. Control charts applications involve the use of several specialized and behavioral decision-making techniques which are exceptionally noteworthy within the program of SPC and designing this methodology plays a critical work in moving forward the firms' normal quality and efficiency.

Engineering process control (EPC) is a general strategy for system optimization and process improvement. EPC deals with the manufacturing process as an input–output system in which the input factors adjusted to achieve the process target. The process output will be an estimation of the process factors and variables that require control. EPC is typically used in the control of continuous production processes. EPC is a collection of different techniques that are used to control the flexible factors and variables to keep the method output near to the target. EPC offers instant response which counteracts changes in the balance of a process and implements corrective actions aiming to reduce the gap between the output and the desired target. A possible approach is to predict the output deviation from target that would occur in case no control actions were considered and then act in order to eliminate this deviation. Proper feedback and feedforward control strategies

can make process control actions possible by indicating when and by how much a process adjustment is needed.

1.2 Statistical process control

Shewhart (1931) introduced the concept of SPC in the 1920's and published his book on the topic. Although, from the time it has been introduced, SPC has been employed in discrete manufacturing environment to decrease error in the product/process, the SPC procedures do not focus on the real-time automatic correction of the result. Therefore, engineers in control utilized engineering process control to observe and correct the error in the process. The aim of statistical process control is to detect and correct the assignable causes that compels the process to go out of control. This process can be applied in both cases when the errors are independent and correlated.

1.3 Engineering process control

Even though statistical process control is commonly employed in order to reduce the process variability, it is not essentially the most optimal technique in various scenarios, specially in the event of a process where the mean drifts as shown in Messina (1992). To tackle these types of processes, engineering process control can be used efficiently. The concept of engineering process control can be classified in three points. Firstly, foresee the next observation. Secondly, to the output classify a random variable. Finally, observe the variable such that the amount of control action to apply can be figured to tweak the variable accordingly.

1.4 Research objective

The overall objective of this thesis is to design SPC (statistical process control) and EPC (engineering process control) jointly using multi-objectives optimization. This approach has not been utilized in the joint design of SPC and EPC as indicated by the literature review.

The specific objectives are: 1- identify relevant objectives for the multi objectives model. 2- formulate the necessary constraints for the mathematical the model. 3- develop an efficient algorithm for solving the model. 4- study the model applicability and sensitivity.

A method known as weighted sum has been used to acquire a solution for the multi-objective optimization problem. In weighted sum method we have multiple objectives some of which need to minimize while others maximized. The method converts all objectives to a single objective function. These objectives are treated as goals, and they are scaled by multiplying each with user specified weights. But these objectives cannot be compared because their values vary. To solve this problem, we normalize the goals. The weighted sum, attempts to find a global Pareto optimal set. A numerical example is used to test the formulated problem and also a sensitivity analysis is carried out.

1.5 Thesis Organization

This thesis is organized in the following chapters:

Chapter 1 provides a general introduction about the topic and research objectives.

Chapter 2 summarizes the literature review.

Chapter 3 presents the problem statement.

Chapter 4 discusses the development of the integrated model.

Chapter 5 presents and discusses the result and the sensitivity analysis.

Chapter 6 conclude and summarize the thesis work and suggest some possible work in the future.

CHAPTER 2

LITERATURE REVIEW

Duncan (1956) was the first to propose the use of single objective for the design of X-bar control chart in which he present a single-objective design for Shewhart X-bar control chart. Duncan used an economic model that considers single assignable cause of production process. In (1971) Duncan proposed multi-assignable causes with a new model. Furthermore, Hu (1984) designed the X-bar control for process shift under non-Poisson distribution. Woodall (1986) figured that the economic design method regularly not effective for designing control chart that are fast for detecting small shift before actual losses happens. Also, in (1986) Lorenzen and Vance compared their model to Duncan (1956) with changing average run length (ARL) of in-control and out-of-control system instead of probabilities of types I and II. Also, they developed different cost functions that were used for the design of statistical and economic control charts. Moreover, Banerjee and Rahim (1988) based on Duncan (1956) proposed a model by considering a Weibull failure mechanism. In (1989) Taguchi et al. specified that the economic loss that occurs due to the deviation of quality characteristic represents approximately a quadratic function. Moreover, Saniga (1989) improved the Shewhart control charts and proposed it as the first statistical economic design and applied it for the R and X chart to determine the parameters. Saniga in his model minimized the objective function subject to constraint on type 1 and the power of the chart. Saniga, in (1989) considered the economic design and statistical design which has three strategies, a) minimize out of control average time to signal (ATS), b) discover an off-target process by optimizing sample interval and sample size and lower and upper control limits without considering the economic principles, and c) maximize ATS state the process in control.

In 1991, Evans and Emberton proposed bi-criterion design of process control charts based on multi-criteria decision making (MCDM). In addition, Amin, R.W. and R.W. Miller (1993) considered the variable sampling intervals (VSI) control charts. After that, Celano and Ficher (1999) optimized the cost of using X-bar control chart and type-I and II error probabilities with multi-objective decision-making approach. Moreover, in (1994), Chung created procedure to find the optimal solution for X-bar chart for the case of multi-assignable causes. Kennedy and Eberhart (1995) developed the evolutionary computation technique which is particle swarm optimization. Later, Castillo et al (1996) introduced a model for the creation of X charts which is subjected to an interactive multicriteria nonlinear optimization technique. The user does not need to indicate the cost of false alarms or losing control in the suggested approach. However, only the sampling costs, which are usually simple to estimate, must be stated. In 1998, Bai and Lee studied the economic design of X-bar control chart in sample intervals of variables. The economic design of X-bar control model take different cost factors into the cost model. Those factors include cost of false alarms, cost of finding and eliminating an assignable cause, cost of production in an out-of-control state, and cost of sampling and testing. This method is used to determine optimal sample size, sampling interval lengths, control limits, and threshold limits in order to choose one of the sampling interval lengths. In the case of the joint economic statistical design of X-bar and S^2 control charts, a statistically restricted model is generated to control both process mean and variance. The goal is to decide the control charts' design parameters, which reduce the overall cost of quality control. To extract the model, a Markov chain approach was used to study economic-statistical design of X-bar and S charts by Yang and Rahim (2000).

Jiang and Tsui (2000) established an economic model for Automatic process control (APC) controlled process monitoring by the SPC. Also he suggested an economic loss-based criterion,

the average quality cost (AQC) criterion, for evaluating SPC chart for monitoring the mechanism managed by APC. Based on the AQC criterion as well as the conventional ARL criterion, three different SPC charting methods, the Shewhart chart, the EWMS chart and the combined EWMA-Shewhart chart are compared. It was found that the AQC criterion usually conforms to ARL criterion even if APC control behavior balances the process change significantly. At the time this occurs control chart output may rely significantly on the size of the cost of the diagnosis. Moreover, the AQC assigns to each run-length likelihood a different weight proportional to the mean shift transition, and thus offers more economic details than ARL.

Extending the related definition of the integrated AQC criterion determine the cost-effectiveness of SPC monitoring under various feedback schemes such as MMSE and PID would be interest. As known that the sample size and frequency greatly influence the choice of control charts. Our current model only addresses a cost model with sample size and frequency set. Extending the model to compare optimum control charts would be interest with the same set of diagnostic, modification, and off-target cost conditions. Moreover, a more rational assumption regarding the arrival of shifts in the current model is necessary.

Moreover, Montgomery (2001) displayed both the deviation and mean of the quality characteristic by using Shewhart's S and X-bar control charts widely. However, Chen and Yang (2002) considered multi assignable causes of economic X-bar control charts with Weibull in control state. Next, Linderman and Choo (2002) proposed the scenario-based approach for robust economic design of a single process. They considered three discrete measures for cost parameters by using several scenarios and calculated the suitable control chart parameters under all scenarios.

In 2004 Bakir and Altunkaynak designed a demonstration for deciding the shifts within the handle mean and process changeability by the assistance of X-bar and R control charts. Also, they changed from single objective to multi-objectives optimization problem to solve the new model and established a multi-objectives economical model created on the statistical measures for R and X-bar charts. However, Chen and Liao (2004) studied a potential combination of design parameters, which includes: in-control average run length in (ARL), predictable cost per hour (EHC), and power of detection (p) after out-of-control status for chosen parameters. In 2004, Chen used Burr studied the statistical economic design of X-bar control charts for the case of non-normal quality features. Later, Gulbay et al. (2004) determined the tightness of the inspection by selecting a suitable alpha-level. Then used the alpha-cut control charts for linguistic data.

Duffuaa et al. (2004), suggested that the integration of SPC and APC together is better than either one of them alone for process control. Also, a scheme to combine statistical process control (SPC), engineering process control (EPC) and Taguchi's quality engineering (TQE) was proposed. Then, to incorporate the proposed scheme, two models were included. To decide if an EPC action should be taken by assessing the cost of the action and quality cost. A model is developed using Taguchi's quadratic loss function. A trade-off between the costs involved offers the response as to whether or not the EPC should be carried out.

Yu F.J. (2005) developed an economic model for variable sampling for continuous-flow process of X-bar control chart. Most of the economic design studies of control charts rely on a fixed sampling interval (FSI), but variable sampling interval (VSI) control charts have been found to be significantly faster in detecting process changes than FSI control charts due to a higher frequency in the sampling rate when any hint of a process change was shown by a sample statistic. For a continuous-flow production process, an economic design for a VSI X-bar control chart was

proposed. The findings of a numerical example taken from an actual case showed that the economic nature of the control charts of the VSI was consistently lower in cost of **loss** than that of the FSI method, which is a combination of four losses function. First part is the average hourly loss when the process is out of control. Second loss function is the expected number of false alarms before the process goes out-of-control. The third is the average hourly cost of finding and repairing the assignable cause. The fourth is the average hourly cost of maintaining the control chart.

In (2007) Zarandi et al. considered fuzzy values for economic parameters and used genetic algorithm for optimizing and apply adaptive neuro-fuzzy inference system to interpret the model. To elaborate more, a fuzzy multi-objective model was proposed for the economic-statistical design of the X-bar control chart, in which fuzzy membership functions express the input parameters. Moreover, to transform the complex fuzzy multi-objective model into a fuzzy rule-base, an Adaptive Neural-fuzzy Inference System (ANFIS) approach was used. Next, to find the best design (input) parameters for control charts, a genetic algorithm (GA) was developed. Finally, by using a numerical example, the proposed solution was checked and validated.

Gulbay and Kahraman (2007) proposed a new approach to fuzzy control chart based on fuzzy transformation methods named as Direct Fuzzy Approach. Linguistic information was converted into numerical values before the control limits are determined. Both control limits and sample values are thus numeric. Using a-cut to provide the ability to determine the tightness of the inspection, certain contributions to fuzzy control charts based on fuzzy transformation methods were made. They developed a modern "Direct Fuzzy Approach (DFA)" as an alternative approach. The proposed solution was very different in the sense that it does not include the use of defuzzification, as opposed to the current fuzzy control charts.

