PATTERN RECOGNITION FOR MANUFACTURING PROCESS VARIATION USING STATISTICAL FEATURES ARTIFICIAL NEURAL NETWORK

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ABSTRACT

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).The traditional statistical process control (SPC) charting schemes are known to be effective in monitoring aspect but nevertheless, they are lack of diagnosis. In recent years, the control chart pattern recognition (CCPR) schemes have been developed for solving this issue. Design consideration involved the modeling of manufacturing process data to select input representation based on raw data. Proper design of artificial neural network (ANN) model is important in developing an effective CCPR scheme. In this research, the multivariate model ANN pattern recognizer, namely Statistical Features – ANN was investigated in monitoring and diagnosing process variation in manufacturing of hard disc drive component. The finding suggests that the scheme was effective to be applied in various types of process variation such as loading error, offsetting tool, and inconsistent pressure in clamping fixture.

ABSTRAK

Dalam industri pembuatan, proses variasi diketahui sebagai sumber utama produk berkualiti rendah. Oleh itu, pemantauan dan proses diagnosis adalah penting ke arah peningkatan kualiti berterusan. Hal ini menjadi lebih mencabar apabila melibatkan dua atau lebih pembolehubah berhubung kait (multivariat). Skim tradisional carta kawalan proses statistik (SPC) diketahui berkesan dalam aspek pemantauan, namun tidak dapat membuat diagnosis. Kebelakangan ini, skim carta corak kawalan (CCPR) telah dibangunkan untuk menyelesaikan isu ini. Reka bentuk melibatkan pemodelan data proses pengeluaran untuk memilih perwakilan input berdasarkan data mentah. Reka bentuk yang betul model rangkaian neural tiruan (ANN) adalah penting dalam membangunkan skim CCPR yang berkesan. Dalam kajian ini, multivariat model ANN pengecam corak dinamakan *Statistical Features – ANN* digunakan dalam memantau dan diagnosis proses variasi dalam pembuatan komponen pemacu cakera keras. Dapatan kajian menunjukkan bahawa skim ini adalah berkesan untuk diaplikasikan dalam pelbagai jenis proses variasi seperti ralat pemasangan bahan kerja, ralat pemasangan mata alat, dan tekanan yang tidak konsisten pada pengapit.

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CHAPTER 1

INTRODUCTION

1.1 Research Background

In order to achieve global competitive advantage, every organization is trying to improve its product quality at each stage of the manufacturing process. It is well known that variation in manufacturing processes has become a major source of poor quality. Wear and tear, vibration, machine breakdown, inconsistent material and lack of human operators are typical sources of process variation (Masood & Hassan, 2009). Manufacturing processes may involve two or more correlated variable and an appropriate procedure is required to monitor these variables simultaneously. This issue is sometimes called multivariate quality control (MQC) and it has opened the basis for extensive research in the field of multivariate statistical process control (MSPC), 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 has caused the out of control signal and how much is the magnitude of out of control. Therefore, this paper proposed a Statistical Feature ANN scheme for monitoring and diagnosis of multivariate process variance in mean shift.

1.2 Problem Statement

In manufacturing, process monitoring and diagnosis is critical towards continuous quality improvement. This becomes more challenging when it involving two correlated variables. Process monitoring refers to the identification of process status either it is within in-control or out-of – control. Process diagnosis refers to the identification of the source variables of out-of-control process. The traditional statistical process control charts (SPC) were known to be effective in monitoring aspects. Nevertheless, they are lack of diagnosis. In recent years, the artificial neural network (ANN) has been developed to solve this problem (Montgomery, 2001). Thus, this study focuses on the an integrated ANN model that is called Statistical Features- ANN.

1.3 Objective of Study

The objectives of this research are:

i. To design a Statistical Features-ANN pattern recognition scheme for monitoring and diagnosis manufacturing process variation.
ii. To evaluate the performance of the scheme in actual manufacturing process application.

1.4 Research Scope

The scopes can be summarized as:

i. Multivariate quality control cases are limited to bivariate process, which is only two correlated variable being monitored and diagnosed.

ii. Bivariate process variable are dependent to each other based on linear cross correlation (ρ)

iii. In a statistically out-of-control condition, predictable bivariate process patterns are limited to upward shift only.

iv. Magnitude of mean shifts in the source variables are limited within ± 3 standard deviations based on control limits of Shewhart control chart.

v. Design and modeling of input data representation in training and pre-testing ANN-based model are based on Lehman (1977) model, whereas the validation tests are performed using three types of variation in process manufacturing for computer Hard Disc Drive (HDD).

CHAPTER 2

LITERATURE REVIEW

This chapter provided the reviews of the concept of SPC control chart monitoring and diagnosis. The traditional SPC chart(s) role for monitoring the existence of unnatural variation in bivariate process, whereas an ANN model roles for diagnosing the sources of variation. In that case, an ANN model is utilized only when necessary, that is, when an out-of-control signal is triggered. An ANN model is continuously utilized, for triggering out-of-control signal and then, for identifying the sources of variation. In conclusion, explanation on why the Statistical Feature - ANN model recognizers was chosen to improve the monitoring and diagnostic in manufacturing process.

2.1 Introduction

In the production HDD, the production process is carried out continuously. Therefore, at regular time intervals, samples of data will be taken to investigate the variation and validate the pattern recognition on the production of HDD.

If a product is to meet or exceed customer expectations, generally it should be produced by a process that is stable or repeatable. More precisely, the process must be capable of operating with little variability around the target or nominal dimensions of the product's quality characteristics. Statistical process control (SPC) is a powerful collection of problem-solving tools useful in achieving process stability and improving capability through the reduction of variability. SPC is one of the greatest technological developments of the twentieth century because it is based on sound underlying principles, is easy to use, has significant impact, and can be applied to any process. Its seven major tools are the histogram or stem-and-leaf plot, the check sheet, the Pareto chart, the cause-and-effect diagram, the defect concentration diagram, the scatter diagram, and the control chart.

2.2 Process Variation

Process variation is known to be a major source of poor quality. 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, 2012).

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 (Masood & Hassan, 2012) . 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.

