FAULT DETECTION AND DIAGNOSIS VIA
IMPROVED MULTIVARIATE STATISTICAL PROCESS CONTROL

NOORLISA BINTI HARUN

UNIVERSITI TEKNOLOGI MALAYSIA

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NOORLISA BINTI HARUN

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In the Name of Allah, Most Gracious, Most Merciful.

I humbly dedicate to…
my beloved family members
my best friend
those who has shaped my life and
those who has influenced my life on the right path.

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ABSTRACT

Multivariate Statistical Process Control (MSPC) technique has been widely used for fault detection and diagnosis (FDD). Currently, contribution plots are used as basic tools for fault diagnosis in MSPC approaches. This plot does not exactly diagnose the fault, it just provides greater insight into possible causes and thereby narrow down the search. Hence, the cause of the faults cannot be found in a straightforward manner. Therefore, this study is conducted to introduce a new approach for detecting and diagnosing fault via correlation technique. The correlation coefficient is determined using multivariate analysis techniques, namely Principal Component Analysis (PCA) and Partial Correlation Analysis (PCorrA). An industrial precut multicomponent distillation column is used as a unit operation in this research. The column model is developed using Matlab 6.1. Individual charting technique such as Shewhart, Exponential Weight Moving Average (EWMA) and Moving Average and Moving Range (MAMR) charts are used to facilitate the FDD. Based on the results obtained from this study, the efficiency of Shewhart chart in detecting faults for both quality variables (Oleic acid, x_{c8} and linoleic acid, x_{c9}) are 100%, which is better than EWMA (75% for x_{c8} and 77.5% for x_{c9}) and MAMR (63.8% for x_{c8} and 70% for x_{c9}). The percentage of exact faults diagnoses using PCorrA technique in developing the control limits for Shewhart chart is 100% while using PCA is 87.5%. It shows that the implementation of PCorrA technique is better than PCA technique. Therefore, the usage of PCorrA technique in Shewhart chart for fault detection and diagnosis gives the best for it has the highest fault detection and diagnosis efficiency.

ABSTRAK

Proses Kawalan Statistik Multipembolehubah (*MSPC)* digunakan secara meluas untuk mengesan dan mengenalpasti punca kesilapan. Pada masa kini, carta penyumbang digunakan untuk mengenalpasti punca kesilapan dalam *MSPC*. Carta ini tidak dapat mengenalpasti punca kesilapan dengan tepat yang mana ia sekadar menunjukkan kemungkinan besar punca kesilapan dan membantu memudahkan pencarian punca kesilapan. Oleh itu, punca kesilapan tidak dapat ditentukan secara langsung. Justeru, kajian ini telah dijalankan bagi memperkenalkan satu pendekatan baru untuk mengesan dan mengenalpasti punca kesilapan melalui teknik korelasi. Pekali korelasi ditentukan melalui kaedah Analisis Statistik Multipembolehubah iaitu Analisis Komponen Utama *(PCA)* dan Analisis Korelasi Separa *(PCorrA)*. Turus penyulingan multikomponen industri digunakan sebagai operasi unit. Model turus ini dibangunkan menggunakan perisian Matlab 6.1. Teknik carta individu yang terdiri daripada Shewhart, *Exponential Weight Moving Average (EWMA)*, dan *Moving Average* dan *Moving Range (MAMR)* digunakan bagi mengesan dan mengenalpasti punca kesilapan. Berdasarkan kepada keputusan yang diperolehi, kecekapan carta Shewhart dalam mengesan kesilapan untuk kedua-dua pembolehubah kualiti (Asid oliek, x_{c8} dan asid linoleik, x_{c9}) adalah 100% yang mana lebih baik berbanding dengan carta *EWMA* (75% bagi x_{c8} and 77.5% bagi x_{c9})dan carta *MAMR* (63.8% bagi x_{c8} and 70% bagi x_{c9}). Peratusan mengenalpasti punca kesilapan secara tepat menggunakan teknik PCorrA bagi carta Shewhart adalah 100% manakala PCA adalah 87.5%. Ini menunjukkan bahawa penggunaan teknik PCorrA adalah lebih baik berbanding teknik PCA. Oleh itu, penggunaan teknik PCorrA dalam carta Shewhart bagi tujuan mengesan dan mengenalpasti punca kesilapan adalah yang terbaik dengan peratusan kecekapan yang paling tinggi.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