Nenes and Tagaras (2007) under Bayesian scheme, economic-statistical model was studied for an adaptive X-bar control chart for shift in the mean of the quality characteristics. A model for the economic design of an adaptive X-bar chart was studied for short production runs subject to the occurrence of assignable factors, which through either increase or decrease the average quality characteristic. The probabilities that the process operates under the influence of an assignable trigger are modified using Bayes' theorem at each sampling case. The sample size and the control limit of all three chart parameters, such as the time before the next instance of sampling, are adaptive and depend on these probabilities. They derived properties that promote the estimation of costs and ultimately the optimization of the proposed method. Then, by comparing its cost against the expected cost of (a) a fixed-parameter Shewhart chart optimized for short runs and (b) a variable-parameter Shewhart chart, optimized for an infinite phase. Then, Vommi and Seetala in 2007 minimized the cost function by use new approach (use interval parameters) in the economic statistical design of X-bar control chart. Also, they proposed a method to robust economic design of X-bar control charts and use genetic algorithm to obtain the best solution, using one of the search tools which was genetic algorithm.

Vommi and Seetala (2007), recommended using a weighted robustness factor, proportional to the likelihood of the scenario, to examine multiple scenarios. To find the optimum parameters of an X-bar control chart, a risk-based approach has been employed. As a search method, the genetic algorithm (GA) was used to find the best design (input) parameters for which to design the control chart. In terms of the risks, they generated and after that compared the results of average based and risk-based designs. The approach proposed, minimizes the possibility that the true parameters to be used in the design will not be known, and it is robust to the true parameter values. A simple, robust methodology for economic design for an X-bar control chart was discussed. In their

specified ranges, the design is robust to the values of the true cost and process parameters. In the design, which is easy to understand, the concept of minimization of maximum risk has been used. This method has the advantage of integrating statistical constraints into the design, which is very important in the design of the control chart, in addition to the simplicity of the methodology. To find the best design parameter set, the genetic algorithm has been used as an efficient search method. This approach mainly assumes that no knowledge on the parameter distribution.

Based on statistical and economic criterion Yang and Sheu (2007) discussed the performance of integrated EPC and SPC charts. To assess the efficiency of the multivariate EPC (MEPC) and multivariate SPC (MSPC) chart, they suggested some statistical and economic parameters, such as the average Euclidean distance from the goal vector and the average quality cost (AQC). In the three MSPC charts, the typical average run length (ARL), average Euclidean distance and AQC are investigated and compared. The results of the simulations show that in detecting minor changes of the mean vector, the MEPC and multivariate generally weighted moving average (MGWMA) chart is more efficient and more economical than both the MEPC / MEWMA chart and the MEPC / Hotelling multivariate chart. Most MEPC schemes are designed to respond to process disruptions and do not make any attempt in the MIMO framework to eliminate the assignable cause. It is possible to use the MSPC chart to monitor, classify and subsequently remove assignable cause. They compared the performance of the MSPC charts in a statistical and economic sense, according to the proposed criteria. If the method has an assignable cause that contribute to sustained changes, combining MEPC and MSPC charts often results in the reduction of overall variability. The MEPC / MGWMA chart is more reliable and more economical than both the MEPC / MEWMA chart and the MEPC / Hotelling multivariate chart, in particular when detecting minor changes of the mean vector due to the added adjustment parameter. The MEPC / Hotelling multivariate chart is the most

efficient when the change is high, unlike the MEPC / MGWMA chart. The proper use of both MEPC and MSPC in multivariate cases will often outperform the use of either alone.

Li et al. (2009) investigated data envelopment analysis (DEA), a multi-criteria Branch and bound method for designing the X-bar control chart. The model decreases the need to indicate the statistical bounds and the difficulty of estimating costs

Asadzadeh and Khoshhahan (2009) obtained the optimal design for control chart once the objective function of the cost was expanded to multi-assignable causes by applying data envelopment analysis. A potential combination of design parameters was considered. The decision-making unit was defined by three attributes: hourly expected cost, chart detection capacity, and average run length in-control. They designed control chart using multiple-objective decision-making. Moreover, since multiple assignable causes occur in actual life, the cost feature was generalized from single to multiple assignable causes. To solve the multiple-objective decision-making (MODM) model, an algorithm using data envelopment analysis was applied. Carolan et al. (2010) considered the X-bar control chart economic design, sampling intervals and sample size variable and adaptive. Then a two-stage model that utilizes continuously variable intervals of sampling was proposed. Modeling the situation as a Markov chain, for any arbitrary set of design parameters, the hourly cost was generated. In contrast with a conventional two-stage approach where the sampling interval alternates between two fixed values, this proposed approach is found to be more economically desirable. A fixed sampling interval, h , sample size n , and position of the control boundary were used in previous work in the field of economic design of X-bar control charts. Improvements to this basic design included the implementation of variable parameters and a two-stage procedure. Also, the economic design of X-bar control charts with continuously variable intervals of sampling was proposed. This study contributed to the field such that it enables the

extremity of the most recent sample to be determined by the sampling interval. The sampling interval proposed here is genuinely continuous and not a fixed pair (for example h_1 and h_2) of sampling intervals. A cost model was built for long-run hourly costs and a tool was given to find the most suitable design parameters. The results of the economic design of \bar{X} -bar charts with discretely variable parameters are compared to those of \bar{X} -bar charts with continuously variable sampling intervals in the economic design. It demonstrates that the proposed continuously variable sampling interval method is more cost-effective than that of the variable form. The suggested continuously variable sampling interval method is superior to the discretely variable parameter model when directly compared using analog process and cost parameters and gave lower the long-run hourly cost (LRHC) in all instances.

Sun and Wang, (2010) proposed integrated SPC and EPC economic design methodology, which analyses the effect of special cause and the economic design of the integration of SPC and APC based on quality statistical properties is given in view of the first order dynamic process with ARIMA disturbance (0,1,1). The operational cost is minimal via this approach and the necessary statistical properties are simultaneously considered. Such research findings which provide some theoretical basis for the design of the control of EWMA variance. In addition, extends the economic design model with constraints on the basis of the general method of integrating the SPC and APC. The model not only ensures that production costs are reduced, but also takes into account the statistical property of the quality overall process, which offers new opportunities and probabilities for improving production quality and cost reduction.

Saif et al. (2011) present an integrated scheme that shows the mutual application of SPC and APC for process monitoring and adjustment under fuzzy logic interaction. The main purpose of their paper was to create an integrated scheme that incorporates the use of process monitoring

techniques from SPC and APC, as well as its adjustment under fuzzy logic interaction. Saif et al. intend to maximize its level of quality and efficiency, as well as robustness, by driving any process under the proposed framework. Also, Akram (2011) suggested process improvement through the use of integrated statistical and automatic processes control approaches. SPC's main emphasis was on process tracking, while APC's focus was on process change. Both techniques were originally thought to be in conflict with each other due to the information gap between the proponents of these two approaches, and their combined usage was entirely out of doubt before their proponents realized that the strategies implemented by these approaches were compatible rather than contradictory.

Safaei, Kazemzadeh, and Niaki (2012) used non-dominated sorting genetic algorithm-II (NSGA-II) to generate the Pareto optimal solution of X-bar control chart. They compound the intangible external costs and the Taguchi lost function in the economic design of X-bar control chart. The most common control charts that can be used to track variable quality characteristics in a production process are the Shewhart charts and by integrating the Taguchi loss function and the intangible external costs, a multi-objective model of the economic statistical architecture of the X-bar control chart is first proposed. The model minimizes the average cost of hourly loss while decreasing the average run length out-of-control and maintaining reasonable in-control average run length. To obtain the Pareto optimal solution of the model, a multi-objective evolutionary algorithm, namely NSGA-II, was generated and used. Next, such sensitivity tests are conducted to analyze the influence of parameter estimation on the output of the table. Then, a comparative analysis with a conventional economic design model showed that the X-bar control charts proposed multiple goal design that gives practitioners a stronger methodology and more realistic performance. The X-bar chart, considering the Taguchi quadratic loss function and, a multi-

objective economic statistical design was proposed. Comparisons with the conventional model of economic design demonstrate that the multi-objective model was proposed can overcome the limitations of traditional models. The results obtained showed the superiority of the proposed method, since the detection capacity of the control chart can be enhanced by a small increase in the hourly expected cost. Then Park et. al (2012), investigated the average run length (ARL) which is determined by processes using APC and SPC. However, as a calculation of economic design, ARL may not be suitable as it does not take into account the difference in run length. Yang et al. (2012) found the optimal design of S and X-bar control charts by using multi-objectives particle swarm optimization algorithm (MOPSO). Akram et al. (2012) studied the integration of SPC and (APC). For process control, SPC was used, while APC was used for process modification. Research regarding an operation incorporating both APC and SPC, a significant amount of work has appeared. Akram et al. discussed the SPC and APC preliminaries and highlighted the key procedures applied by both.

In 2013 Faraz and Saniga used genetic algorithm for optimizing two objective functions for single objective economic statistical control chart. As an alternative to control charts, they discussed multi-objective models as the primary instruments of statistical process control. Instead of providing a single optimal solution, these provide a collection of optimal solutions and thus allow the consumer to tailor their solution to the temporal imperative of a particular industrial situation. They proposed a solution to a well-known industrial problem and compared optimal multi-objective models to single objectives economic models. Amiri et al. (2013) considered multi-objectives economic-statistical design of MEWMA control chart. The cost function, however, often depends on statistical characteristics and, as the primary objective, minimizing it was not an effective method of economic statistical design of control charts. The targets considered by the

authors were: to include the likelihood of Type I error, the power of the X-bar control chart, and the Average Time to Signal (ATS); the corresponding constraints are used. Then, to obtain the Pareto optimal control chart design solutions, a Multi-Objective Genetic Algorithm for Economic Statistical Design (MOGAESD) was proposed. Then, Bashiri et al. (2013) extended the work of Amiri et al. by including ATS and cost function to the model and suggested to use a multi-objectives genetic algorithm to get the optimal design of X-bar control chart with multiple assignable causes.