In any production process, regardless of how well designed or carefully maintained it is, a certain amount of inherent or natural variability will always exist. This natural variability or "background noise" is the cumulative effect of many small, essentially unavoidable causes. In the framework of statistical quality control, this natural variability is often called a "stable system of chance causes." A process that is operating with only chance causes of variation present is said to be in statistical control. In other words, the chance causes are an inherent part of the process. Other kinds of variability may occasionally be present in the output of a process. This variability in key quality characteristics usually arises from three sources: improperly adjusted or controlled machines, operator errors, or defective raw material. Such variability is generally large when compared to the background noise, and it usually represents an unacceptable level of process performance. We refer to these sources of variability that are not part of the chance cause pattern as assignable causes of variation. A process that is operating in the presence of assignable causes is said to be an out-of-control process.

These chance and assignable causes of variation are illustrated in Fig. 2.1. Until time t_1 the process shown in this figure is in control; that is, only chance causes of variation are present. As a result, both the mean and standard deviation of the process are at their in-control values (say, μ_0 and σ_0). At time t_1 an assignable cause occurs. As shown in Fig. 2.1, the effect of this assignable cause is to shift the process mean to a new value $\mu_1 > \mu_0$. At time t_2 another assignable cause occurs, resulting in $\mu = \mu_0$, but now the process standard deviation has shifted to a larger value $\sigma_1 > \sigma_0$. At time t_3 there is another assignable cause present, resulting in both the process mean and standard deviation taking on out-of-control values. From time t_1 forward, the presence of assignable causes has resulted in an out-of-control process. Processes will often operate in the in-control state for relatively long periods of time. However, no process is truly stable forever, and, eventually, assignable causes will occur, seemingly at random, resulting in a shift to an out-of-control state where a larger proportion of the process output does not conform to requirements. For example, when the process is in control, most of the production will fall between the lower and upper specification limits (LSL and USL, respectively). When the process is out of control, a higher proportion of the process lies outside of these specifications. (Mastenbroek, 2010)

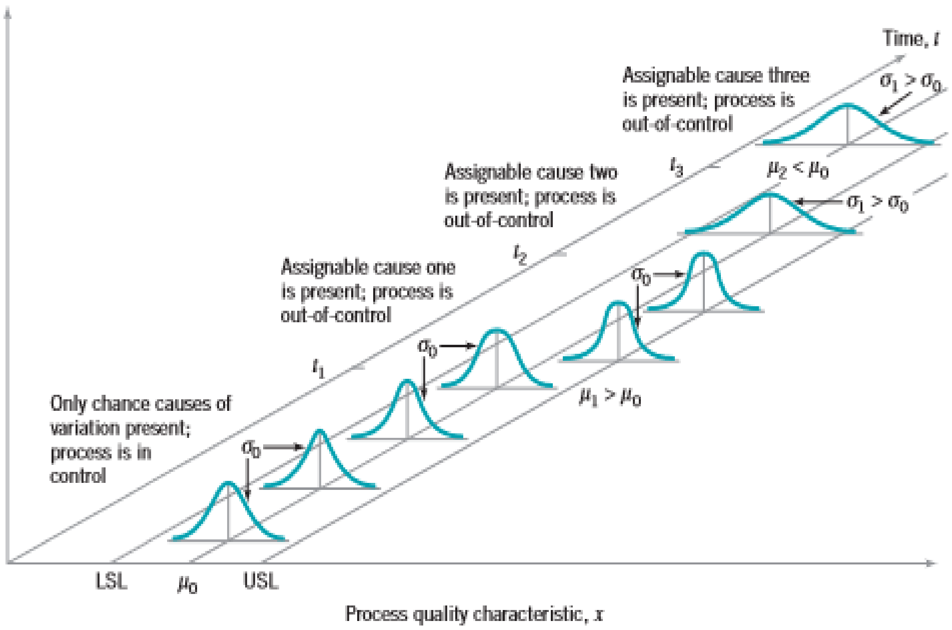


Figure 2.1 : Chance and assignable causes of variation.

A major objective of statistical process control is to quickly detect the occurrence of assignable causes of process shifts so that investigation of the process and corrective action may be undertaken before many nonconforming units are manufactured. The control chart is an on-line process-monitoring technique widely used for this purpose. Control charts may also be used to estimate the parameters of a production process, and, through this information, to determine process capability. The control chart may also provide information useful in improving the process. Finally, the eventual goal of statistical process control is the elimination of variability in the process. It may not be possible to completely eliminate variability, but the control chart is an effective tool in reducing variability as much as possible.

2.3 Statistical Process Control (SPC)

Statistical process control (SPC) is one of the most effective tools quality management (TQM), which is used to monitor and minimize process variations. The concepts of Statistical Process Control (SPC) were initially developed by Dr. Walter Shewhart of Bell Laboratories in the 1920's, and were expanded upon by Dr. W. Edwards Deming, who introduced SPC to Japanese industry after WWII. After early successful adoption by Japanese firms, Statistical Process Control has now been incorporated by organizations around the world as a primary tool to improve product quality by reducing process variation. Dr. Shewhart identified two sources of process variation: Chance variation that is inherent in process, and stable over time, and Assignable, or Uncontrolled variation, which is unstable over time - the result of specific events outside the system. Dr. Deming relabeled chance variation as Common Cause variation, and assignable variation as Special Cause variation.

Control charts are the most widely applied SPC tools used to reveal abnormal variations of monitored measurements. Common causes are considered to be due to the inherent nature of normal process. Assignable causes are defined as abnormal shock to the processes, which should be identified and eliminated as soon as possible. When an abnormal variation is signaled by control chart, quality practitioners or engineers search for the assignable causes and take some necessary correction and adjustments to bring the out-of-control process back to the normal state. In many quality control settings, the manufacturing process may have two or more correlated quality characteristics and an appropriate approach is needed to monitor all these characteristics simultaneously. The usual practice has been to maintain a separate chart for each characteristic. However, this could result in some fault out-of-control alarms when the characteristics are highly correlated.

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, as shown in Fig. 2.2.

