# SYNERGISTIC ARTIFICIAL NEURAL NETWORK SCHEME FOR MONITORING AND DIAGNOSIS OF MULTIVARIATE PROCESS VARIATION IN MEAN SHIFTS

MOHD FAIRUZ BIN MARIAN

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To Haji Marian bin Ibrahim, Hajah Noraini binti Abdullah, Hajah Rosminah binti Bibet, Zuliazura binti Haji Mohd Salleh and Dhia Diyanah binti Mohd Fairuz

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# ABSTRACT

In quality control, monitoring and diagnosis of multivariate out of control condition is essential in today's manufacturing industries. The simplest case involves two correlated variables; for instance, monitoring value of temperature and pressure in our environment. Monitoring refers to the identification of process condition either it is running in control or out of control. Diagnosis refers to the identification of source variables ($X_1$ and $X_{2)}$ for out of control. In this study, a synergistic artificial neural network scheme was investigated in quality control of process in plastic injection moulding part. This process was selected since it less reported in the literature. In the related point of view, this study should be useful in minimizing the cost of waste materials. The result of this study, suggested this scheme has a superior performance compared to the traditional control chart, namely Multivariate Exponentially Weighted Moving Average (MEWMA). In monitoring, it is effective in rapid detection of out of control without false alarm. In diagnosis, it is able to accurately identify for source of variables. Whereby, diagnosis cannot be performed by traditional control chart. This study is useful for quality control practitioner, particularly in plastic injection moulding industry.

# ABSTRAK

Pada hari ini dalam kawalan kualiti industri pembuatan, pemantauan dan diagnosis keadaan pembolehubah berbilang yang berada di luar kawalan adalah sangat penting. Sebagai contoh  kes termudah adalah melibatkan dua pembolehubah yang berkait, seperti pemantauan nilai suhu dan tekanan dalam persekitaran kita. Pemantauan merujuk kepada pengenalpastian keadaan proses sama ada ianya berjalan dalam kawalan atau di luar kawalan. Diagnosis merujuk kepada pengenalpastian sumber pembolehubah ($X_1$ atau $X_2$) yang terletak pada keadaan luar kawalan. Dalam kajian ini, satu skema rangkaian neural tiruan sinergistik telah dikaji bagi kawalan kualiti dalam proses penghasilan komponen plastik acuan suntikan. Proses ini dipilih kerana ianya kurang dilaporkan dalam kajian literatur terdahulu. Dalam masa yang, kajian ini boleh digunakan dalam mengurangkan kos pembaziran bahan. Keputusan kajian menunjukkan bahawa skema ini mepunyai prestasi yang lebih baik berbanding carta kawalan tradisional yang dinamakan Purata Bergerak Pemberat Exponen Pembolehubah Berbilang (MEWMA). Dalam pemantauan, skema dapat mengesan dengan pantas keadaan luar kawalan tanpa amaran palsu. Dalam diagnosis, skema boleh mengenalpasti sumber pembolehubah. Di mana diagnosis ini tidak boleh dilakukan oleh carta kawalan tradisional. Kajian ini berguna kepada pengamal kawalan kualiti terutamanya dalam industri plastik acuan suntikan.

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# LIST OF SYMBOLS

| | | |
|---|---|---|
| $\alpha$ | - | Type I error ($\alpha$ risk) |
| $\beta$ | - | Type II error ($\beta$ risk) |
| $\lambda$ | - | Constant parameter for EWMA control chart |
| $\rho$ | - | Correlation coefficient for bivariate process |
| $\mu$ | - | Mean |
| $\sigma$ | - | Standard deviation |
| $\mu_0$ | - | Mean for in-control samples |
| $\sigma_0$ | - | Standard deviation for in-control samples |
| $\sigma_{ij}$ | - | Covariance for bivariate samples |
| $\sum$ | - | Covariance matrix for bivariate samples or basic summation |
| $X_t$ | - | Original observation samples at time/point t |
| $Z_t$ | - | Standardized observation samples at time/point t |
| $N$ | - | Random normal variates |
| $\overline{x}$ | - | Sample mean |
| $H_0$ | - | Null hypothesis |

# CHAPTER 1

# INTRODUCTION

## 1.1 Research Background

Poor quality due to process variation is known as a major issue in manufacturing processes. Manufacturing process may involve two or more correlated variables and an appropriate procedure is required to monitor these variables simultaneously. These techniques are often referred as multivariate SPC (MSPC) procedures. The main problem of multivariate quality control charts is that they can detect an out of control event but do not directly determine which variable or group of variables has caused the out of control signal and how much is the magnitude of out of control. Incorporating pattern recognition in the control charting scheme can address this problem. With a certain control chart pattern (CCP), the diagnosis search can be shortened if one has knowledge of the CCP type (e.g., a shift or a trend) and corresponding knowledge of which process factors could cause these CCPs. Therefore, timely recognition of CCPs is a crucial task in SPC for determining the potential assignable causes.