Lupo (2014) considered random process shifts and Taguchi function to improve the multi-objectives design of X-bar control chart by applying mixed integer models. Also, by considering Taguchi and random shifts of the process, Luop used mixed integer numerical model to optimize the multi-objectives X-bar control chart. Integrating both SPC and APC techniques was highlighted in Saif (2014) by tracking and removing the assignable causes of variance, SPC minimizes uncertainty, while APC achieves the same purpose by managing manipulated process variables to maintain the process outputs on target. Initially, both methods were perceived to be in competition with each other, before their supporters realized that the strategies being introduced were complementary. Moreover, Mobin et al. (2015) used (NSGA-II) to generate the Pareto optimal frontier of an X-bar control chart. The economic use of a control chart includes the design of the optimum parameters for the sample size, the frequency of sampling and the chart control limits. Through a two-stage multi-objective optimization process, Mobin et al. investigated the X-bar control chart design. In creating an X-bar control chart, the multi-objective formulation represents the different objective needs. Morabi et al. (2015) proposed a design of X-bar chart by using particle swarm algorithm to optimize a multi-objectives control charts with fuzzy process parameters. Control charts design involves choosing such design parameters as sample size,

control limits, and frequency of sampling. The design of X-bar control charts was formulated as a multiple objective decision-making problem (MODM) defined by three criteria: estimated hourly cost, average run length in control, and control chart detection capacity. They recommended a hybrid approach based on an evolutionary algorithm in order to solve the MODM problem. An epsilon constraint was implemented with particle swarm optimization (PSO) was utilized to solve the multi-objective model. Safaei et al., (2015), designed control charts to track the service and production processes. The fact that there were unknown parameters in many processes was an obstacle to obtaining the best control graph design. The economic statistical design (ESD) of the X-bar control chart was discussed, using a robust optimization method that takes into account interval estimates of unknown parameters. To obtain the robust scheme of the control chart, a heuristic algorithm was developed. Numerical and simulation studies indicate that the proposed X-bar control chart provides practitioners with a stronger methodology and more accurate solutions. Then, Moghaddam et al. (2016) presented an economic design for multi-objectives of aggregate count of adjustment control chart. Also, proposed a multi-objective optimization approach for the combined radar-radiometer soil moisture estimation was provided with emphasis on physics-based techniques. The estimation of soil moisture was demonstrated by applying this method to high-resolution SMAP radar and coarse-resolution radiometer data. Then, comparisons were made with the active-passive soil moisture production data result of the SMAP baseline. A strong agreement was observed between the two techniques, especially in the capture of the spatial distribution of soil moisture. In (2016) Tavana et al. utilized two methods to overcome the fact that the method used for single-objective optimization is not appropriate when a multi-objective optimization problem is to be solved as it may contradict each other. Also in this work various optimization problems are solved by multi-objective particle swarm optimization algorithm

(MOPSO). MOPSO can be used to solve computationally intractable optimization problems as the MOPSO algorithm is a direct and easy method according to Tavana et al. (2016).

Seif, Asghar (2018) presented the Modified Average Time to Signal (AATS) control chart with a multi-objective economic statistical design of VSS T^2 as the statistical objective and the estimated cost per hour as the economic target. Also, they proposed a multiple assignable cause for the shift process using multi-objectives genetic algorithm for economic design of control chart and T^2 control chart. The above review reveals that the economic cost of the joint design of SPC and EPC have not be designed jointly in a single multi-objectives optimization

John (2019) developed an integrated engineering process control (EPC) and statistical process control (SPC) methodology. Design, methodology and approach-Pulp bleaching were a mechanism by which cellulose was removed by chemical treatment from impurities found in cooked wood chips. Since the responses were automatically correlated, to model the responses, dynamic regression was used. Then, by fuzzy optimization technique, the optimal chemical dose that would maximize the pulp brightness and viscosity at the same time was calculated. The author was trying to build an integrated EPC-SPC methodology for monitoring and managing multiple performance features simultaneously. Using a dynamic regression technique, the approached aim was to develop models for each output characteristic and identify the optimum adjustment required using fuzzy logic.

Imanian et al. (2020), control charts were applied to the output of the managed process by using automated process control; consequently, points which were beyond the predefined control limits were marked. SPC and control charts were used for the first time to track and regulate the managed pressure drilling (MPD) process. It was demonstrated that applying SPC to the APC performance will increase confidence in controlling the process in the presence of random and special causes

and under different operating conditions. A novel five-step approach to monitoring and managing the MPD process was therefore used in their analysis. Imanian used control charts for the first time not only to enhance the control of "APC monitoring systems" but also to assess the efficiency of various methods of APC. The fuzzy adaptive APC approach showed the best performance in managing the MPD process during the drilling activity of oil wells, based on the current and previous evaluation criteria.

APC can more precisely control individual process parameters, but it is unable to manage the distribution for those parameters. It also can not anticipate the controlled output process and the control state. Since SPC is contrary to APC, it will learn to balance their weakness and carry more control effects from other strong points. Regardless of the fact that it is triggered by an assignable cause or a random disruption, the combination of the SPC and APC system will keep the process in control. The smart integration of APC and SPC is an optimization method for controlling the production process. Based on the difference in the control object, intellectualized approaches may be used, such as artificial intelligence, fuzzy control, artificial neural net and expert system. However, the use of APC techniques for process regulation and the use of SPC techniques for monitoring has been used by most of the integration strategies contained in the literature, while others derived SPC controllers based on the APC loop knowledge and applied their use alone; this does not provide a real sense of integration. Previous studies have focused on integration of SPC and APC by using single objective. They used several methods and charts such as Shewart control chart, EWMA control chart, MMSE-controlled process, Proportional-integral controller, fuzzy logic and Taguchi quality loss function. However, integrating SPC and EPC using multi-objectives

is not yet performed. The main purpose of this thesis is to design statistical process control (SPC) and engineering Control (EPC) jointly using multi-objectives optimization.

CHAPTER 3

PROBLEM STATEMENT

3.1 Introduction

This chapter presents the joint design of SPC and EPC. It will also discuss the targets and goals that are required for applying SPC and EPC. As these two methods are applied in different sectors, the importance of the methods will also be explained in their respective areas.

3.2 Problem Statement

SPC and EPC have been identified as two different approaches used to assess the quality improvement and process adjustments. These methods were developed in isolation from each other and are widely utilized in various sectors. SPC examines the causes of variation and then eliminates them whereas EPC is frequently employed to reduce the variability by applying online adjustments of some process inputs on a regular basis. Initially, both techniques were believed to conflict each other, until it was realized that the methods are complementary. The design of SPC includes the determination of sample size, sampling frequency and control chart limits. The determination of the design parameters are made based on statistical or economic objectives. The statistical design of SPC takes into consideration the average run length (ARL), type I and type II errors. Various models are developed in the literature and presented in the previous chapter. EPC was developed with the aims to control processes and make the quality characteristic remains closer to the target. In the design of EPC the following items are determined first: The loss cost due to product characteristic (A), production measurement cost (B), production cost adjustment (C), production tolerance (Δ), present production measurement interval (n_0), present production control limit (D_0). The aim of the economic design of EPC is to determine the optimal parameters that include the sampling frequency and the limits of the production control. In the joint design of

SPC and EPC it is required to identify all relevant constraints as they relate to SPC and EPC design. Then the constraints will be used to develop the multi-objectives optimization model together with an efficient algorithm to solve the model. The use of the model will be demonstrated by a realistic example.

CHAPTER 4

THE INTEGRATED MODEL

4.1 Introduction

The purpose of this chapter is to present a multi-objective optimization model for the joint design of SPC and EPC and demonstrate its utility by a numerical example. The model results indicated that

- 1- The Taguchi cost is proportional to the expected net income, as Taguchi cost increase, the expected income decrease.
- 2- The value of the interval between samples (h) ranges between 0.5 and 0.85 hour.
- 3- The power of the SPC chart range between 0.913732 and 1.

The rest of the chapter is organized as follows:

Section 4.2 states the model including notations, assumption and its details followed by a numerical example in section 4.3. Section 4.4 presents the algorithm developed for solving the model and the model results. Section 4.5 outlines the results of the sensitivity analysis.

4.2 The Proposed Model

This section is organized in several subsection. Subsection 4.2.1 presents the notations and the model assumptions followed by subsection 4.2.2 that provides the multi-objective model in dividing its objectives and constraints. Then subsection 4.2.3 presents the adjustment of the model.

This subsection presents the model notations and the model assumptions. The following notations are used for the model development.

4.2.1 Model Notation and Assumption

The following table defines the acronyms used throughout the thesis.

Table 4.1 Table of acronyms used for the model

<p>$E(A)$: The expected net income per hour.</p> <p>$E(C)$: The expected net cost per cycle.</p> <p>$E(T)$: The expected cycle length.</p> <p>W_t: average time taken to find the assignable cause after a point has been found to fall outside the control chart limits.</p> <p>B: cost per measurment of the production characteristics.</p> <p>C: cost per adjustment.</p> <p>D: adjustment or control limit.</p> <p>$\frac{1}{\lambda}$: the average time for occurrence of the assignable cause.</p> <p>λ: Assignable cause follows poisson process with rate λ.</p> <p>h: interval between samples.</p> <p>k: the control limit within terms of standard diviation</p> <p>n: sample size.</p> <p>V_0: net income per hour of operaion in the in – control state.</p> <p>V_1: net income per hour of operaion in the out – of – control state.</p> <p>a_1: fixed component of sample cost.</p> <p>a_2: variable components of sample cost.</p> <p>a_3: the cost of finding an assignable cause.</p> <p>a'_3: the cost of investigating a false alarm.</p> <p>a_4: The hourly penalty cost associated with production in the out of control state</p>

α : the probability of false alarm (type – I error).

β : the probability of type – II error.

$P = 1 - \beta$: the probability that the assignable cause will be detected.

g : A constant used to estimate the average time of sampling, inspection, evaluation and plotting for each sample (gn).

σ : standard deviation

τ : The expected time of occurrence of the assignable cause within the interval between two samples

$P(s)$: The detection power of the economical control chart (after out of control status),

p_L : The lower bound of the economical control chart detection power

α_U : The upper bound of the type – I error

l : time lag of measurement

σ_m^2 : measurement error

$\Phi(z)$: The probability density function of the standardized normal distribution

δ : The number of standard deviations σ in the shift of process mean μ_0

Δ : tolerance of the product characteristic

A : in – plant cost of reworking or scrapping a unit that falls outside of tolerance interval

\bar{u} : predicted average number of product between successive adjustment

u_0 : current average number of products (unit) between successive adjustment.

D_0 : current adjustment or control limit.

In this model development, the below assumptions were implemented:

- 1- The process start in statistical control status.
- 2- Only one type of assignable causes can lead to a fixed shift in the process.
- 3- The assignable cause is a Poisson process which has rate of λ , and the time interval where the process holds an in-control status is an exponential random variable which has a rate of $\frac{1}{\lambda}$ hours.
- 4- The sampling data is assumed to follow normal distribution.