a_{ij}	-	Wilson constant
n	-	Number of retained principal component
A	-	Square matrix
A_b	-	Bottom column area
A_t	-	tray active area
A_i, B_i, C_i	-	Antoine constant for component i
A^*, B^*, C^*, D^*	-	Constant for liquid heat capacity
$A_2,\ D'_{.001},\ D'_{.999}$	-	Constant for MA and MR control limit
β	-	Weighting factor
B	-	Bottom flow rate
$C_{j,k}$	-	Correlation coefficient between variable j and variable k
δ	-	Shifted value in standard deviation unit
D	-	Distillate flowrate
F_{Detect}	-	Fault Detection
$F_{Diagnose}$	-	Fault Diagnosis
ΔH_{vap}	-	Heat of vaporization
$\Delta H_{vap,n}$	-	Heat of vaporization at normal boiling point
h_N	-	Liquid enthalpy leaving each tray
h_b	-	Enthalpy for bottom stream
h_{ow}	-	Over weir height
H, h	-	CuSum control limits
H_N	-	Vapor enthalpy leaving each tray

$\mathbf{I}$	-	Identity matrix
K_c	-	Controller Gain
K_p	-	Static Gain,
L_{28}	-	Liquid flowrate at tray 28
$L_{H,\,P}$	-	Pumparound drum height
L_f	-	Liquid feed flowrate
$L_{H,\,Re}$	-	Reflux drum liquid level
$L_{H,\,B}$	-	Bottom liquid level
L	-	Width of the control limit
M	-	Number of observations
M_{B}	-	Bottom molar hold-up
MW	-	Molecular weight
M_{Re}	-	Reflux drum molar hold-up
M_P	-	Pumparound drum molar hold-up
M_N	-	Molar hold up at tray N
N	-	Number of stages
p	-	Number of observations
P	-	Pumparound flowrate
P_{ci}	-	Critical pressure of component i
P_i^{sat}	-	Vapor pressure for component i
P_{tot}	-	Total pressure of the system
ρ	-	Liquid density
Q_R	-	Reboiler heat duty
Q	-	Number of variables for response variables
$\mathbf{R}$	-	Correlation matrix
$\mathbf{r_{j,k}}$	-	Correlation value between variable j and variable k
Re	-	Reflux flowrate
R	-	Universal gas constant
r_k	-	Autocorrelation coefficient

S	-	Sidedraw flowrate
$\mathbf{S}$	-	Variance-Covariance matrix
$\mathbf{s}_{j,k}$	-	Covariance value of variable *j* and variable *k*
s	-	NOC standard deviation
T	-	Temperature of the system
T_{ci}	-	Critical temperature of component *i*
T_{ri}	-	Reduced temperature of component *i*
$T_{b,i}$	-	Boiling point for component *i*
$T_{\boldsymbol{APC}}$	-	APC sampling time
$T_{\boldsymbol{SPC}}$	-	SPC sampling time
$\mathbf{t}$, $\mathbf{u}$	-	Latent vectors
τ	-	Time Constant
τ_D	-	Derivative Time Constant
τ_I	-	Integral Time Constant
θ	-	Dead time
$\mathbf{V}$	-	Eigenvector matrix
$\mathbf{v}$	-	Eigenvector or loading vectors
V	-	Vapor flowrate
V_{ci}	-	Critical volume for component i
V_i	-	Liquid molar volume of component *i*
W_L	-	Weir length
ω	-	Critical accentric factor of component *i*
$\mathbf{w}$	-	Un-normalized eigenvectors
$\bar{x}$	-	NOC mean
$\bar{x}_1$	-	Shifted mean
x_i	-	i^{th} observation in the process
$x_{\boldsymbol{ij}}$	-	Value of the *i-th* row and *j-th* column matrix
x_{ij}^s	-	Standardized variable
x	-	Liquid phase mole fraction

x_S	-	Sidedraw mole fraction
x_{Re}	-	Reflux mole fraction
x_P	-	pumparound liquid mole fraction
x_D	-	Distillate mole fraction
γ_i	-	Liquid phase activity coefficient for component *i*
y	-	Vapor phase mole fraction
z_i	-	The i^{th} EWMA statistic
Z_{ci}	-	Critical compressibility factor for component *i*
ϕ_i	-	Vapor fugacity coefficient for component *i*
Λ_{ij}	-	Wilson binary interaction parameter for component *i* and *j*