Various artificial neural networks (ANN)-based pattern recognition schemes have been developed for monitoring and diagnosis of multivariate process variation in mean shifts. In literatures, since late 1980s, control chart pattern recognition (CCPR) has become an active area of research. However, there is a lack of updated critical review on such issues. Therefore, this paper proposed a synergistic ANN scheme for monitoring and diagnosis of multivariate process variance in mean shifts. To achieve 'balanced monitoring and accurate diagnosis', this study proposes a synergistic multivariate exponentially weighted moving average (MEWMA)-ANN scheme for two-phases monitoring and diagnosis of some reference multivariate patterns.

## 1.2 Problem Statement

In manufacturing industries, process variation is known to be a major source of poor quality. As such, process monitoring and diagnosis is critical towards continuous quality improvement. This becomes more challenging when involving two or more correlated variables (multivariate). Process monitoring refers to the identification of process status either it is running within a statiscally in-control or out-of-control condition, whereas process diagnosis refers to the identification of the source variables of out-of-control process. The traditional statiscal process control (SPC) charting schemes were known to be effective in monitoring aspect. Nevertheless , they are lack of diagnosis. In recent years, the artificial neural network (ANN) based pattern recognition schemes are mainly ultilize either a generalized (single) model ANN pattern recognizer and/or raw data based input representation, which resulted in limited performance. In this study, an integrated ANN model that is called "Synergistic" pattern recognizer involves ultilization of raw data-based and statistical features input representations.

## 1.3 Project Objectives

The objectives of this project are:

i. To investigate the effectiveness of the synergistic ANN pattern recognition scheme in monitoring and diagnosing process variation in mean shifts.
ii. To evaluate the performance of the scheme in comparison with traditional control chart.

## 1.4 Project Scopes

This research proposal project scope is listed as below:

i. Multivariate quality control cases are limited to bivariate process, which is only two correlated variable being monitored and diagnosed.
ii. Bivariate process variables are dependent to each other based on linear cross correlation (ρ).
iii. In a statically out-of-control condition, predictable bivariate process patterns are limited to sudden shifts (upward shift and downward shift) in the source variables.
iv. Magnitudes of mean shifts in the source variables are limited within ± 3 standard deviations based on control limits of Shewhart control chart.
v. The foundation modeling and simulation for bivariate correlated samples are based on established model (Lehman, 1977), whereas the validation tests are performed using industrial data.

## 1.5 Summary

SPC Control chart have been known to be a good tool in quality control. However traditional SPC control chart was used only for process monitoring and identifying process variation. The drawback for conventional control charts was that they rely on currently observed data not on previous data sets. In addition, they cannot identify and indicate whether there is any special disturbance in process. Today, advance SPC charting demand for better statistical analysis capability especially for multivariate cases through control chart pattern identification. The development in statistical software technology has encouraged investigation on the application of artificial neural network (ANN) for automated pattern recognition of control chart patterns (CCPs). The namely synergistic ANN scheme developed should be capable to identify the source of multivariate process variation rapidly and correctly with minimum false alarm. The primary objective is to enable develop an ANN-based scheme for monitoring with minimum false alarm and high performance in recognition accuracy.

## 1.6 Dissertation Outline

This project was summarized in Figure 1.1. The first chapter describes the introduction of the project. This is followed by an extensive literature review in Chapter 2 that provided background information in the related fields and research trends leading to the current issue addressed in this project. Chapter 3 then presents the project methodology adopted for carry out the focused objectives. In Chapter 4 the proposed methodologies were then applied into, design development and testing for the synergistic scheme, performance results and evaluation later then discusses. The conclusions and recommendations are highlighted in the final chapter.