4.2.2 Multi-objective Model for The Design of the X-bar Control Chart

It is assumed that the assignable cause is a Poisson process that has rate of λ . Therefore, the time interval where the process holds an in-control status is an exponential variable which has a rate of $\frac{1}{\lambda}$ hours. The sampling data is assumed to follow normal distribution. The process mean changes from μ_0 to $\mu_0 + \delta * \sigma$, δ is known, when an assignable cause occurs. W_t is the time it takes between detecting an out-of-control point and restoring the process to in-control status and even if there is a detection of an out-of-control point the process is not fixed.

Four measurable performances can be obtained by taking into account the mentioned assumptions.

Firstly, on account of the Poisson occurrence of the assignable cause, $\frac{1}{\lambda}$ is the expected time interval that the process remains in statistical control status. Secondly, equation 4.1 shows the error in each sampling (probability of false alarm, $\alpha(s)$). While the process is in control state. it can be defined as the reciprocal of the ARL. Thirdly, equation 4.2 represents the conditioned expectation time of assignable cause that occurs between every two succeeding samples (provided the assignable cause takes place in the respective range). Moreover, the time interval between succeeding samples is denoted by h . Finally, equation 4.3 denotes the detection power $P(s)$ after the process enters in

out-of-control status, for each sample. Where $\frac{1}{p}$ denotes the expected number of samples taken prior to detecting the mean shift and $\Phi(z)$ is the standard normal probability density function.

$$\alpha(s) = 2 \int_{-\infty}^{-k} \Phi(z) dz \quad (4.1)$$

$$\tau = \frac{\int_{jh}^{(j+1)h} \lambda e^{-\lambda t} (t - jh) dt}{\int_{jh}^{(j+1)h} \lambda e^{-\lambda t} dt} = \frac{1 - (1 + \lambda h)e^{-\lambda h}}{\lambda(-e^{-\lambda h})} \quad (4.2)$$

$$p(s) = \int_{-\infty}^{-k-\delta\sqrt{n}} \Phi(z) dz + \int_{k-\delta\sqrt{n}}^{\infty} \Phi(z) dz \quad (4.3)$$

Various types of operating measures can be found in the review including the measures as shown above. For example, an estimate of the number of samples while the position of the process is in a state of statistical control. The estimate can be evaluated to be $\frac{1}{\lambda h}$, and therefore the number of false alarms expected in this period can be derived to be calculated by $\frac{\alpha(s)}{\lambda h}$. Observing Fig.4.1, it is easy to understand the complete process cycle and both the status: in-control out-of-control.

g is defined as the mean time elapsed, when every sample goes through inspection, evaluating, plotting and sampling. This constant g is proportionate to n (sample size). Hence $g * n$ is known as the time delay in this phase. The time elapsed between each consecutive samples is defined as h in Fig.4.1. In the duration of two samples, the expected time of occurrence of the assignable cause can be defined as τ . The duration of dealing with the assignable cause and returning the process to the status of in-control can be defined by a constant W_t .

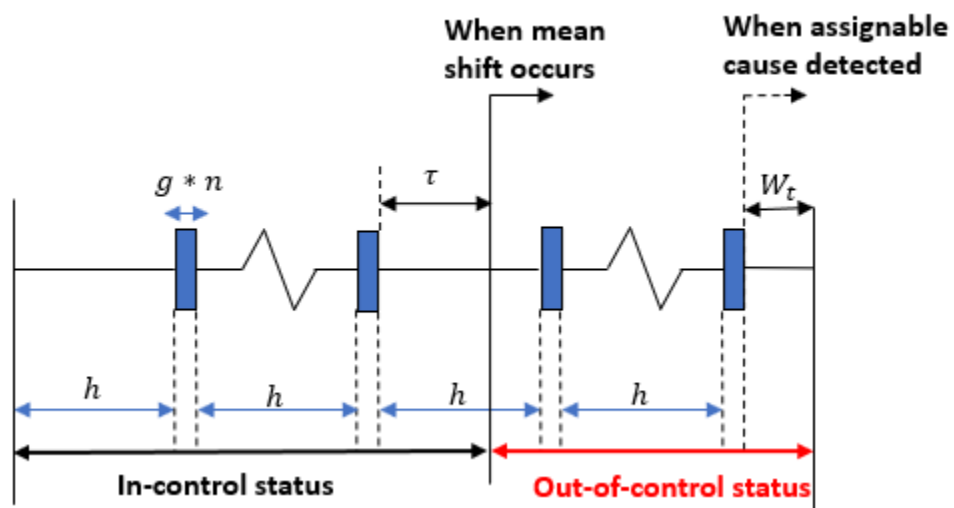


Figure 4.1 Single process cycle

Model Objectives Functions

Objective 1

$$L = \frac{B}{n} + \frac{C}{\bar{u}} + \frac{A}{\Delta^2} \left[\frac{D^2}{3} + \frac{D^2}{\bar{u}} \left(\frac{n+1}{2} + l \right) + \sigma_m^2 \right] \quad (4.4)$$

Objective 1 represent the total quality cost per product where the first term shows the diagnosis cost per product and the second term shows the adjustment cost per product, last term consists of the loss when process in-control and out of control, additional to that measurement error respectively.

Objective 2

$$E(A) = \frac{E(C)}{E(T)} = V_0 - \frac{(a_1 + a_2 n)}{h} - \frac{a_4 \left(\frac{h}{1-\beta} - \tau + gn + W_t \right) + a_3 + \frac{a'_3 \alpha e^{-\lambda h}}{1 - e^{-\lambda h}}}{\frac{1}{\lambda} + \frac{h}{1-\beta} - \tau + gn + W_t} - Br - \frac{C}{D} \quad (4.5)$$

Objective 2 represent the expected net income per hour. First term is the net income per hour of operation in the in-control state V_0 , the second term $(a_1 + a_2 n)$ represent the cost of taking a sample of size n, the third term a_4 represent the penalty cost of operating in the out-of-control state for one hour, third term represent the cost of finding an assignable cause a_3 , fourth term was the cost of investigating a false alarm is a'_3 , fifth term B represent the cost per measurement and last term represents the cost per adjustment over the control limit D .

Objective 3

$$p(s) = \int_{-\infty}^{-k-\delta\sqrt{n}} \Phi(z) dz + \int_{k-\delta\sqrt{n}}^{\infty} \Phi(z) dz \quad (4.6)$$

Objective 3 represent the detection power $p(s)$, where $\Phi(z)$ can be obtained from the prepared table of standard normal cumulative distribution function or from the following formulation

$$\Phi(z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} du \quad (4.7)$$

Model Constrains

In our multi-objective model, the decision variables are sample size (n), the time interval between successive sample (h), the control- limit width in term of standard deviation σ (k) and adjustment or control limit (D). The decision variables in the control chart constrains are n, h, k and D denote by $s = (n, h, k, D)$, For the problem in the aforementioned multi-objective control chart note that $n \in \mathbb{Z}^+$ is discrete and h, k and D are continuous variable such as $h, k, D \in \mathbb{R}^+$. Complex multi-objective decision-making methods using computer algorithm can be applied to select the best compromise solution for the previous mathematical model.

In the multi-objective economic design of the X-bar control chart four decision variables (n, h, k, D) must satisfy also following context: -

$$n_{min} \leq n \leq n_{max} \quad (4.8)$$

The range of sample size (n) is confined between two values one of them will be the minimum and other will be the maximum.

$$h_{min} \leq h \leq h_{max} \quad (4.9)$$

h (the sampling time interval) has a range set between two values and the unit of h is hour.

$$k_{min} \leq k \leq k_{max} \quad (4.10)$$

There is a range for the control limit width of the standard deviation σ .

$$D_{min} \leq D \leq D_{max} \quad (4.11)$$

Adjustment or control limit range will be between two values.

$$p(s) \geq P_L \quad (4.12)$$

Represents the lower bound of the detection power.

$$\alpha(s) \leq \alpha_U, \forall s = (n, h, k, D) \quad (4.13)$$

Represents the upper bound on the type-I error

α_U : the upper bound of the type-1 error.

P_L : the lower bound of the detection power

$p(s)$ shows the power of control chart and α type I error or the probability of false alarm

4.2.3 Adjustment or control limit (parameter D)

In case of a deviation of a quality characteristic from the target, then the process is adjusted to make the quality characteristic be closer to the target. In the United State (Taguchi, G. 1985) in case if there was a deviation from the quality target but non-defective produced then no actions were taken, they are mainly focusing in minimizing the control cost.

On the other hand, in Japan (Taguchi, G. 1985) they focus to minimize the deviation of the quality characteristic from the target. Generally, two factors lead to the optimal solution which are the cost-emphasis and quality-emphasis methods.

In feedback control system, measuring the quality characteristic of the products produced by a process. If the result of the measured quality characteristic differs from the target, then the process condition will be adjusted to make the quality characteristic close to the target. Adjustment and

measurement of the process conditions is costly, and for the feedback control system there were a small number of factories using the quality control which is based on economic matter.

4.3 Numerical Example (parameter D)

The following example was obtained from Montgomery book (2009) and Taguchi (1989).

“It is estimated that the fixed cost of taking a sample is $\$1(a_1)$. The variable cost of sampling is estimated to be $\$0.10$ per item (a_2), and it takes approximately 1 min (0.0167h) to measure and record the wall thickness of an item (g). The magnitude of the shift (δ) is approximately two standard deviations. Process shifts occur at random with a frequency of about one every 20 hours of operation. The exponential distribution with parameter $\lambda= 0.05$ is a reasonable model for the time the process in control. The average time required to investigate an out-of-control signal is 1 hour (W_t). The cost of investigating an action signal that results in the elimination of an assignable cause is $\$25$ (a_3), whereas the cost of investigating a false alarm is $\$50$ (a'_3). the manufacturer estimates that the penalty cost of operating in the out-of-control state for one hour is $\$100$ (a_4)” (Castillo et al., 1996, p. 467-474). Loss due to a defective piece $\$6$ (A), measurement cost $\$ 1.5$ (B), adjustment cost $\$12$ (C), time lag is 3 unit (l), net income per hour of operation in the in-control state is 200 (V_0), observed average adjustment interval (u_0) 180 unit, current control limit $3\mu m$ (D_0), tolerance limit $10 \mu m$ (Δ).”

Constrains

$$2 \leq n \leq 20$$

$$2 \leq k \leq 4$$

$$2 \leq D \leq 3$$

$$\alpha(s) \leq 0.05$$

$$p(s) \geq 0.7$$

The proposed algorithm to solve the model consists of the following main steps and also described in figure 4.2

- 1- Set Range for some decision variables (n,k,D)
- 2- Set values for parameters ($\lambda, B, C \dots$ etc)
- 3- Set the limitations that are involved in fulfilling the objectives (n,k,D, α, p)
- 4- Assign weight for each objective function.

Note that the summation of all objective function weight must be equal to 1.

- 5- Solve the multi-objectives optimization model as single objective for the joint design of SPC and EPC using BARON.

