A SCHEME FOR BALANCED MONITORING AND ACCURATE DIAGNOSIS OF BIVARIATE PROCESS MEAN SHIFTS

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ABSTRACT

Monitoring and diagnosis of mean shifts in manufacturing processes become more challenging when involving two or more correlated variables. Unfortunately, most of the existing multivariate statistical process control schemes are only effective in rapid detection but suffer high false alarm. This is referred to as imbalanced performance monitoring. The problem becomes more complicated when dealing with small mean shift particularly in identifying the causable variables. In this research, a scheme to enable balanced monitoring and accurate diagnosis was investigated in order to improve such limitations. Design considerations involved extensive simulation experiments to select input representation based on raw data and statistical features, recognizer design structure based on individual and synergistic models, and monitoring-diagnosis approach based on single stage and two stages techniques. The study focuses on correlated process mean shifts for cross correlation function, ρ = 0.1 ~ 0.9 and mean shift, μ = ± 0.75 ~ 3.00 standard deviations. Among the investigated designs, an Integrated Multivariate Exponentially Weighted Moving Average with Artificial Neural Network scheme gave superior performance, namely, average run lengths, ARL_1 = 3.18 ~ 16.75 (for out-of-control process) and ARL_0 = 452.13 (for in-control process), and recognition accuracy, RA = 89.5 ~ 98.5%. The proposed scheme was validated using an industrial case study from machining process of audio-video device component. This research has provided a new perspective in realizing balanced monitoring and accurate diagnosis of correlated process mean shifts.

ABSTRAK

Pemantauan dan diagnosis ke atas anjakan purata dalam proses pembuatan menjadi semakin mencabar apabila melibatkan dua atau lebih pembolehubah terkorelasi. Walau bagaimanapun, skema kawalan proses statistik pembolehubah berbilang yang sedia ada hanya berkesan bagi pemantauan secara deras tetapi memberikan amaran palsu yang tinggi. Ini merujuk kepada keupayaan pemantauan yang tidak seimbang. Masalah menjadi lebih rumit apabila melibatkan anjakan purata yang kecil terutama dalam mengenalpasti pembolehubah penyebab variasi. Dalam kajian ini, skema untuk membolehkan pemantauan seimbang dan diagnosis tepat telah dikaji bagi memperbaiki kelemahan tersebut. Pertimbangan rekabentuk melibatkan ujikaji simulasi yang mendalam bagi memilih perwakilan masuk berasaskan kepada data mentah dan sifat-sifat statistik, rekabentuk struktur pengecam berasaskan kepada model-model individu dan tergabung, serta pendekatan pemantauan-diagnosis berasaskan kepada teknik-teknik satu peringkat dan dua peringkat. Kajian ditumpukan ke atas anjakan purata proses terkorelasi pada fungsi korelasi rentas, ρ = 0.1 ~ 0.9 dan anjakan purata proses, μ = ± 0.75 ~ 3.00 sisihan piawai. Di antara rekabentuk-rekabentuk yang dikaji, skema tersepadu Purata Bergerak Pemberat Exponen Pembolehubah Berbilang bersama Rangkaian Neural Tiruan telah menghasilkan keputusan yang terbaik, iaitu, purata panjang larian, ARL_1 = 3.18 ~ 16.75 (bagi proses luar kawalan) dan ARL_0 = 452.13 (bagi proses dalam kawalan) serta ketepatan pengecaman, RA = 89.5 ~ 98.5%. Skema yang dicadangkan telah diuji sah menggunakan kajian kes perindustrian di dalam proses pemesinan komponen peralatan audio-video. Kajian ini telah memberikan perspektif baru dalam merealisasikan pemantauan seimbang dan diagnosis tepat ke atas anjakan purata proses terkorelasi.

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LIST OF ABBREVIATIONS

ANFIS	-	Adaptive neural fuzzy inference system
ANN	-	Artificial neural network
ARL	-	Average run length
ARL_0	-	In-control ARL
ARL_1	-	Out-of-control ARL
ART	-	Adaptive resonance theory
ASQ	-	American society of quality technology
BPN	-	Back propagation network
BPR	-	Bivariate pattern recognition
CCPs	-	Control chart patterns
CUSUM	-	Cumulative sum
DISSIM	-	Dissimilarity
DOE	-	Design of experiment
DT	-	Decision tree
EPC	-	Engineering process control
ES	-	Expert system
EWMA	-	Exponentially weighted moving average
FIS	-	Fuzzy inference system
FMS	-	Flexible manufacturing system
GA	-	Genetic algorithm
HDD	-	Hard disc drive
i.i.d.	-	Identically and independently distributed
LCL	-	Lower control limit
LEWMA	-	Last value of exponentially weighted moving average
LVQ	-	Learning vector quantization
MCUSUM	-	Multivariate cumulative sum
MEPC	-	Multivariate engineerinf process control