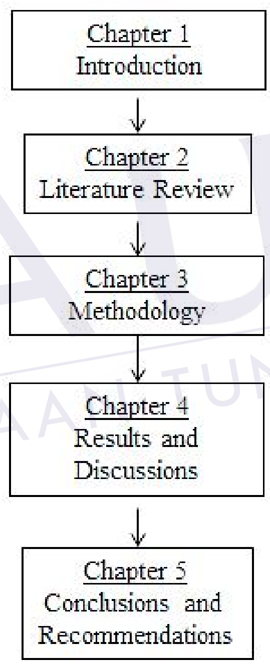


Figure 1.1: Dissertation outline

# CHAPTER 2

# LITERATURE REVIEW

This chapter provided the reviews of the concept of SPC control chart monitoring and diagnosis. It were also review the investigation and development of previous multivariate statistical process control (MSPC) scheme in term of raw data-based input, statistical feature input representations and scheme improvement. In conclusion, explanation on why the design of synergistic ANN model recognizers was chosen to improve the monitoring-diagnostic capability was given.

## 2.1 Introduction

Nowadays, manufactures are on pressure to produce products that have high quality but with a low cost. Product cost and quality were influenced by many factors and one of the factors that strongly influence both was manufacturing process variation. These variations exist because no production process is perfect and usually controlling this variation was done by implementing process quality control especially by using SPC.

The main concern of process quality control is to achieve and maintain an acceptable level of the desired process quality characteristic consistently. In this connection, accurate monitoring and control of the manufacturing system is very important. Commonly, eight types of control chart patterns (CCPs), as shown in Figure 2.1 were encountered in different manufacturing environments (Masood & Hassan, 2010).

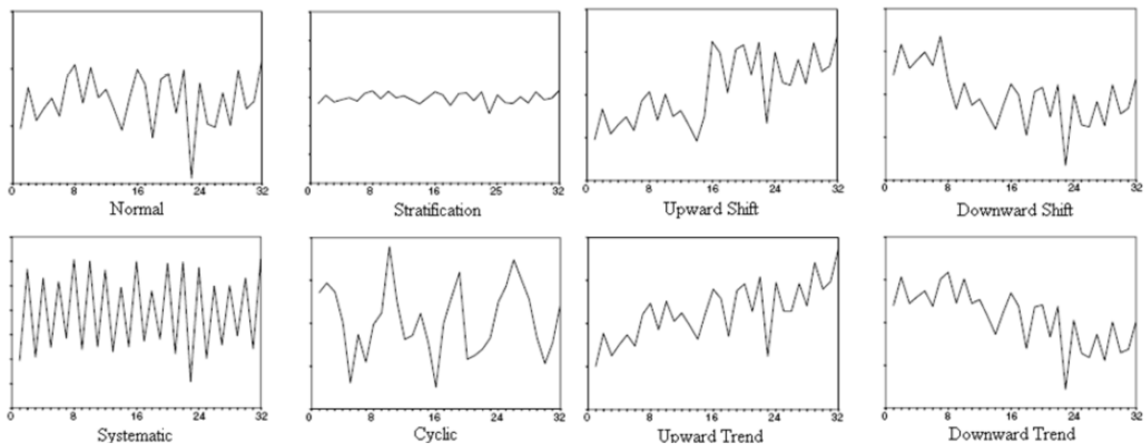


Figure 2.1: Various control chart patterns

The patterns can be classified as natural/normal and unnatural/abnormal (Montgomery, 2013). The basic significance of a natural pattern is that it indicated a process under control. Unnatural patterns identified a process when it is out control. Natural causes are considered to be due to the inherent nature of normal process. Assignable causes are defined as unnatural shock to the processes, which should identify and eliminated as soon as possible in order to narrow down and shorten the length of diagnosis process (Yu & Xi, 2009). However, recognition of unnatural patterns found to be a critical task in SPC (Wenhai & Dwayne, 1992). Over the years, numerous numbers of studies have been study and suggesting the quality control practitioners to detect unnatural control chart patterns. Nevertheless, this suggestion is unworthy due to lack of experience, knowledge and skill to identify, interpret and analysis the unnatural patterns from the practitioners. Moreover this scenario results in excessive number of false alarm. This is happening most of the times on the shop floor people implement the control charts.

The usual practice has been to maintain a separate (univariate) chart for each characteristic. Unfortunately, this can give some misleading result when the quality characteristic is highly correlated. One of the solutions to overcome this issue is to extend the univariate analysis by plotting a statistic that measures the overall deviations of the multivariate observations from the target (Chen & Wang, 2004).

## 2.2 Process Variation

Process variation is known to be a major source of poor quality (Zainal Abidin & Masood, 2012). Traditionally, statistical process control (SPC) was used to monitor and identify process variation. Advances, variation reduction efforts as such process monitoring and diagnosis should be critically applied towards quality improvements (Masood & Hassan, 2009).