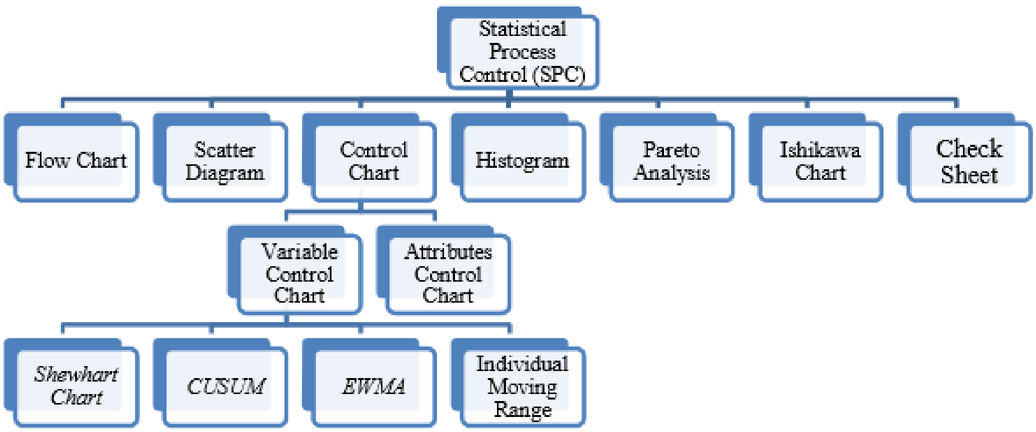


Figure 2.2 : Basic statistical process control tools specification

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.

In order to achieve global competitive advantage, every organization is trying to improve its product quality at each stage of the manufacturing process. Statistical process control (SPC) is one of the most effective tools of total quality management, which is used to monitor process variations and improve the quality of production. Control charts, mostly in the form of X bar chart, are widely used as aids in maintaining quality and achieving the objective of detecting trends in quality variation before defective parts/products are actually produced. In any continuous manufacturing process, variations from the established standards are mainly of two types. One is assignable cause variation, such as those due to faulty manufacturing equipment or irresponsible personnel or defective material or a broken tool. The other one is normal chance variation, resulting from the inherent non-uniformities that exist in machines or operators or materials or processes. The X bar chart usually exhibits various types of patterns, e.g., normal (NOR), stratification (STA), systematic (SYS), increasing trend (UT), decreasing trend (DT), upward shift (US), downward shift (DS), cyclic (CYC), and mixture (MIX), as shown in Fig. 2.3.

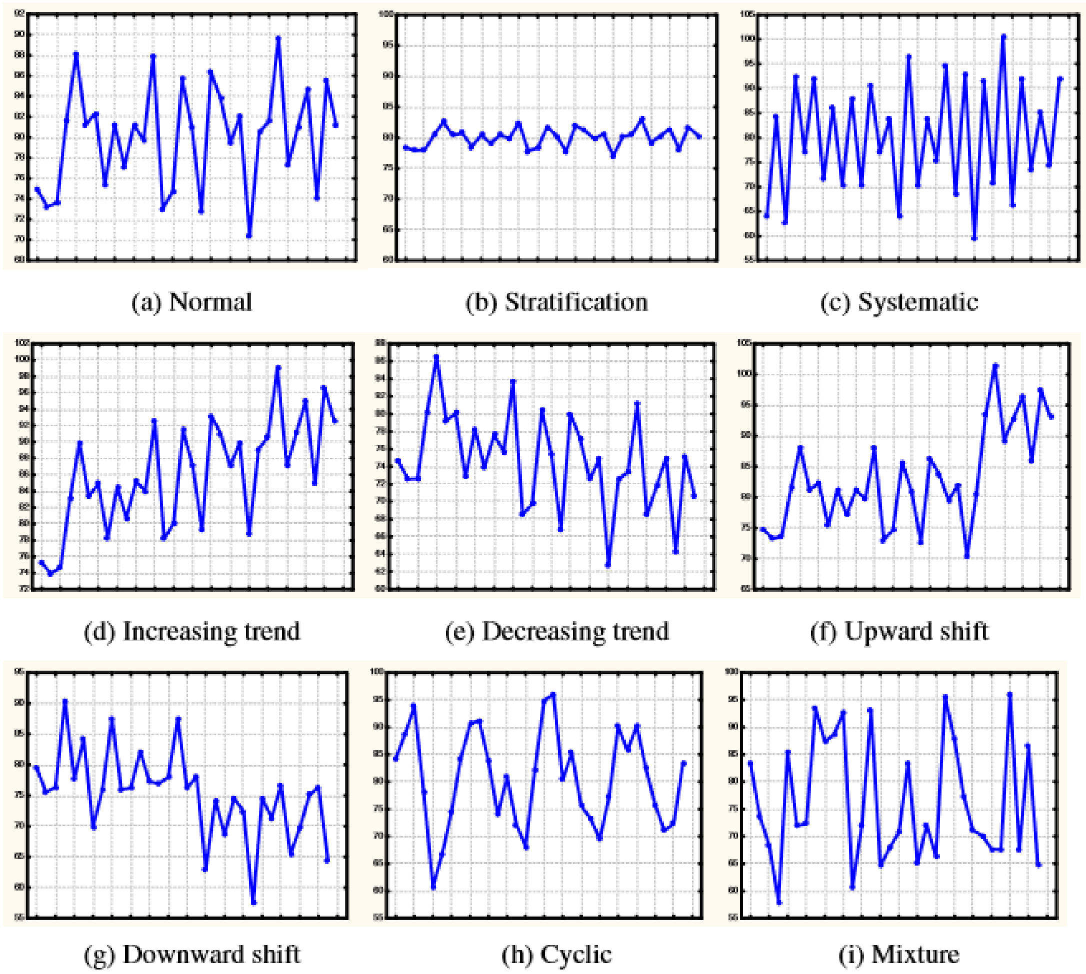


Figure 2.3 : Nine control chart patterns

Only the normal pattern is indicative that the process is operating under random chance causes, i.e., in statistical control. The remaining patterns are unnatural and are associated with impending problems requiring pre-emptive actions. The task of control chart pattern (CCP) recognition is basically associated to accurately identify the unnatural CCPs so that prompt corrective actions can be initiated by the operators. Identification and analysis of the unnatural patterns require considerable experience and skill from the part of the quality control practitioners. However, usually, they are lacking the skill and expertise needed for interpretation of the control chart patterns. Therefore, the development of a knowledge-based expert system can help the operators and quality control practitioners to identify the possible sources of variation and take necessary decisive actions.