- I. Calculate the values of Taguchi cost objective function.
- II. Calculate the values of the expected income per hour objective function.
- III. Calculate the values of the detection power of the chart objective function.
- IV. Calculate the values of the weighted sum.

- 6- Find the optimal weighted sum.
- 7- Find the optimal Taguchi cost objective function.
- 8- Find the optimal expected income per hour objective function.
- 9- Find the optimal detection power of the chart objective function.
- 10- Find the optimal value of the decision variables (n, h, k, D).
- 11- Find the optimal Pareto chart.

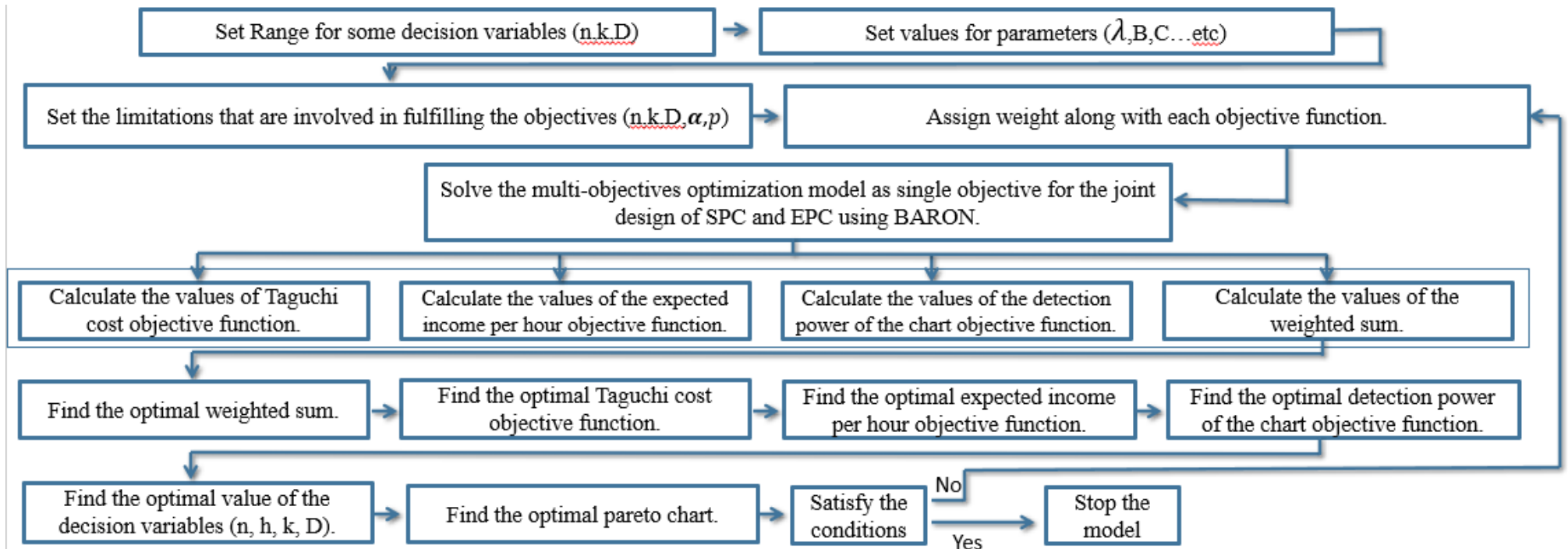


Figure 4.2 The proposed solution algorithm

4.4 Results and Analysis

A program is developed to solve the integrated model which is a multi-objectives optimization model for the joint design of SPC and EPC by using the BARON solver embedded in GAMS software. As the problems in this model are factorable, in the branch-and-reduce algorithm solver (BARON).

Different weights are used for each objective to find the optimal point for each weight. Basically, when the weight is close to 1, the optimal result for the respective objective and when it is close to zero it will give the worst result. A total of 33 experiments were tried for different weights for the objectives functions in Table 4.2 and result at the end with the Pareto optimal points obtained by performing a domination check as shown in Table 4.3. It can be observed from the results in Table 4.2 that the optimal value of the weighed sum is between 0 and 1. The value of interval between samples (h) between 0.5 and 0.85. while the power objective function values are between 0.913732 and 1. However, the values of the expected income objective function fall between 172.0839 and 177.2175. Also, the values of the Taguchi cost objective function are in the range of 4.469333 and 7.907547. These observations can also seen from the Fig 4.3.

The comparison between detection power objective function and the expected net income objective function is shown in the Fig4.4, while Fig4.5 describes the relation between detection power objective function and Taguchi cost objective function. Moreover, Fig4.6 illustrate the relation of Taguchi cost with the expected net income objective function.

Alpha has no proportional relation with the expected income per hour (objective function) and the value of interval between samples (h), such that when alpha decrease then the expected income per hour will increase and the value of interval between samples (h) increase. However, when beta decrease then the power of chart will increase.

Table 4.2 Weighted sum method results

#	Weights			Optimal obj	Taguchi cost	Income	Power	variable			
	W1	W2	W3		obj1	obj2	obj3	N	K	D	h
1	0.1	0.8	0.1	0.10536	7.18868	177.1105	0.97128	4	2.1	3	0.55864
2	0.1	0.7	0.2	0.11285	7.18868	177.1105	0.97128	4	2.1	3	0.55865
3	0.1	0.6	0.3	0.12035	7.18868	177.1105	0.97128	4	2.1	3	0.55865
4	0.2	0.7	0.1	0.18134	6.84776	176.9725	0.97128	4	2.1	2.9	0.55865
5	0.3	0.6	0.1	0.21289	5.31651	176.1105	0.97128	4	2.1	2.4	0.55864
6	0.4	0.5	0.1	0.19480	4.53644	175.3961	0.97126	4	2.1	2.1	0.55864
7	0	1	0	0.00000	7.90755	177.2175	0.91373	3	2.1	3	0.52192
8	1	0	0	0.00001	4.46933	172.0839	0.99929	7	2.1-4	2.1	0.84769
9	0	0	1	0.00000	7.90755	172.0839	1	20	2.1	2.1-3	0.84769
10	0.8	0.1	0.1	0.04554	4.47384	174.9776	0.99744	6	2.1	2.1	0.60673
11	0.1	0.1	0.8	0.04996	4.46933	174.7496	0.99929	7	2.1	2.1	0.62689
12	0.7	0.1	0.2	0.04627	4.47384	174.9776	0.99744	6	2.1	2.1	0.60673
13	0.7	0.2	0.1	0.08629	4.49264	175.2004	0.99115	5	2.1	2.1	0.58480
14	0.2	0.1	0.7	0.04973	4.46933	174.7496	0.99929	7	2.1	2.1	0.62689
15	0.2	0.6	0.2	0.18426	6.51840	176.8247	0.97128	4	2.1	2.8	0.55865
16	0.6	0.3	0.1	0.12490	4.49264	175.2004	0.99115	5	2.1	2.1	0.58481
17	0.6	0.1	0.3	0.04699	4.47384	174.9776	0.99744	6	2.1	2.1	0.60673
18	0.6	0.2	0.2	0.08856	4.49264	175.2004	0.99115	5	2.1	2.1	0.58480
19	0.2	0.2	0.6	0.09266	4.47384	174.9776	0.99744	6	2.1	2.1	0.60673
20	0.3	0.1	0.6	0.04916	4.47384	174.9776	0.99744	6	2.1	2.1	0.60675
21	0.1	0.3	0.6	0.11104	6.17717	176.4702	0.99116	5	2.1	2.7	0.58481
22	0.9	0.05	0.05	0.02343	4.47384	174.9776	0.99744	6	2.1	2.1	0.60675
23	0.05	0.05	0.9	0.02616	4.46933	174.7496	0.99929	7	2.1	2.1	0.62689
24	0.5	0.3	0.2	0.12717	4.49264	175.2004	0.99115	5	2.1	2.1	0.58481
25	0.5	0.2	0.3	0.09049	4.47384	174.9776	0.99744	6	2.1	2.1	0.60673
26	0.5	0.4	0.1	0.16127	4.53644	175.3961	0.97126	4	2.1	2.1	0.55864
27	0.5	0.1	0.4	0.04771	4.47384	174.9776	0.99744	6	2.1	2.1	0.60675
28	0.3	0.5	0.2	0.19839	5.04493	175.8931	0.97128	4	2.1	2.3	0.55864
29	0.2	0.5	0.3	0.17960	5.86717	176.2993	0.99116	5	2.1	2.6	0.58481
30	0.1	0.5	0.4	0.12006	7.17736	176.9147	0.99116	5	2.1	3	0.58481
31	0.4	0.1	0.5	0.04844	4.47384	174.9776	0.99744	6	2.1	2.1	0.60675
32	0.1	0.4	0.5	0.11711	7.17736	176.9147	0.99116	5	2.1	3	0.58481
33	0.3	0.2	0.5	0.09194	4.47384	174.9776	0.99744	6	2.1	2.1	0.60673

Table 4.3 Domination check

#	Weights			Optimal obj	Taguchi cost	Income	Power	Variable			
	W1	W2	W3		obj1	obj2	obj3	N	K	D	h
1	0.1	0.8	0.1	0.10536	7.18868	177.1105	0.97128	4	2.1	3	0.55864
2	0.2	0.7	0.1	0.18134	6.84776	176.9725	0.97128	4	2.1	2.9	0.55865
3	0.3	0.6	0.1	0.21289	5.31651	176.1105	0.97128	4	2.1	2.4	0.55864
4	0.4	0.5	0.1	0.19480	4.53644	175.3961	0.97126	4	2.1	2.1	0.55864
5	0	1	0	0.00000	7.90755	177.2175	0.91373	3	2.1	3	0.52192
6	0	0	1	0.00000	7.90755	172.0839	1	20	2.1	2.1-3	0.84769
7	0.8	0.1	0.1	0.04554	4.47384	174.9776	0.99744	6	2.1	2.1	0.60673
8	0.1	0.1	0.8	0.04996	4.46933	174.7496	0.99929	7	2.1	2.1	0.62689
9	0.7	0.2	0.1	0.08629	4.49264	175.2004	0.99115	5	2.1	2.1	0.58480
10	0.2	0.6	0.2	0.18426	6.51840	176.8247	0.97128	4	2.1	2.8	0.55865
11	0.1	0.3	0.6	0.11104	6.17717	176.4702	0.99116	5	2.1	2.7	0.58481
12	0.3	0.5	0.2	0.19839	5.04493	175.8931	0.97128	4	2.1	2.3	0.55864
13	0.2	0.5	0.3	0.17960	5.86717	176.2993	0.99116	5	2.1	2.6	0.58481
14	0.1	0.4	0.5	0.11711	7.17736	176.9147	0.99116	5	2.1	3	0.58481