MEWMA	-	Multivariate exponentially weighted moving average
MGWMA	-	Multivariate generalized weighted moving average
MRDCT	-	Multi-resolution discrete cosine transform
MRWA	-	Multi-resolution wavelet analysis
MLP	-	Multilayer-perceptron
MMSV	-	(Mean) x (mean square value)
MPCA	-	Moving principle component analysis
MPR	-	Multivariate pattern recognition
MQC	-	Multivariate quality control
MSD	-	(Mean) x (standard deviation)
MSE	-	Mean square error
MSPC	-	Multivariate statistical process control
PCA	-	Principle component analysis
PLS	-	Partial least square
PM	-	Performance measures
PR	-	Pattern recognition
RA	-	Recognition accuracy
RAM	-	Random access memory
RBF	-	Radial basis function
SOM	-	Self-organizing mapping
SPC	-	Statistical process control
SPCPR	-	Statistical process control pattern recognition
SQE	-	Statistical quality engineering
SS	-	Point (time) the sudden shift begins
SVM	-	Support vector machine
trainlm	-	Levenberg-Marquardt
traingdx	-	Gradient descent with momentum and adaptive learning rate
UCL	-	Upper control limit
VAR	-	Vector autoregressive residual
VSI	-	Variable sampling interval

LIST OF SYMBOLS

α	-	Type I error (α risk)
β	-	Type II error (β risk)
λ	-	Constant parameter for EWMA control chart
ρ	-	Correlation coefficient for bivariate samples
μ	-	Mean
σ	-	Standard deviation
μ_0	-	Mean for in-control samples
σ_0	-	Standard deviation for in-control samples
σ_{12}	-	Covariance for bivariate samples
χ^2	-	Chi-square statistics
Σ	-	Covariance matrix for bivariate samples or basic summation
t_0	-	time/point the sampling begins or the shift begins
X_t	-	Original observation samples at time/point t
Z_t	-	Standardized observation samples at time/point t
WS	-	Window size for pattern recognition
b	-	Random noise level for normal pattern
σ'	-	Random noise level for stratification pattern
s	-	Mean shift for sudden shift patterns
g	-	Trend slope for trend patterns,
a	-	Cycle amplitude for cyclic pattern
T	-	Cycle period for cyclic pattern
d	-	Systematic departure for systematic pattern
n	-	Random normal variates
H	-	Upper control limit for MEWMA control chart
N	-	Standardized normal distribution for bivariate samples
R	-	General correlation matrix for bivariate samples

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CHAPTER 1

INTRODUCTION

1.1 Background of the Research

The American Society for Quality Control defines quality as *the totality of features and characteristics of a product or service that bears on its ability to satisfy stated or implied needs* (Johnson and Winchell, 1990). Recently, customer demand towards quality products has increased thoroughly in line with advances in communication and information technologies. Their expectation and satisfaction level have become more dynamic, diversifies and complex.

Figure 1.1 illustrates the scenario leading to the current research issue. Based on engineering point of view, advances in manufacturing technology and growth in customer demand has become the push-pull factors that motivate manufacturers to focus on product miniaturization. Continuous quality improvement is implemented towards manufacturing smaller scale (compact), higher capability and cost effective products for various applications such as computer, television, hand phone, audio-video, video-camera, among others. Production is moving towards precision (minimum variation, tight tolerance), minimum cost (minimum waste, rework, fault) and systematic decision making (computerized, intelligence system).