2.4 Shewhart Control Charts

A control chart is a graphical and analytic tool for monitoring process variation. The natural variation in a process can be quantified using a set of control limits. Control limits help distinguish common-cause variation from special-cause variation. Typically, action is taken to eliminate special-cause variation and bring the process back in control. It is also important to quantify the common-cause variation in a process, as this determines process capability.

The Control Chart platform provides a variety of control charts, as well as run charts. To support process improvement initiatives, most of the control chart options display separate control charts for different phases of a project on the same chart. Control charts, also known as Shewhart charts (after Walter A. Shewhart) or process-behavior charts, in statistical process control are tools used to determine if a manufacturing or business process is in a state of statistical control. If analysis of the control chart indicates that the process is currently under control (i.e., is stable, with variation only coming from sources common to the process), then no corrections or changes to process control parameters are needed or desired. In addition, data from the process can be used to predict the future performance of the process. If the chart indicates that the monitored process is not in control, analysis of the chart can help determine the sources of variation, as this will result in degraded process performance (McNeese & William, 2006). A process that is stable but operating outside of desired (specification) limits (e.g., scrap rates may be in statistical control but above desired limits) needs to be improved through a deliberate effort to understand the causes of current performance and fundamentally improve the process (Wheeler & Donald J., 2000).

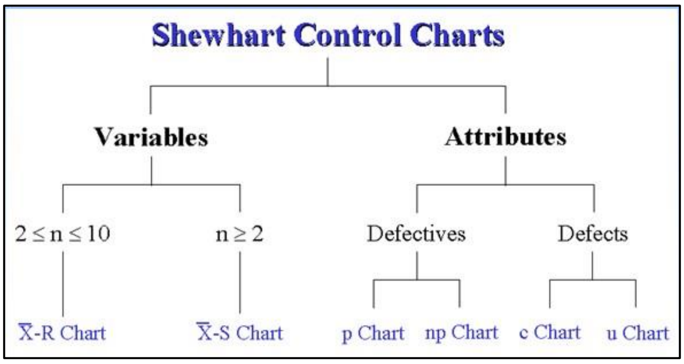


Figure 2.4 Shewhart Control Chart

The control chart is one of the seven basic tools of quality control (Nancy R. Tague, 2004). Typically control charts are used for time-series data, though they can be used for data that have logical comparability (i.e. you want to compare samples that were taken all at the same time, or the performance of different individuals), however the type of chart used to do this requires consideration (A Poots & T Woodcock, 2012). A control chart is a graphical and analytic tool for monitoring process variation. The natural variation in a process can be quantified using a set of control limits. Control limits help distinguish common-cause variation from special-cause variation. Typically, action is taken to eliminate special-cause variation and bring the process back in control. It is also important to quantify the common-cause variation in a process, as this determines process capability.

To support process improvement initiatives, most of the control chart options display separate control charts for different phases of a project on the same chart, as shown in Table 2.1.

Table 2.1 : Types of charts

Chart	Process Observation	Process Observation Type
$\bar{x}$ and R chart	Quality characteristic measurement within one subgroup	Variables
$\bar{x}$ and s chart	Quality characteristic measurement within one subgroup	Variables
IMR chart	Quality characteristic measurement for one observation	Variables
p-chart	Fraction nonconforming within one subgroup	Attributes
np-chart	Number nonconforming within one subgroup	Attributes
c-chart	Number of non-conformances within one subgroup	Attributes
u-chart	Non-conformances per unit within one subgroup	Attributes

Some practitioners also recommend the use of Individuals charts for attribute data, particularly when the assumptions of either binomially distributed data (p- and np-charts) or Poisson-distributed data (u- and c-charts) are violated (Wheeler & Donald J.,2000). Two primary justifications are given for this practice. First, normality is not necessary for statistical control, so the Individuals chart may be used with non-normal data (Staufer & Rip, 2010). Second, attribute charts derive the measure of dispersion directly from the mean proportion (by assuming a probability distribution), while Individuals charts derive the measure of dispersion from the data, independent of the mean, making Individuals charts more robust than attributes charts to violations of the assumptions about the distribution of the underlying population (Wheeler & Donald J., 2000). It is sometimes noted that the substitution of the Individuals chart works best for large counts, when the binomial and Poisson distributions approximate a normal distribution. i.e. when the number of trials $n > 1000$ for p- and np-charts or $\lambda > 500$ for u- and c-charts.

The most common use method in current industries is control chart or Shewhart Charts. These control charts are constructed by plotting product's quality variable over time in sequence plot as shown in Figure 2.5.