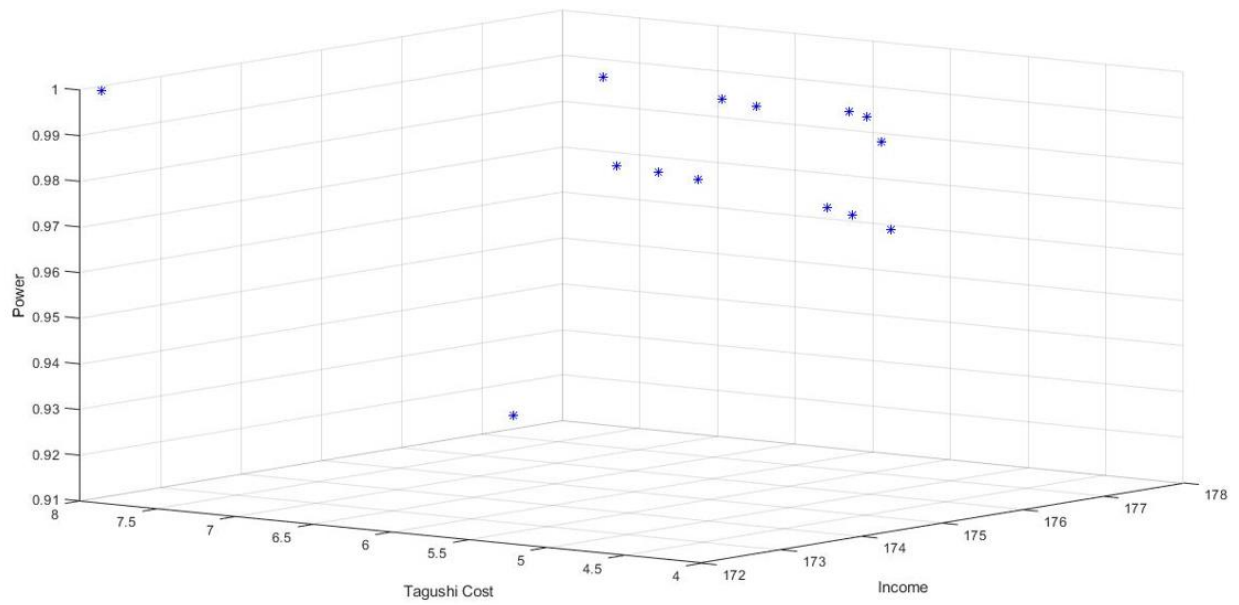


Figure 4.3 Optimal points of the objectives function

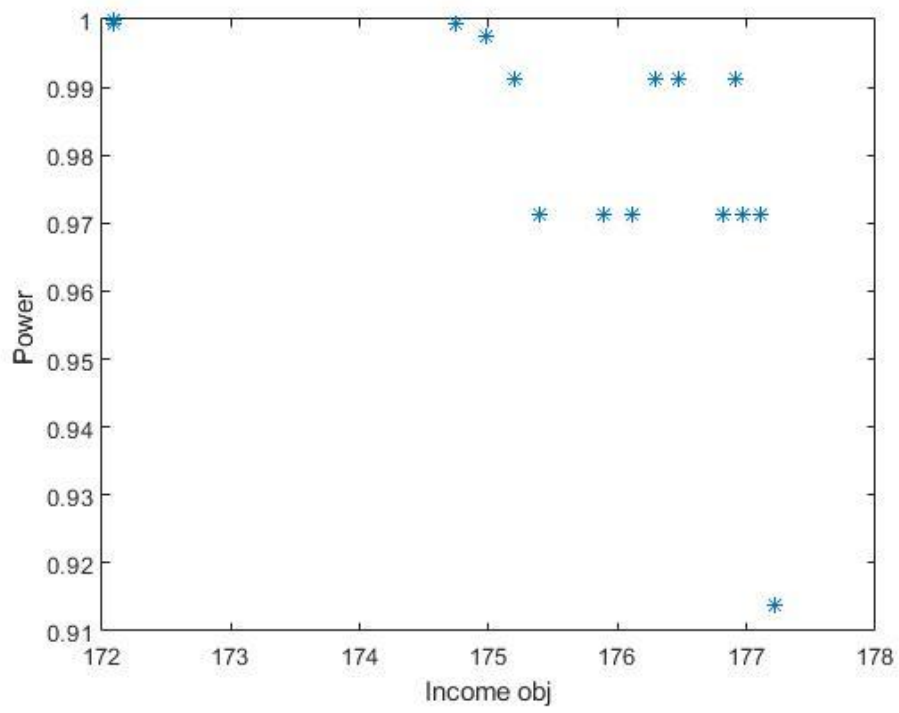


Figure 4.4 Power vs. Income

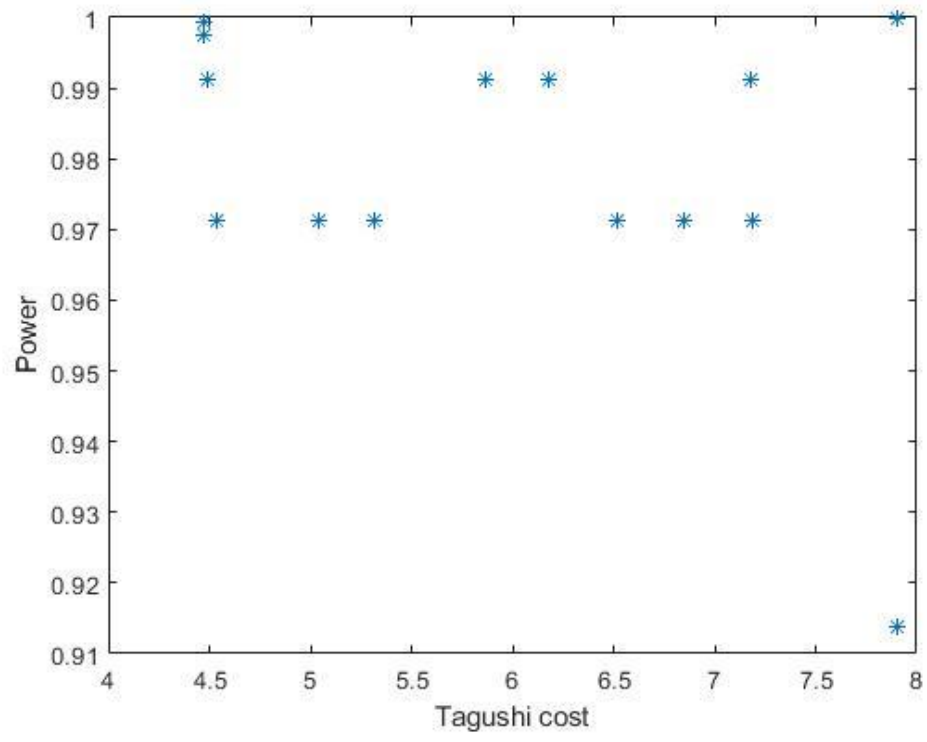


Figure 4.5 Power vs. Taguchi Cost

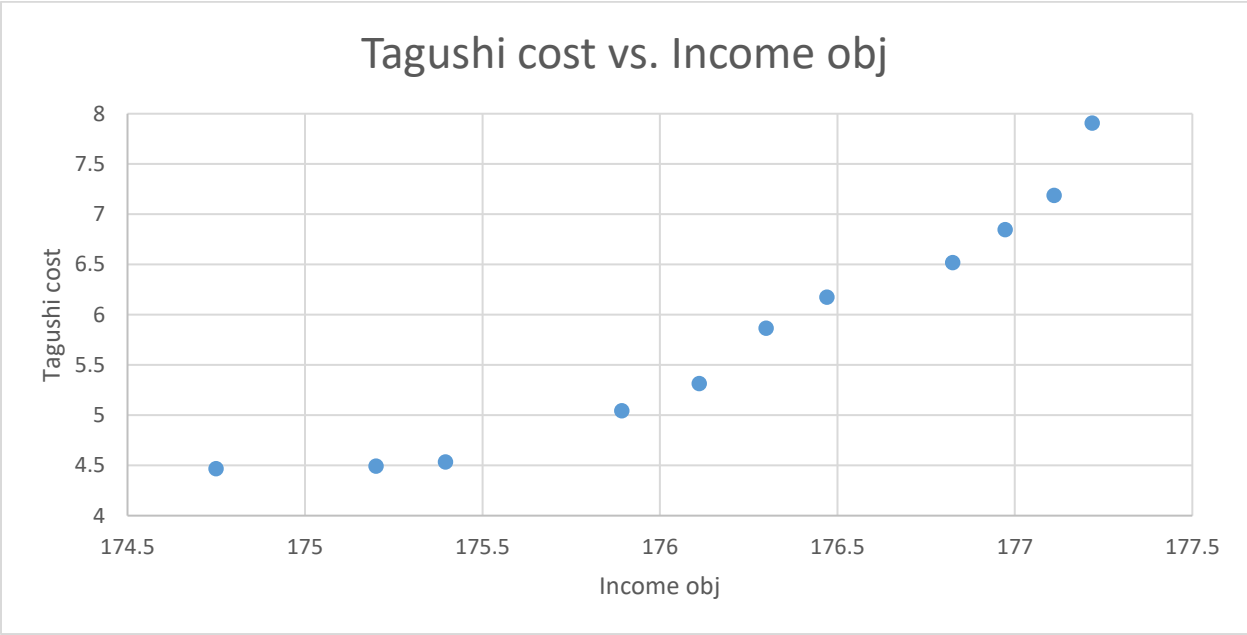


Figure 4.6 Taguchi Cost vs. Income

4.5 Sensitivity Analysis

In this section we will analyze the parameters and see how it will affect the objectives. Figure 4.6 shows that Taguchi cost objective function is proportional to the expected net income objective function and after the expected net income exceeds 176 then it increases rapidly. Next, considering sigma (standard deviation) and see how it effects the power of the chart. As it can be seen in Fig4.7, as the value of sigma increases the value of power is reduced. This is because sigma is inversely proportional to power. Third, it is clear how Taguchi cost is affected when changing in-plant cost as well as the measurement cost as shown in Fig4.8 and Fig4.9. It can be seen as in-plant cost and measurement cost are increased Taguchi cost function is increased as well. This is understandable as in-plant cost (cost of rework or scrap) falls outside the tolerance unit and when that is increased it will increase total cost function. Furthermore, when the cost per measurement of the product characteristic increase then the total cost function will increase because the cost of measurement is part of the total cost function. Finally, as it shown in Fig4.10 and Fig4.11, the expected net income objective function is affected by the penalty cost and the required average time to find the assignable cost. It can be realized as the average time to find the assignable cost and penalty cost are increased then the expected net income objective function is decreased.