Variation may be defined as any unwanted condition or as the difference between a current and a desired end-state. Both product performance and manufacturing processes exhibit variation. Wear and tear, vibration, machine breakdown, inconsistent raw material and lack of human operators' skills are the common sources of variation in manufacturing process. To manage and reduce variation, the variation must be traced back to its source. Variation occurs in all natural and man-made processes. If variation cannot be measured, it is only because the measurement systems are of insufficient precision and accuracy. Process variance reduces the capacity of the industries because processes become either under- or over-utilized. Process variance reduces the ability to detect potential problems and increases the difficulty of discovering the root cause of problems.

The causes of variation in product performance and manufacturing processes are varying by the type of technology, its maturity, and the experience of the organization and its suppliers. Variation in manufacturing processes causes significant expense in nearly every industry. Variation during production results in products that are not truly identical and thus do not perform identically in the marketplace. Some units were performing as expected, but others may fail early and incur additional costs. Some may even be unsafe and lead to recalls and lawsuit. To prevent these outcomes, manufacturers often expand large sums reworking products to address problems arising from process variation. Almost all of these costs can be eliminated by addressing the root cause; the focus of efforts should be on reducing variation in the process as opposed to reacting to the unfortunate outcomes of variation. Tools such as statistical experimental design, analysis, and statistical process control, can be used to improve process control and reduces variation, delivering impressive bottom line savings.

## 2.3 Quality Engineering

Quality may be defined in many ways. Quality has become one of the most important consumer decision factors in the selection among competing products and services (Haridy & Wu, 2009). Therefore, understanding and improvement quality are key factors leading to business success, growth and enhanced competitiveness. Quality engineering is the set of operational, managerial and engineering activities that a manufacturer uses to ensure that the quality characteristics of a product are the nominal or required levels that match customer expectations. Quality characteristics can be divided into several types as mentioned by Montgomery (2013).

1. **Physical** : depth, width, current, hardness
2. **Sensory**: colour, smell, taste
3. **Time orientation**: reliability, durability, serviceability

Most of manufacturers find it hard to provide the customer with high quality characteristics of a product that are always identical from unit to unit. This is called variability. No two products are identical. Since variability can only be described in statistical terms, statistical analysis methods play as a backbone in quality improvement methods. Among the others statistical method known, Statistical Process Control (SPC) is one of the most widely used tools for quality control and improvement in manufacturing industries (Chen *et al.*, 2007). The origin of SPC dates back to the 1920s and 1930s at the Western Electric Company and Bell Telephone Laboratories. There are chart for variables data (measurement data) and charts for attributes data (count data). The diagram of basic SPC tools classification illustrates in Figure 2.2.

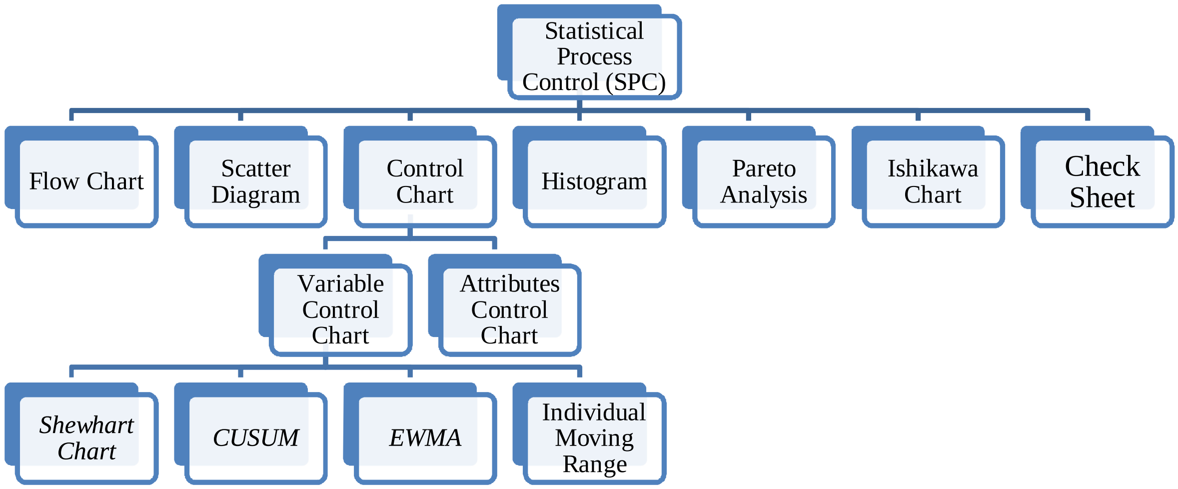


Figure 2.2: Basic statistical process control tools specification

## 2.4 Statistical Process Control (SPC)

SPC is a technique used in a manufacturing environment to ensure quality parts are produced. Montgomery (2013) highlighted statistical process control is one of the most effective tools of total quality management whose main function is to monitor and minimize process variations. There are many ways to implement process control. Key monitoring and investigating tools include:

i. Histograms
ii. Check Sheets
iii. Pareto Charts
iv. Cause and Effect Diagrams
v. Defect Concentration Diagrams
vi. Scatter Diagrams
vii. Control Charts

A control chart is the primary tool of SPC and is basically used to monitor the process characteristics, e.g., the process mean and process variability (Duncan, 1988, Montgomery, 2013). The most common types of variable control charts for variables include: (1) Average and Range (X bar and R) Charts (2) Average and Standard Deviation (X and S) Charts (3) Individual and Moving Range (X and MR) Charts .Among applied tools, Shewhart control chart are the most widely applied SPC tools used to reveal abnormal variations of monitored measurements (Yu & Xi, 2009). The uses of control charts are to plot measurements of part dimensions being produced. These charts are used to alert the operator to shifts in the mean of the measurement. The measurements are also used to compute process capability indexes such as $C_{pk}$ and $C_p$. The definition of the $C_p$ given in Equation (2.1) implicitly assumes that the process is centered at the nominal dimension.

$$Cp = \frac{USL-LSL}{6\sigma} \qquad (2.1)$$

If the process is running of center, its actual capability will be less than indicated by the $C_p$. It is convenient to think of $C_p$ as a measure of potential capability, that is, capability with centered process. If process is not centered, a measure of actual capability is often used. This ratio is called $C_{pk}$ as defined in Equation (2.2).

$$Cp = min[\frac{USL-\mu}{3\sigma}, \frac{\mu-LSL}{3\sigma},] \qquad (2.2)$$

In effect, $C_{pk}$ is a one-sided Process Capability Ratio (PCR) that is calculated relative to the specification limit nearest to the process mean. Montgomery (2013) provides guidelines on appropriate values of the PCR and relating fallout for a normally distributed process in statistical control to the value of $C_p$. Many big company use $C_p$ =1.33 as a minimum acceptable target and $C_p$ =1.66 as a minimum target for strength, safety or critical characteristic, some company require that internal processes and those at suppliers achieve a $C_{pk}$ =2.0. The indexes indicate how good a process is at producing parts that meet specification. Upon the out-of control is alarmed, the assignable causes for the abnormal process need to be identified and removed in order to bring the process back to normal. A stable production process is the key element of quality improvement. Depending on the number of process characteristics to be monitored, there are two basic types of control charts, Univariate Control Chart and Multivariate Control Chart.

### 2.5 Univariate Statistical Process Control (USPC)

USPC is the monitoring and control of one quality necessary. In normal application this is usually practice by separating each quality characteristic and analysis their control chart independently (Masood & Hassan, 2010). This will take more time and give some misleading result when the characteristics are highly correlated (El-Midany *et al.*, 2010).

There are few types of Control Charts that have been developed. Shewhart charts are sensitive to large process shifts and the probability of detecting small mean shifts fast is rather small. The CUSUM (Cumulative Sum) chart is very effective for small shifts but has disadvantages where CUSUM is relatively slow to respond to large shifts. Also, special patterns are hard to see and analyze. The Exponentially Weighted Moving Average (EWMA) is a statistic for monitoring the process that averages the data in a way that gives less and less weight to data as they are further removed in time. In contrast, attempting to monitor such variables separately using univariate SPC charting scheme would increase false alarms and leading to wrong decision making. However, monitoring each process variable with separate Shewhart control chart ignores the correlation between variables and does not fully reflect the real process situation. Nowadays, the process industry has become more complex than it was in the past and inevitably that number of process variables need to be monitored has increased dramatically. Thus only monitor a single parameter or output at a time. Therefore they cannot detect changes in the relationship between multiple parameters. Very often, these variables are multivariate in nature and using Shewhart control charts becomes insufficient. One approach to overcome these downsides is to extend the univariate analysis by plotting a statistic that measures the overall deviations of the multivariate observations from the target.

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