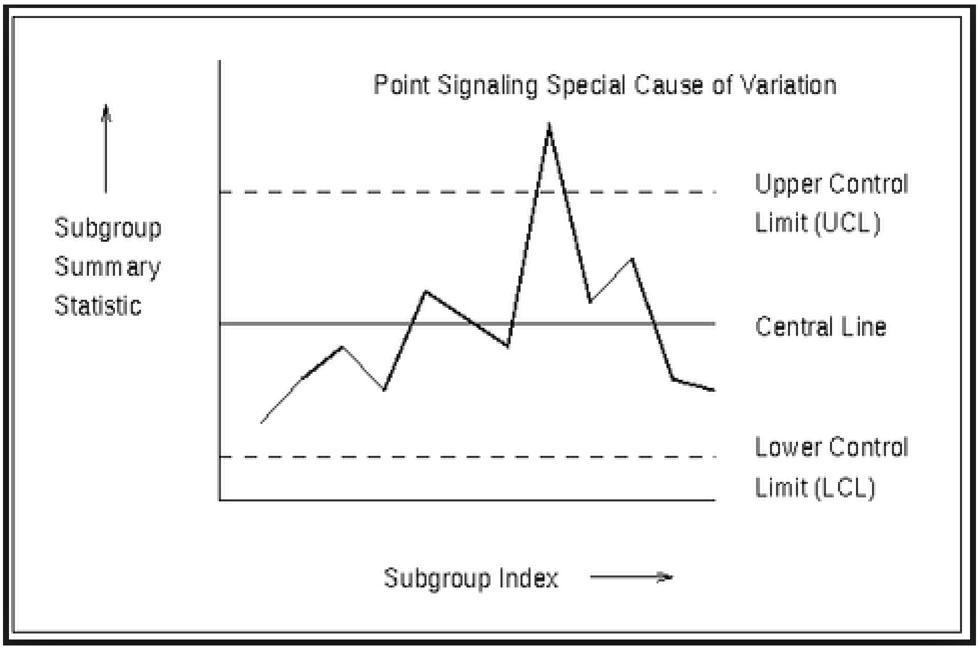


Figure 2.5 : Shewhart Charts

A control chart contains a center line, an upper control limit and a lower control limit. A point that plots within the control limits indicates the process is in control. In this condition no action is necessary. A point that plots outside the control limits is evidence that the process is out of control. In this condition, investigation and corrective action are required to find and eliminate assignable cause(s) (Umit and Cigdem, 2001). Let w be a sample statistic that measure some quality characteristic of interest and suppose that the mean of w is μw and the standard deviation of w is σw. Then the center line, upper control limit and lower control limit as shows in equation (2.1).

$$UCL = \mu w + L\sigma w$$
$$\text{Center Line} = \mu w \qquad (2.1)$$
$$UCL = \mu w - L\sigma w$$

2.5 Control Limits

Control limits, also known as natural process limits, are horizontal lines drawn on a statistical process control chart, usually at a distance of ±3 standard deviations of the plotted statistic from the statistic's mean. A point falling within the control limits means it fails to reject the null hypothesis that the process is statistically in-control, and a point falling outside the control limits means it rejects the null hypothesis that the process is statistically in-control. Therefore, the statistical Type I error α (Rejecting the null hypothesis H0 when it is true) applied in Shewhart control chart means the process is concluded as out-of control when it is truly in-control. Same analog, the statistical Type II error β (failing to reject the null hypothesis when it is false) means the process is concluded as in-control when it is truly false.

2.6 Average Run Length

The Average Run Length is the number of points that, on average, will be plotted on a control chart before an out of control condition is indicated (for example a point plotting outside the control limits).

The performance of control charts can also be characterized by their average run length. Average run length is the average number of points that must be plotted before a point indicates an out-of-control condition (Montgomery, 1985). We can calculate the average run length for any Shewhart control chart according to:

$$ARL = \frac{1}{P} \qquad (2.2)$$

Where P or Type I error is the probability that an out-of-control event occurs. Therefore, a control chart with 3 sigma control limits, the average run length will be

$$ARL = \frac{1}{P} = \frac{1}{0.027} = 370 \qquad (2.3)$$

This means that if the process remains in-control, in average, there will be one false alarm every 370 samples.

2.7 Pattern Recognition in SPC

Pattern recognition is the science of making inferences from perceptual data, using tools from statistics, probability, computational geometry, machine learning, signal processing, and algorithm design (Masood & Hassan, 2010). The techniques of pattern recognition have been successfully used in many areas such as applications in engineering, science, medicine, and business. In particular, advances made during the last half century, now allow computers to interact more effectively with humans and the natural world examples such as speech recognition, word recognition and finger print identification (Wen & Dwayne 1994). The effectiveness of the use of SPC control charts depends largely on recognizing out-of control conditions in terms of patterns, pattern recognition is an important issue in SPC, as unnatural patterns exhibited by control charts can be associated with specific assignable causes adversely affecting the process. Traditional Shewhart control charts signal only a simple decision, such as within or outside the control limits, based on the most recent observation (Wen & Dwayne, 1994).

Control chart pattern recognition (CCPR) has become an active area of research since late 1980s (Masood & Hassan, 2010). Since control chart pattern recognition is an important step for industrial production processes, many researchers have made efforts toward finding various efficient methods for recognizing unnatural patterns in control charts. Hwarng and Hubele (1993) used a back-propagation neural network technique for detecting X-bar control charts. Cheng (1997); Guh and Hsieh (1999) used a neural network approach for recognizing an unnatural control chart pattern.

Today, control chart pattern recognition has become an active area of research. Zorriassatine, Tannock & O'Brian (2003) provided a useful review on the application for CCPR. However, it is still limited research and updated review on ANN-based CCPR schemes. There were several pattern recognition approaches done by several researchers. Swift (1987), done a research on SPC control chart pattern recognition using a dichotomous decision tree approach. Swift & Mize (1995) and Cheng (1995), used of expert systems. Expert system also known as rule-based that contain information explicitly. If required, the rules can be modified and updated easily. While the performance of this system was promising, it was reported that the template-matching is currently computationally too expensive to implement in a real-time application scheme (Cheng, 1997).

2.8 Artificial Neural Network in Pattern Recognition

Traditionally, statistical process control (SPC) was used only for monitoring and identifying process variation. Advances in SPC charting have moved from merely statistical and economic control to diagnosis purposes through control chart pattern identification. The development in soft computing technology such as artificial intelligence (AI) has encouraged investigation on the application of expert systems, artificial neural network (ANN) and fuzzy sets theory for automated recognition of control chart patterns (CCPs). Application of ANN-based models, among others, has realized the computerized decision making in SPC towards replacing human interpretation. The modernization of the SPC schemes is ultimately aims to diagnose the source of variation with minimum human intervention (Masood & Hassan, 2009).

Recently, many studies used ANNs in order to detect patterns more efficiently than the traditional approach and their goal is the automatic monitoring and diagnosis of the patterns such as shown in Figure 2.6 below.

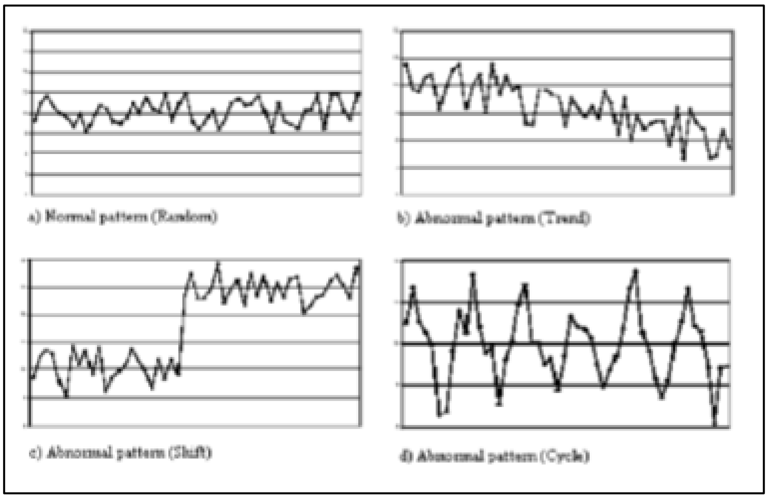


Figure 2.6 : Typical normal and abnormal patterns

El-Midany et al (2010) documented, two approaches in applying ANNs to control charts analysis, they are generally:

1. Uses of ANN to detect deviation in mean and/or variance.
2. Uses of ANN to identify abnormal patterns using trained recognizer.