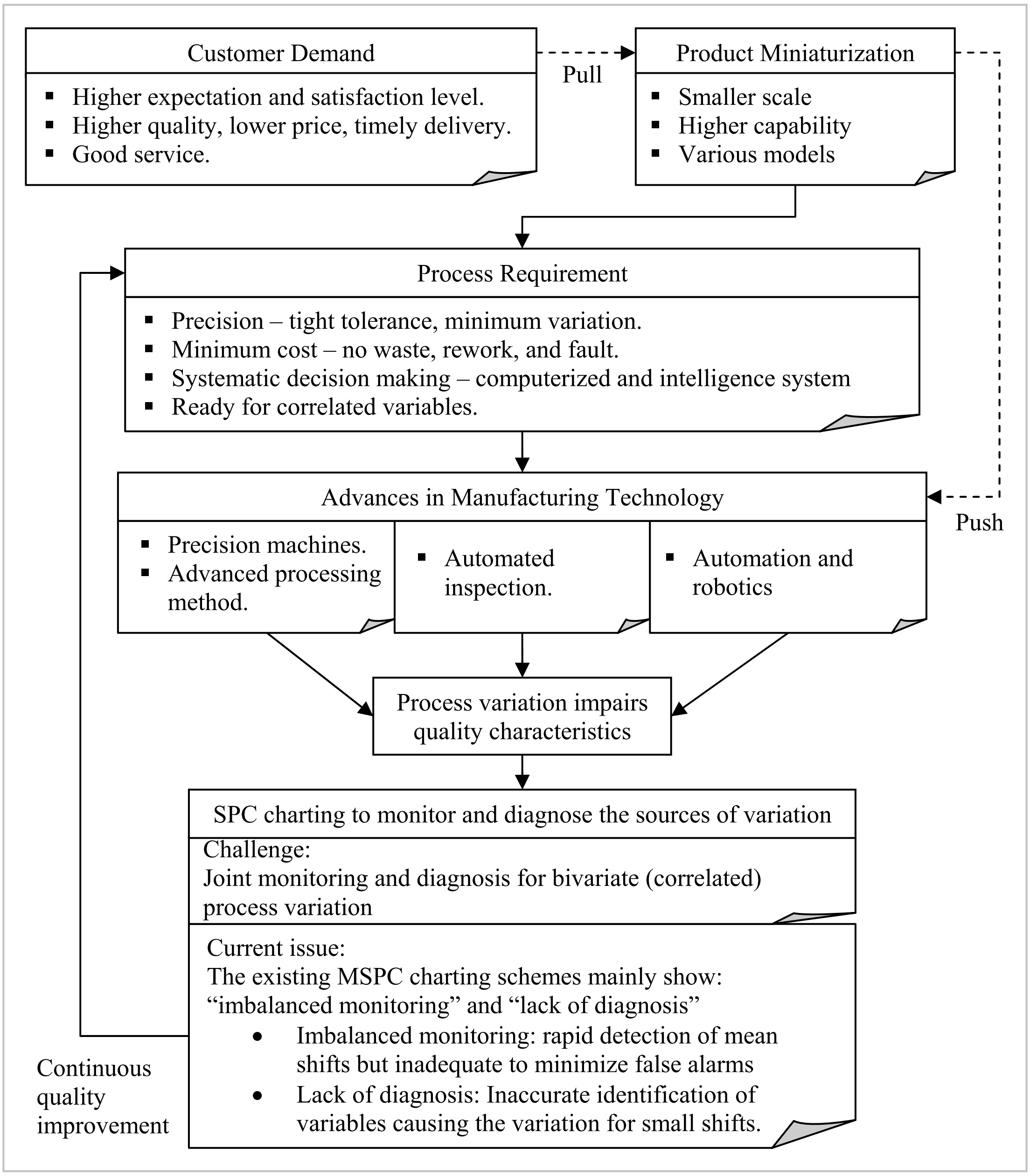


Figure 1.1 : Scenario leading to the current research issue

Advances in manufacturing technology such as processing machines, material handling system, and measuring and inspection system have enabled automation to be applied into product manufacturing and quality control. Despite such advances, unnatural process variation that is unavoidable has become a major source of poor quality products. Process variation can be caused by tool wear and tear, vibration, machine breakdown, inconsistent material, and lack of experienced operators, among others.

Variation in manufacturing process environment causes no parts or products can be produced in exactly the same size and properties. Process variation as shown in Figure 1.2 can be influenced from chance causes (random error) and/or assignable causes (systematic errors). The figure shows that from initial time t_0 to period t_1, process mean (μ_0) and standard deviation (σ_0) are in-control. Disturbance due to assignable causes can be indicated in three situations. Firstly, at time t_1, an assignable cause may shift the process mean ($\mu_1 > \mu_0$) but maintain the dispersion (σ_0). Secondly, at time t_2, it may change the dispersion ($\sigma_2 > \sigma_0$) but maintain the mean (μ_0). Thirdly, at time t_3, other assignable cause may effects both process mean and dispersion to be out-of-control, $\mu_3 < \mu_0$ and $\sigma_3 > \sigma_0$. Grant and Leavenworh (1996) stated that lack of control usually cause the changes in process mean, while cause no or little changes in process dispersion.