LIST OF ABBREVIATIONS

APC	-	Automatic Process Control
DoF	-	Degree of Freedom
EWMA	-	Exponential Weight Moving Average
FDD	-	Fault Detection and Diagnosis
ISPC	-	Improved Statistical Process Control
MA	-	Moving Average
MESH	-	Mass, Equilibrium, Summation, Heat
MR	-	Moving Range
MSA	-	Multivariate Statistical Analysis
MSPC	-	Multivariate Statistical Process Control
NIPALS	-	Non-iterative Partial Least Squares
NOC	-	Normal Operating Condition
OC	-	Out of Control
PCA	-	Principal Component Analysis
PCorrA	-	Partial Correlation Analysis
PV	-	Process Variable
QV	-	Quality Variable
SPC	-	Statistical Process Control
USPC	-	Univariate Statistical Process Control

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Introduction

A major technological challenge facing the processing industries is the need to produce consistently high quality product. This is particularly challenging in high demanding situations where processes are subject to varying raw material properties, changing market needs and fluctuating operating conditions due to equipment or process degradation. The need to provide industry with techniques, which enhance process performance, will require new methodologies to be adopted that are capable of being used across a spectrum of industrial processing operations and on a wide range of products (Simoglou *et al.*, 2000).

Modern industrial processes typically have a large number of operating variables under closed loop control. These loops used to compensate for many types of disturbances and to counteract the effect of set point change. This is necessary to achieve high product quality and to meet production standards. Although these controllers can handle many types of disturbances, there are faults in the process such as line blockage, line leakage, sensor fault, valve fault and controller fault that cannot be handled adequately. In order to ensure that process is operating at normal operating condition as required, faults must be detected, diagnosed and removed. These activities, and their management, are called as Statistical Process Control, SPC (Miletic *et al*., 2004).

The combination of Statistical Process Control (SPC) charts and multivariate analysis approach is used for Fault Detection and Diagnosis (FDD) in the chemical process. Principal Component Analysis (PCA) and Partial Correlation Analysis (PCorrA) are the techniques used in this study. A precut multicomponent distillation column that has been installed with controllers is used as the study unit operation. Improved Statistical Process Control method is implemented to detect and diagnose various kinds of faults, which occur in the process.

1.2 Research Background

Statistical methods are used to monitor the performance of the process over time in order to detect any process shifts from the target. Most of Statistical Process Control (SPC) techniques involve operations on single response variables such as weight, pH, temperature, specific gravity, concentration and pressure. This traditional SPC is used to monitor and verify that the process remains in statistical control based on small number of variables. The state of statistical control means that the process or product variables remain close to the target. Normally the fault in the process is seek through the usage of SPC chart, i.e., the final product quality variables. Measuring quality variables alone are not enough to describe the process performance (Kourti *et al*., 1996). In this study, both quality variables and process variables are monitored. This can be done by developing the correlation coefficient between quality variables and process variables using multivariate analysis technique. In traditional SPC, once the quality variables detected out of statistical control signal, it is then left up to process operators and engineers to try to diagnose the cause of out of control using their process knowledge (MacGregor and Kourti, 1995).

Chemical processes are becoming better instrumented with the advances of process sensors and data acquisition systems. There are massive amount of data being collected continuously and these variables are often correlated. Multivariate statistical analysis has been developed in order to extract useful information from process data and utilize it for process monitoring (Kresta *et al*., 1991). Normally, multivariate statistical analysis technique is combined with SPC chart using Hotelling' s T^2 and Q statistics to plot the graph for fault detection and diagnosis. Even though this conventional method provides good results for fault detection, there is difficulty in applying this method to diagnose faults because it does not provide a causal description of the process that can be used as the basis for fault diagnosis. Currently, contribution plots are used as the basic tools for fault diagnosis in the multivariate statistical approaches. However, this plot cannot exactly diagnose the cause but it just provides greater insight into possible causes and thereby narrows the search. The cause of the faults cannot be found in a straightforward manner.