Since late 1980s, control chart pattern recognition (CCPR) has become an active area of research. A useful review on the application of ANN for CCPR was provided by Zorriassatine and Tannock (1998). Since then much progress has been made in which the performance of ANN-based CCPR schemes have been enhanced through feature-based and wavelet-denoise input representation techniques, modular and integrated recognizer designs, and multivariate process monitoring and diagnosis. However, there is a lack of updated critical review on such issues.

ANN is a massively parallel-distributed processor that has the ability to learn, recall and generalize knowledge (Haykin, 1999). It is recognized as an important and emerging methodology in the area of classification. ANN is flexible, adaptive and can better handle noise and changes in the patterns. The advantage with an ANN-based pattern recognizer is that it does not require the provision of explicit rules or templates. Rather, it learns to recognize patterns from examples during the training phase. It has the ability to classify an arbitrary pattern not previously encountered. ANN offers useful properties and capabilities such as non-linearity, input and output mapping, adaptability and fault tolerance, among others. These attributes are needed for recognizing and classifying data which are often contaminated with noise, unknown distribution and incomplete as found in CCPs (Schalkoff, 1997; Haykin, 1999).

ANN acquires knowledge through a learning process and inter-neuron connection strengths (synapse weights) are used to store the knowledge. A learning algorithm is used to modify the synapse weights so as to achieve the target. ANN can tailor itself to the training data. A well-trained ANN is able to generalize knowledge. It will produce a reasonable output for input that has never been encountered during training/learning. Although ANN training requires considerable computation, the recall process is very fast. ANN is also suitable for implementation using very-large-scale-integrated (VLSI) technology such as in the form of chip that can replace the need for continuously monitoring by personal computer (Zurada, 1992; Patterson, 1996; Scalkoff, 1997; Haykin, 1999).

CHAPTER 3

METHODOLOGY

This chapter focuses on the method or process of this study. The appropriate method is necessary in carrying out this study in order to ensure the quality of the produced results and its reliability. Accurate planning allows the data and information collected analyzed easily.

This chapter explains the working procedures to complete the whole project. Methodology also indicates the procedural steps that need to be follow to ensure that the project will be completed on time. All procedures and methods have been listed down to give a guideline on project progress and to ensure the project completed as planned. All the activities were listed on the Gantt chart as shown in Figure A.1 (in Appendix A). Figure 3.1 illustrated the explanation on the methodologies in Statistical Features-ANN scheme in monitoring and diagnosis of bivariate process variation in mean shifts.

In this research, single-stage monitoring scheme for improving the balanced monitoring and accurate diagnosis was investigated by Statistical Feature-ANN. Framework for the proposed scheme are summarized in Figure 3.2.The purpose data collection is to achieve the objectives of this study.

3.1 Research Flow Chart

Figure 3.1 illustrated the methodology flow chart of research study that will be carried out.