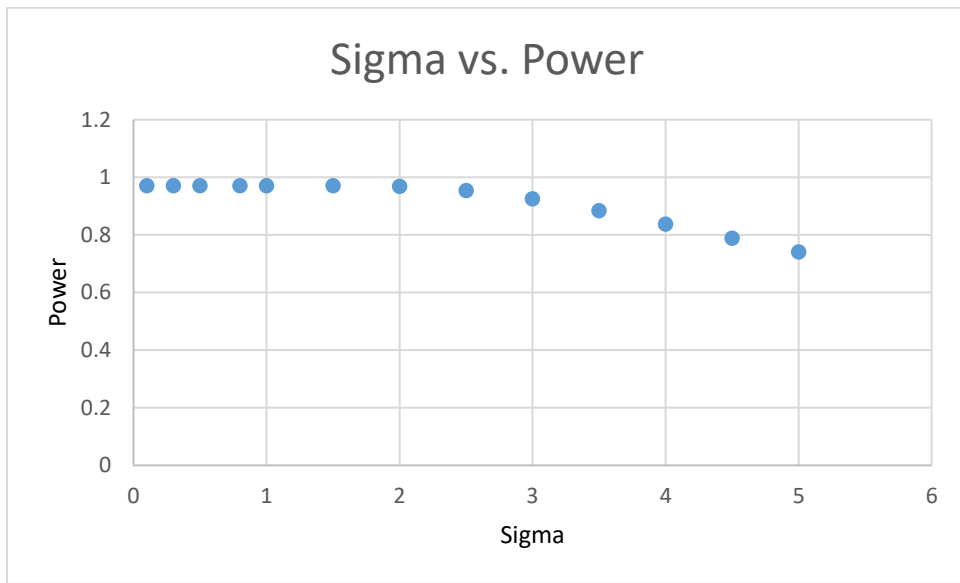


Figure 4.7 Sigma vs. Power

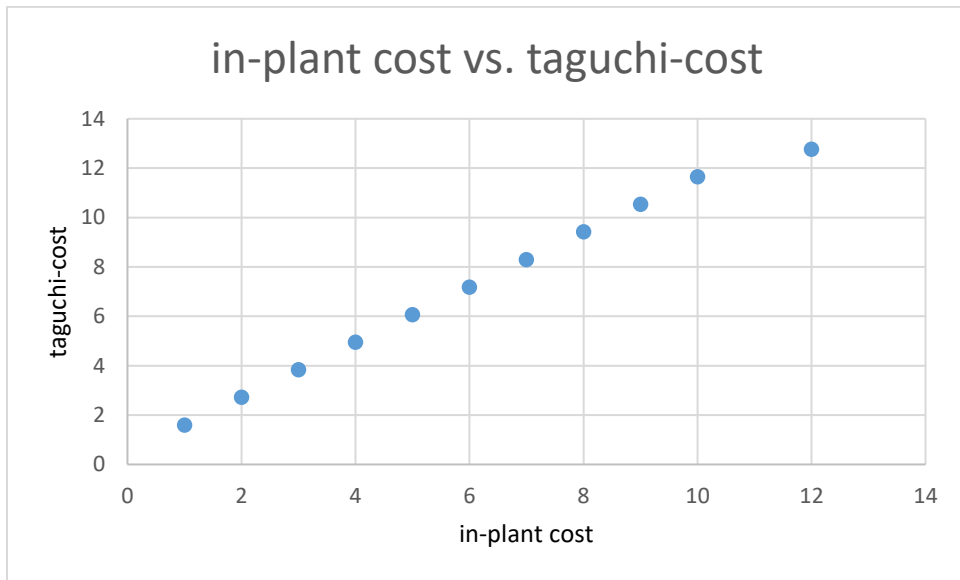


Figure 4.8 In-plant cost vs. Taguchi-cost

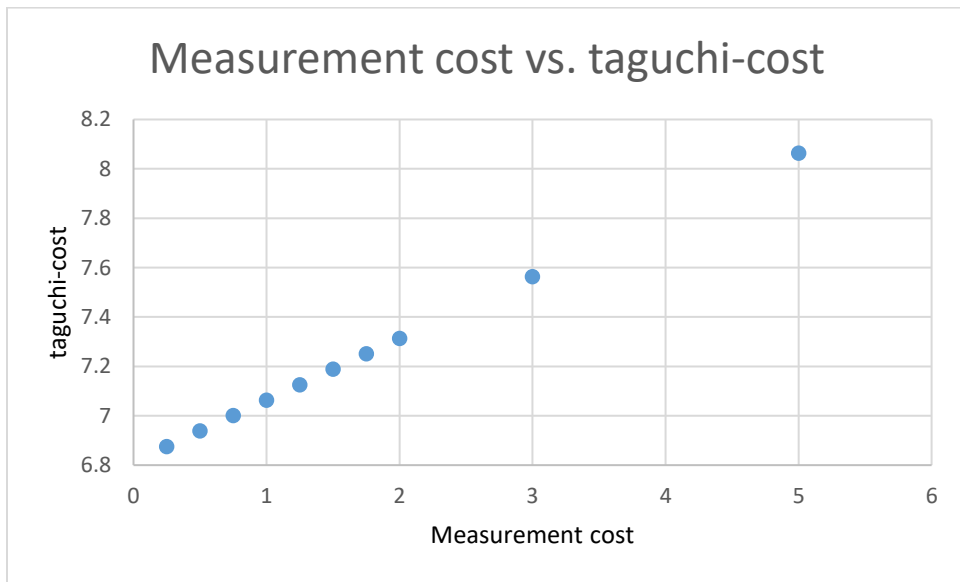


Figure 4.9 Measurement cost vs. Taguchi-cost

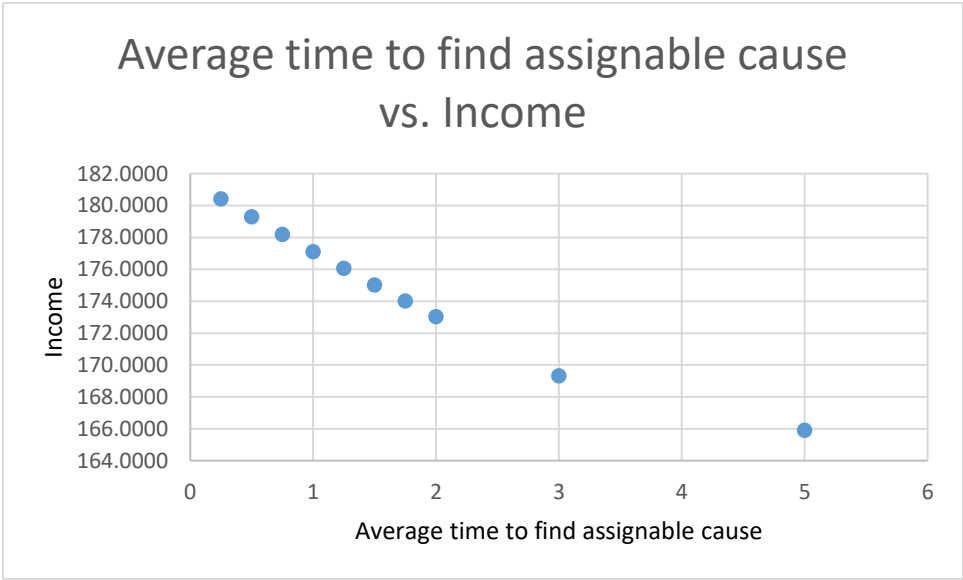


Figure 4.10 Average time to find assignable cause vs. Income

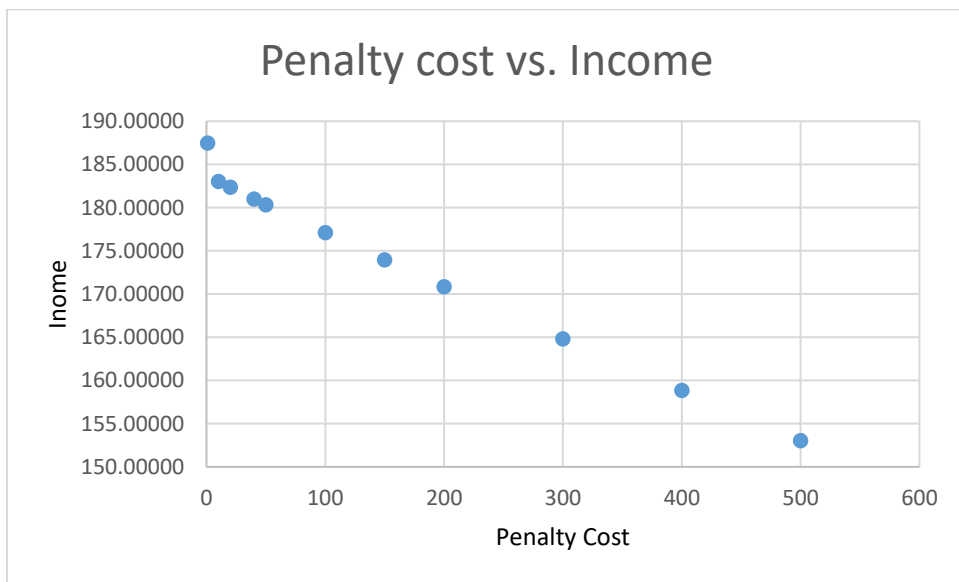


Figure 4.11 Penalty cost vs. Income

CHAPTER 5

CONCLUSION

SPC and EPC are two techniques that complement each other in the area of process control. The goal of Statistical Process Control is to observe the process for assignable causes of variation, detecting them identifying their causes and removing the causes to bring the process in control. However, Engineering Process Control manipulates the process input to minimize the effects of the disturbances to reduce the deviation of the process output from the set target. In this thesis a different types of process control techniques have been presented in the literature review.

A hybrid process control techniques has been developed combining SPC and EPC via a multi-objectives optimization model. The model design both SPC and EPC together to detect faults and control process. To clarify the use of the integrated two process control approaches, a numerical example has been discussed in chapter 4 of the thesis. It has been observed that the integration of SPC and EPC leads to the earliest detection of assignable causes. Furthermore, in order to guarantee the results are held in various situations of assignable causes and are amidst of various EPC controllers a sensitivity analysis has been executed.

To assess the performance of the designed hybrid process control techniques sensitivity analysis is conducted. The algorithm showed the designed technique is robust.

FUTURE WORK

The work in this thesis can be extended further by developing different objectives functions to capture other dimensions of quality.

The resulting model may require developing the algorithm in this thesis further. This may be achieved by utilizing meta-heuristic to obtain global solutions.

The developed model in this thesis could be enhanced by applying it to real cases and other practical situations.

A third direction of extending the model is to consider introducing issues of uncertainties in the multi-objectives model such as the cost of type I and II errors may be unknown and uncertain.