To overcome the limitation of contribution plot using multivariate analysis technique to diagnose fault, Improved SPC chart is introduced in this study. Multivariate analysis approach is applied in the SPC realm procedure to detect and diagnose the faulty condition in different approach. The multivariate analysis method is used to develop the control limits of SPC charts. The correlation coefficient calculated from multivariate analysis technique is applied to improve the SPC chart. The quality variables data is incorporated in the control chart during the faulty condition for fault detection purpose, while the process variables which has been correlated with the quality variables is used for fault diagnosis. Therefore, the Improve SPC charts applied is not only for quality variables but also for process variables. By monitoring the process variables, the cause of faulty condition, which affects the quality variables, could be identified directly. This will help the operator to take proper action immediately after faults exist in the process.

1.3 Objectives of the Research

1. To determine the performance of the Improved Statistical Process Control charts; which are Shewhart individual and Shewhart range, Exponential Weight Moving Average (EWMA) and Moving Average and Moving Range (MAMR) chart for fault detection.
2. To utilize multivariate analysis technique, Principal Component Analysis (PCA), and Partial Correlation Analysis (PCorrA), for developing the relationship between the process variable(s) and the quality variable(s) for fault diagnosis.

1.4 Scopes of the Research

The scopes of the research are:

1. A simulated precut multicomponent distillation column model from the literature is used as a case study. The model consists of controllers with various kinds of disturbances and operating conditions.
2. A set of Normal Operating Condition (NOC) data and a set of Out of Control (OC) data are generated using this simulated distillation column.
3. Normal operating statistical model is developed using the multivariate techniques, PCA and PCorrA via correlation coefficient approach between the quality variable(s) and the process variable(s).
4. The Shewhart individual and Shewhart range, Exponential Weight Moving Average (EWMA), and Moving Average and Moving Range (MAMR) charts are developed.
5. The faulty condition is incorporated into the process model in order to see the performance of the control charts to detect the fault(s) and to find the cause of the fault(s).

6. The results of fault detection and diagnosis are then discussed further.

1.5 Contributions of the Research

In this research, a new approach known as Improved Statistical Process Control for fault detection and diagnosis is introduced. Multivariate analysis technique, Principal Component Analysis, PCA and Partial Correlation Analysis, PCorrA are used to develop the correlation coefficient between quality variables and process variables. This technique is incorporated in the Improved SPC chart as a fault diagnosis tools to find the cause of the faulty condition. Improved SPC charts are applied for both quality variables and process variables which have been correlated with quality variables of interest.

1.6 Chapter Summary

This thesis contains seven chapters. The first chapter comprises of the introduction of the research, research background, objectives of the research, scopes of the research and contributions of this research. Chapter 2 reviews the multivariate analysis techniques and the concept of multivariate analysis technique used in this study, which are Principal Component Analysis (PCA) and Partial Correlation Analysis (PCorrA).

Chapter 3 consists of the concept of Statistical Process Control, SPC chart, detail explanation on SPC charts; Shewhart, EWMA and MAMR and the way to construct these charts. This chapter also presents the implementation of multivariate analysis technique in SPC chart to develop Improve SPC chart.

Chapter 4 expresses the reasons for choosing distillation column as the case study. This chapter also presents the dynamic modeling of the columns, formulation of dynamic simulating algorithm, establishment of dynamic simulation program, controller tuning and explanation on Automatic Process Control, APC time sampling. The performances of the written simulation program are compared with HYSYS simulator.

Chapter 5 mainly contains the procedure for fault detection and diagnosis. This chapter contains variables selection to perform process fault detection and diagnosis, determination of SPC sampling time, generating of normal operating condition data, out of control data and the development of correlation coefficient using PCA and PCorrA to relate the quality variables with process variables.

Chapter 6 presents the result and discussion of the research. The results are systematically presented. Discussions are made on the performance of each Improved SPC chart to detect known fault in the process and the efficiency of the proposed method to conduct fault diagnosis with application of multivariate statistical analysis. Chapter 7 contains the conclusions of the research and suggestions to the future SPC research activities.

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