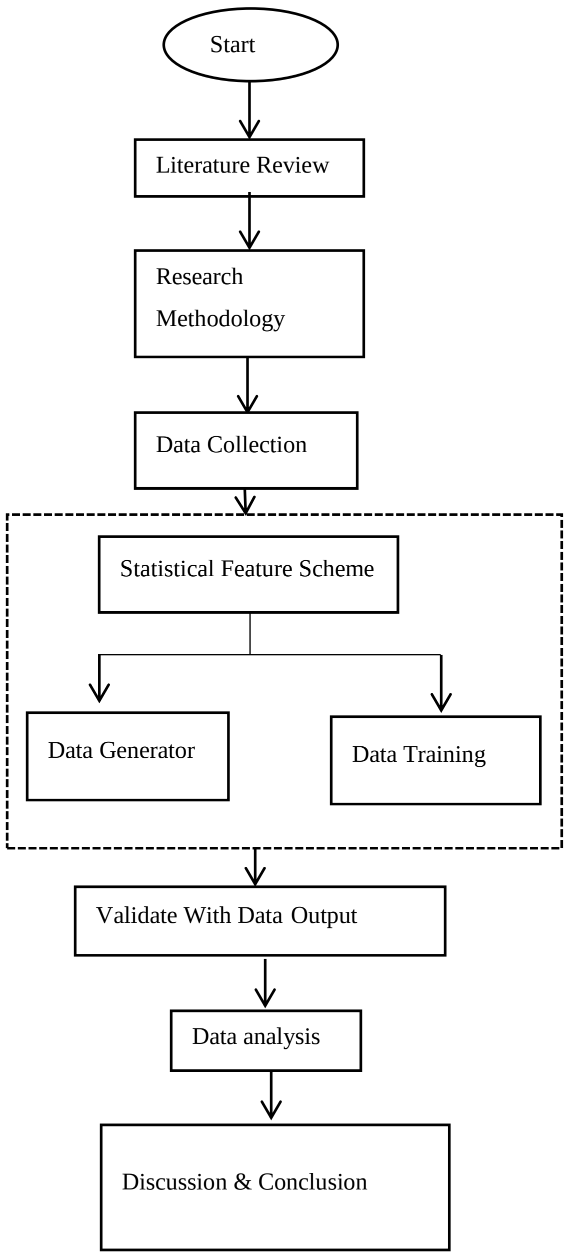


Figure 3.1: Research flow chart

3.2 Project Methodology

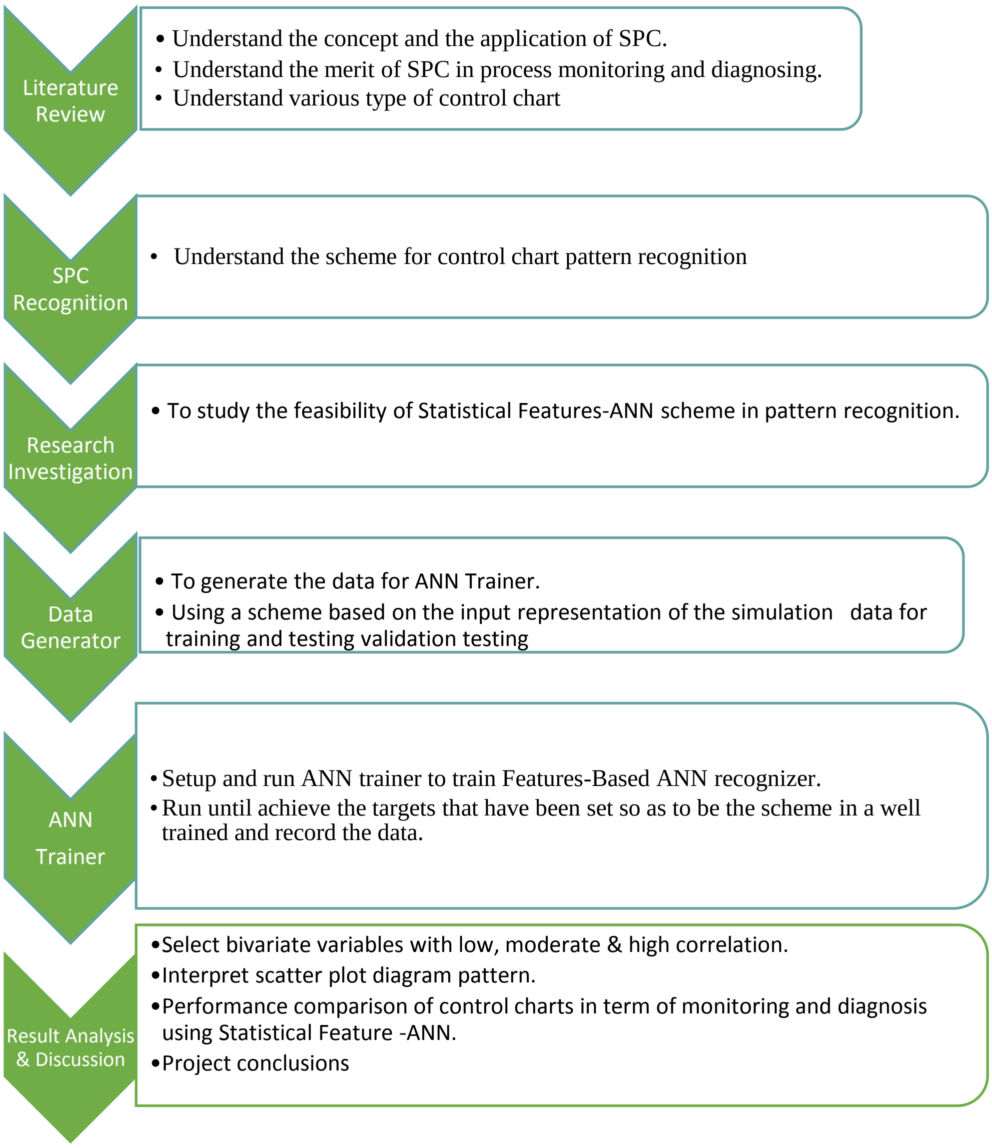


Figure 3.2: Overview of project methodology in this research

3.3 Modeling Of Bivariate Process

Bivariate process is the simplest case in MQC when only two process variables are being monitored dependently. Let $X_{1i} = (X_{1-1}, \ldots, X1\text{-}24)$ and $X_{2i} = (X_{2-1}, \ldots, X_{2-24})$ represent data streams for process variable 1 and process variable 2 based on observation window - 24 samples. Observation windows for both variables start with samples i_{th} = (1,…, 24). Then, it is followed with (i_{th} +1), (i_{th} + 2), …., and so on.

In a statistically stable state, samples for both process variables are identically and independently distributed with zero mean ($\mu_0 = 0$) and unity standard deviation (σ_0 =1). They yield random patterns when separately plotted on the Shewhart control charts and yield an ellipse pattern when plotted on a scatter diagram. Scatter diagram can indicate a measure of degree of linear relationship between two variables, i.e., cross correlation of data. Increasing the values of correlation will result in slim ellipses, as shown in Figure 3.3

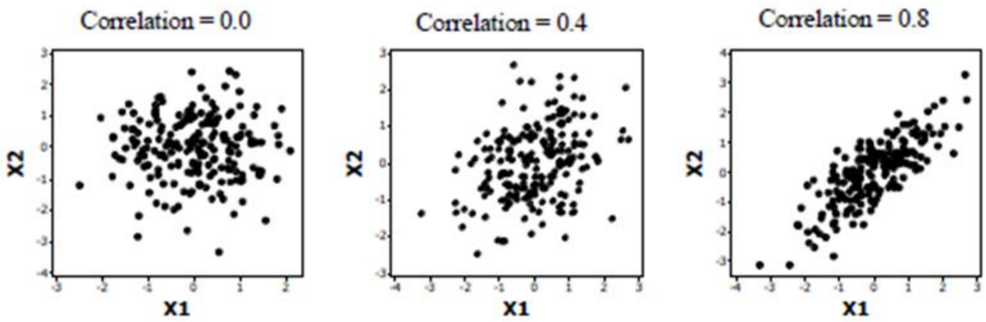


Figure 3.3 Bivariate stable process patterns with different data correlation

Depending on process, the bivariate samples can be in low correlation (ρ = 0.1 – 0.3), moderate correlation (ρ = 0.4 – 0.6) or high correlation (ρ = 0.7 – 0.9). Data correlation (ρ) shows a measure of degree of linear relationship between two variables.