REFERENCES

- [1] Shewhart, Walter Andrew. Economic control of quality of manufactured product. Macmillan And Co Ltd, London, 1931.
- [2] Duncan, A. J. (1956). The economic design of X charts used to maintain current control of a process. *Journal of the American Statistical Association*, 51(274), 228–242.
- [3] Duncan, A. J. (1971). The economic design of charts when there is a multiplicity of assignable causes. *Journal of the American Statistical Association*, 66(333), 107–121.
- [4] Hu, P. W., (1984) "Economic Design of an X Control Chart Under Non- Poisson Process Shift," Abstract, TIMS/ORSA Joint National Meeting, San Francisco, 87.
- [5] Taguchi, G. (1985). Quality Engineering in Japan. *Communications in Statistics - Theory and Methods*, 14(11), 2785–2801.
- [6] Woodall, W. H. (1986). Weaknesses of the economic design of control charts. *Technometrics*, 28(4), 408–409.
- [7] Lorenzen, T. J., & Vance, L. C. (1986). The economic design of control charts: a unified approach. *Technometrics*, 28(1), 3–10.
- [8] Banerjee, P.K., Rahim, M.A. (1988). Economic design of \bar{X} -control charts under Weibull shock model. *Technometrics*. 30:407–414
- [9] Taguchi, Genichi, et al. *Quality Engineering in Production Systems*. McGraw-Hill, 1989.
- [10] Ross, P.J. (1989) *Taguchi Techniques for Quality Engineering*. McGraw Hill, Singapore. G.W. Evans, G.R. Emberton, Bicriterion design of process control charts, *International Journal of Production Economics* 22 (2) (1991) 1411-1500
- [11] Saniga, E. M. (1989). Economic statistical control-chart designs with an application to and R charts. *Technometrics*, 31(3), 313–320.
- [12] W. S. Messina, "Strategies for the integration of statistical and engineering process control," Arizona State University, 1992.
- [13] Amin, R.W. and R.W. Miller (1993). "A Robustness Study of X charts with Variable Sampling Intervals," *Journal of Quality Technology*, Vol.25. PP.36-44

- [14] Chung, K. J. (1994). An algorithm for computing the economically optimal X-control chart for a process with multiple assignable causes. *European Journal of Operational Research*, 72(2), 350–363.
- [15] Castillo, E. D., Mackin, P., & Montgomery, D. C. (1996). Multiple-criteria optimal design of X control charts. *IIE transactions*, 28(6), 467–474.
- [16] Bai, D.S., Lee, K.T. (1998). An economic design of variable sampling interval X control chart. *International Journal of Production Economics* 54: 57-64.
- [17] Celano, G., & Fichera, S. (1999). Multi-objective economic design of an X control chart. *Computers & Industrial Engineering*, 37(1), 129–132.
- [18] Yang, S. and Rahim, M. A. (2000). “Economic statistical design of X and s² control charts: A Markov chain approach”. *Communications in Statistics - Simulation and Computations*, 29, 3, pp. 845–873.
- [19] Jiang, W., Tsui, K.L., 2000. An economic model for integrated APC and SPC control charts. *IIE Transactions* 32 (6), 505–513.
- [20] Kennedy, J., Kennedy, J. F., Eberhart, R. C., & Shi, Y. (2001). *Swarm intelligence*. Morgan Kaufmann.
- [21] Montgomery, Douglas C. (2001), *Design and Analysis of Experiments*, John Wiley & Sons, Inc., New York
- [22] Chen, Y. S., & Yang, Y. M. (2002). Economic design of x-control charts with Weibull in-control times when there are multiple assignable causes. *International Journal of Production Economics*, 77(1), 17–23.
- [23] K. Linderman and A.S. Choo, “Robust economic control chart design,” *IIE Transactions*, vol.34, 2002, pp. 1069-1078
- [24] Chen, Y. K., & Liao, H. C. (2004). Multi-criteria design of an X control chart. *Computers & Industrial Engineering*, 46(4), 877–891.
- [25] Bakir, M. A. & Altunkaynak 2004. The optimization with the genetic algorithm approach of the multi-objective, joint economical design of the x and R control charts. *Journal of Applied Statistics*, 31,753-772.
- [26] Duffuaa, S.O., Khursheed, S.N. and Noman, S.M. (2004) ‘Integrating statistical process control, engineering process control, and Taguchi’s quality engineering’, *Int. J. Product Research*, Vol. 42, No. 19, pp.4109–4118.
- [27] Chen, Y.K., 2004. Economic design of X⁻ control charts for non-normal data using variable sampling policy. *International Journal of Production Economics* 92, 61–74.

- [28] Gulbay, M., Kahraman, C., and Ruan, D., “ α -Cut Fuzzy Control Charts for Linguistic Data”, *International Journal of Intelligent Systems* 19, 1173–1195 (2004).
- [29] Yu FJ (2005) An economic design for a variable-sampling-interval X control chart for a continuous-flow process. *International journal of advanced manufacturing technology*. 25(3–4): 370–376
- [30] Zarandi, M.H.F., Alaeddini, A., Türksen, I.B. and Ghazanfari, M. (2007) “A neuro-fuzzy multi-objective design of Shewhart control charts”, *Proceedings of Analysis and Design of Intelligent Systems using Soft Computing Techniques*, 41, pp.842–852.
- [31] V. B. Vommi, S.N. Murty Seetala, “A new approach to robust economic design of control charts”. *Applied Soft Computing*, Vol.7, 2007, 211-228.
- [32] L. Yang and S. Sheu, “Economic design of the integrated multivariate EPC and multivariate SPC charts,” *Quality and Reliability Engineering International*, vol. 23, 2007, pp. 203-218.
- [33] V. B. Vommi, S.N. Murty Seetala, “A simple approach for robust economic design of control charts”. *Computers and Operations Research*, Vol.34, 2007, 2001-2009.
- [34] Li, Z., Kapur, K. C., & Chen, T. (2009). A new approach for multi-criteria design of an X control chart. In *Proceedings of the 8th international conference on reliability, maintainability and safety (ICRMS)* (pp. 1364–1367).
- [35] Montgomery, D., 2009. *Introduction to statistical quality control*, 6th edition.
- [36] Asadzadeh, S., & Khoshalhan, F. (2009). Multiple-objective design of an X control chart with multiple assignable causes. *The International Journal of Advanced Manufacturing Technology*, 43(3-4), 312–322.
- [37] Sun, Q. and Wang, X. (2010) ‘Economic design of integrating SPC and APC with quality constraints’, *Proceedings of 2010 Chinese Control and Decision Conference (CCDC)*, Xuzhou, China, 26–28 May 2010, pp.69–72.
- [38] Akram, M.A. (2011) ‘Process enhancement through integrated statistical and automatic process control techniques’, MSc thesis, Systems Engineering Department, King Fahd University of Petroleum & Minerals, p.171
- [39] Saif AW, Akram MA, Rahim MA (2011) A fuzzy integrated SPC/APC scheme for optimized levels of process quality, performance and robustness. *Int J Exp Design Proc Optim* 2(2):161–189

- [40] Safaei, A. S., Kazemzadeh, R. B., & Niaki, S. T. A. (2012). Multi-objective economic statistical design of X control chart considering Taguchi loss function. *The International Journal of Advanced Manufacturing Technology*, 59(9-12), 1091–1101.
- [41] Yang, W. A., Guo, Y., & Liao, W. (2012). Economic and statistical design of and S control charts using an improved multi-objective particle swarm optimization algorithm. *International Journal of Production Research*, 50(1), 97–117.
- [42] Park M, Kim J, Jeong MK, Hamouda AMS, Al-Khalifa KN, Elsayed EA (2012) Economic cost models of integrated APC controlled SPC charts. *Int J Prod Res* 50(14):3936–3955
- [43] Akram, M.A., Saif, A-W.A. and Rahim, M.A. (2012) ‘Quality monitoring and process adjustment by integrating SPC and APC: a review’, *Int. J. of Industrial and Systems Engineering*, Vol. 11, No. 4, pp.375–405.
- [44] Faraz, A., & Saniga, E. (2013). Multi-objective genetic algorithm approach to the economic statistical design of control charts with an application to X and S(square) Charts. *Quality and Reliability Engineering International*, 29(3), 407–415.
- [45] Bashiri, M., Amiri, A., Doroudyan, M.H. and Asgari, A., "Multi-objective genetic algorithm for economic-statistical design of X control chart", *Scientia Iranica*, Vol. 20, No. 3, (2013), 909-918.
- [46] Lupo, T (2014). Economic-statistical design approach for a VSSI X chart considering Taguchi loss function and random process shifts. *Int. J. Reliab. Q. Saf. Eng.*,
- [47] Abdul-Wahid A. Saif, "The Need for Integrating Statistical Process Control and Automatic Process Control". The 9th 2014 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM2014), 9-12 December 2014, Selangor, Malaysia.
- [48] Mobin, M., Li, Z., & Massahi Khoraskani, M. (2015). Multi-objective X control chart design by integrating NSGA-II and data envelopment analysis. In *Proceedings of the 2015 industrial and systems engineering research conference (ISERC)* (pp. 1–10).
- [49] Safaei AS, Kazemzadeh RB, Gan H (2015) robust economic-statistical design of X control chart. *Int J Prod Res* 53(14):4446–4458
- [50] M. Moghaddam, S. Chan, N. Das, S. Kim, D. Entekhabi, and R. Akbar. (2016) A multi-objective optimization approach to combined radar-radiometer soil moisture estimation. In *IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, pages 3074–3077.
- [51] Bakhtiarifar, M.H., Amiri, A. and Alaeddini, A. (2017) ‘Economic-statistical design of X Shewhart control charts with fuzzy parameters’, *J. of Intelligent & Fuzzy Systems*, Vol. 32, No. 13, pp.3961–3971.

- [52] Seif, A. (2018). Multi-objective genetic algorithm for economic statistical design of the T2 control chart with variable sample size: The updated Markov chain approach. *Journal of Testing and Evaluation*, 46, 1209–1219.
- [53] Bobby John, Shreya Singhal, (2019) "An application of integrated EPC–SPC methodology for simultaneously monitoring multiple output characteristics", *International Journal of Quality & Reliability Management*.
- [54] Mahdi Imanian, Mahdi Karbasian, and Aazam Ghassemi (2020) 'Managed Pressure Drilling Using Integrated Process Control ', *Iranian Journal of Oil & Gas Science and Technology*,

Vitae

Name	OMAR HAMOUD AHMED DEHWAH
Email	Odehwah@gmail.com
Address	Dhahran, Saudi Arabia
Academic Background	M.S. (SYSTEM ENGINEERING) KFUPM B.S. (SYSTEM ENGINEERING) KFUPM