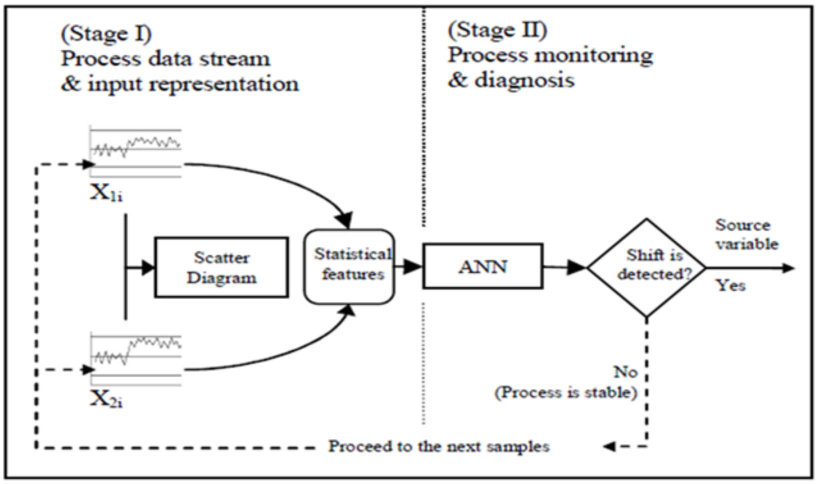


Figure 3.4: Conceptual diagram for the statistical features-ANN recognizer

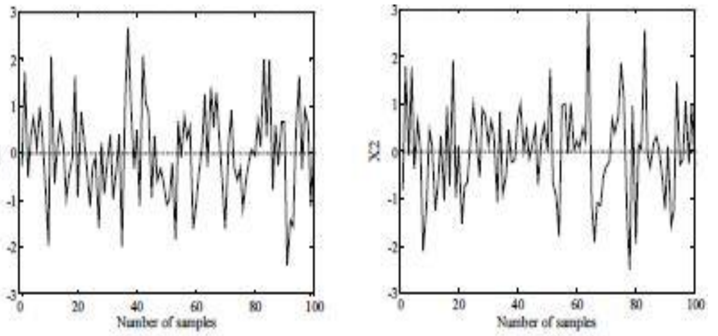
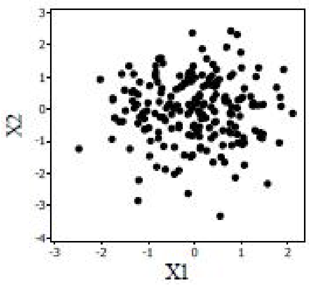
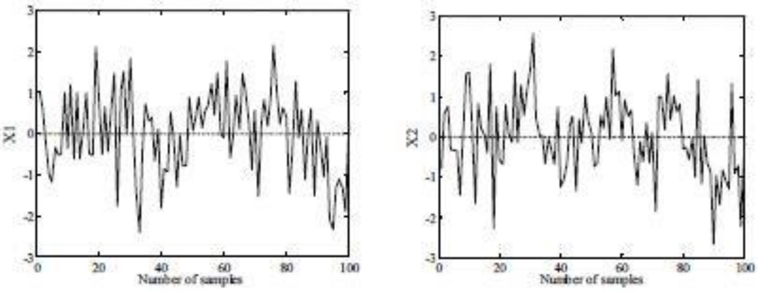
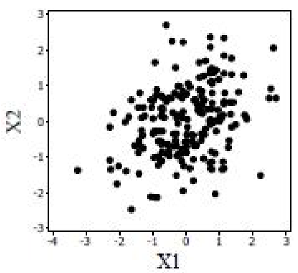
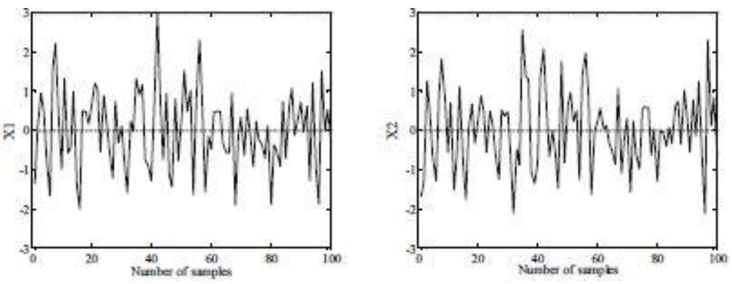
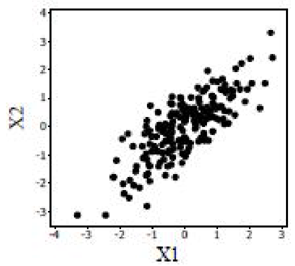
Shewhart Control Chart	Scatter Diagram
Low Correlation 	Low Correlation 
Moderate Correlation 	Moderate Correlation 
High Correlation 	High Correlation 

Figure 3.5 Shewhart Control Chart and Scatter Diagram

3.4 Input Representation

Input representation (input data) was an approach to represent the pattern of input signals to an ANN identifier. Generally, the occurrence of assignable causes over X1i and/or X2i can be identified by common causable patterns such as upward and downward shifts, upward and downward trends, cyclic, systematic, and mixture. This study concerns on upward-shift and downward-shift patterns. Seven possible conditions of bivariate process mean shifts with positive correlation were considered, as summarized in Table 3.1.

1. Normal (0,0): Both X_{1i} and X_{2i} are stable
2. Up-shift (1,0): X_{1i} in upward-shift, X_{2i} remain stable
3. Up-shift (0,1): X_{2i} in upward-shift, X_{1i} remain stable
4. Up-shift (1,1): Both X_{1i} and X_{2i} in upward-shifts
5. Down-shift (1,0): X_{1i} in downward-shift, X_{2i} remain stable
6. Down-shift (0,1): X_{2i} in downward-shift, X_{1i} remain stable
7. Down-shift (1,1): Both X_{1i} and X_{2i} in downward-shifts

Table 3.1 Seven possible conditions of bivariate process mean shifts

	Normal (0, 0)	**Up-shift (1, 0)**	**Up-shift (0, 1)**	**Up-shift (1, 1)**
X_{1i}	Normal	Upward-shift	Normal	Upward-shift
X_{2i}	Normal	Normal	Upward-shift	Upward-shift
		Down-shift (1, 0)	**Down-shift (0, 1)**	**Down-shift (1, 1)**
X_{1i}		Down-shift	Normal	Down-shift
X_{2i}		Normal	Down-shift	Down-shift

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