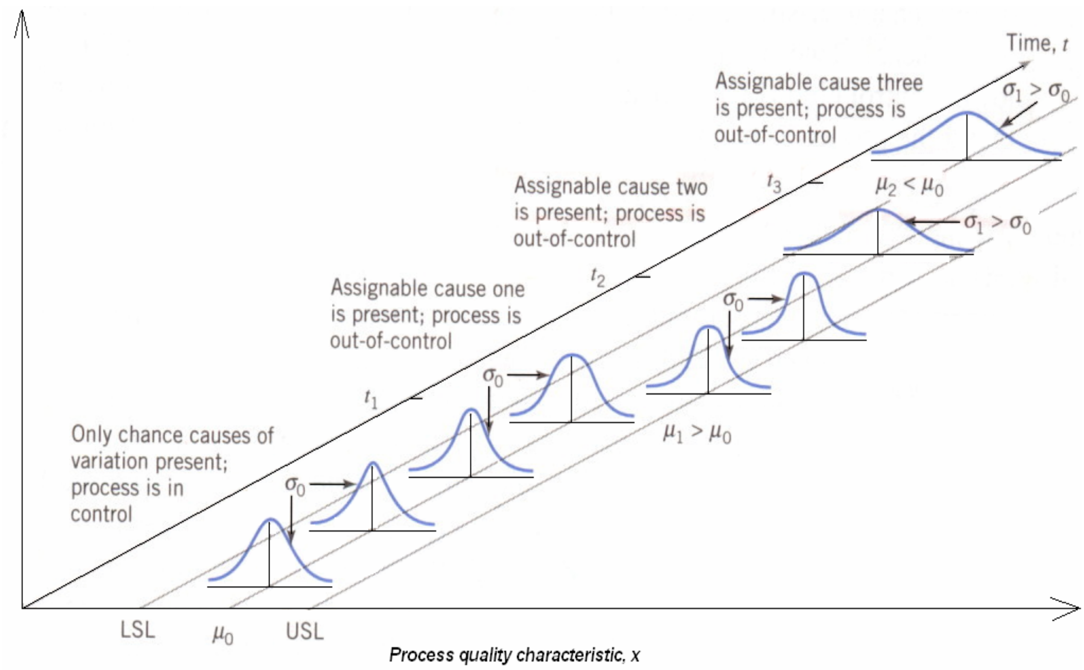


Figure 1.2 : Process variation (Montgomery, 2005)

In order to maintain and improve the quality, effort towards minimizing process variation in manufacturing environment has become an important issue in quality control. Statistical quality engineering (SQE) tools have been developed for systematically reducing variability in the key process variables or quality characteristics of the product (Montgomery, 2005). Statistical process control (SPC) charting is one of the SQE tools that useful for monitoring and diagnosing process variation. Researches in design of SPC charting schemes focused on heuristic, smaller shift detection, process pattern identification and automated pattern recognition. Besides minimizing process variation, such advances are ultimately aim to minimize human intervention through computerized decision making.

In the related study, many manufacturing processes involve two or more dependent variables, whereby an appropriate scheme is required to monitor and diagnose such variables jointly. In contrast, attempting to monitor such variables separately using univariate SPC charting scheme would increase false alarms and leading to wrong decision making. This joint monitoring-diagnosis concept is called multivariate quality control (MQC). The main challenge in MQC is the need for an effective MSPC charting scheme for monitoring and diagnosing of bivariate process variation in mean shifts. In recent years, the artificial neural network-based pattern recognition schemes have been developed for this purpose. Such advanced schemes are generally more effective in detecting process mean shifts rapidly compared to the traditional MSPC charting schemes such as T^2, multivariate cumulative sum (MCUSUM) and multivariate exponentially weighted moving average (MEWMA) control charts. Unfortunately, it showed a limited capability to avoid false alarm (average run length of in-control process, $ARL_0 \approx 200$) as compared to the *de facto* level for univariate SPC charting schemes ($ARL_0 \geq 370$). In this research, this scenario is called "imbalanced monitoring" as illustrated in Figure 1.3. In diagnosis aspect, the existing schemes are also inadequate to accurately identify the sources of variation, particularly in dealing with small mean shifts. These situations have resulted in poor decision making and lead to unnecessary troubleshooting. In order to improve these limitations, it is necessary to investigate improved scheme towards "balanced monitoring" and "accurate diagnosis". The intended scheme should be able to detect process mean shifts rapidly (average run length of out-of-control process, $ARL_1 \Rightarrow 1$) with minimum false alarm ($ARL_0 \geq 370$) and correctly identify the sources of variation (recognition accuracy, $RA \geq 95\%$).

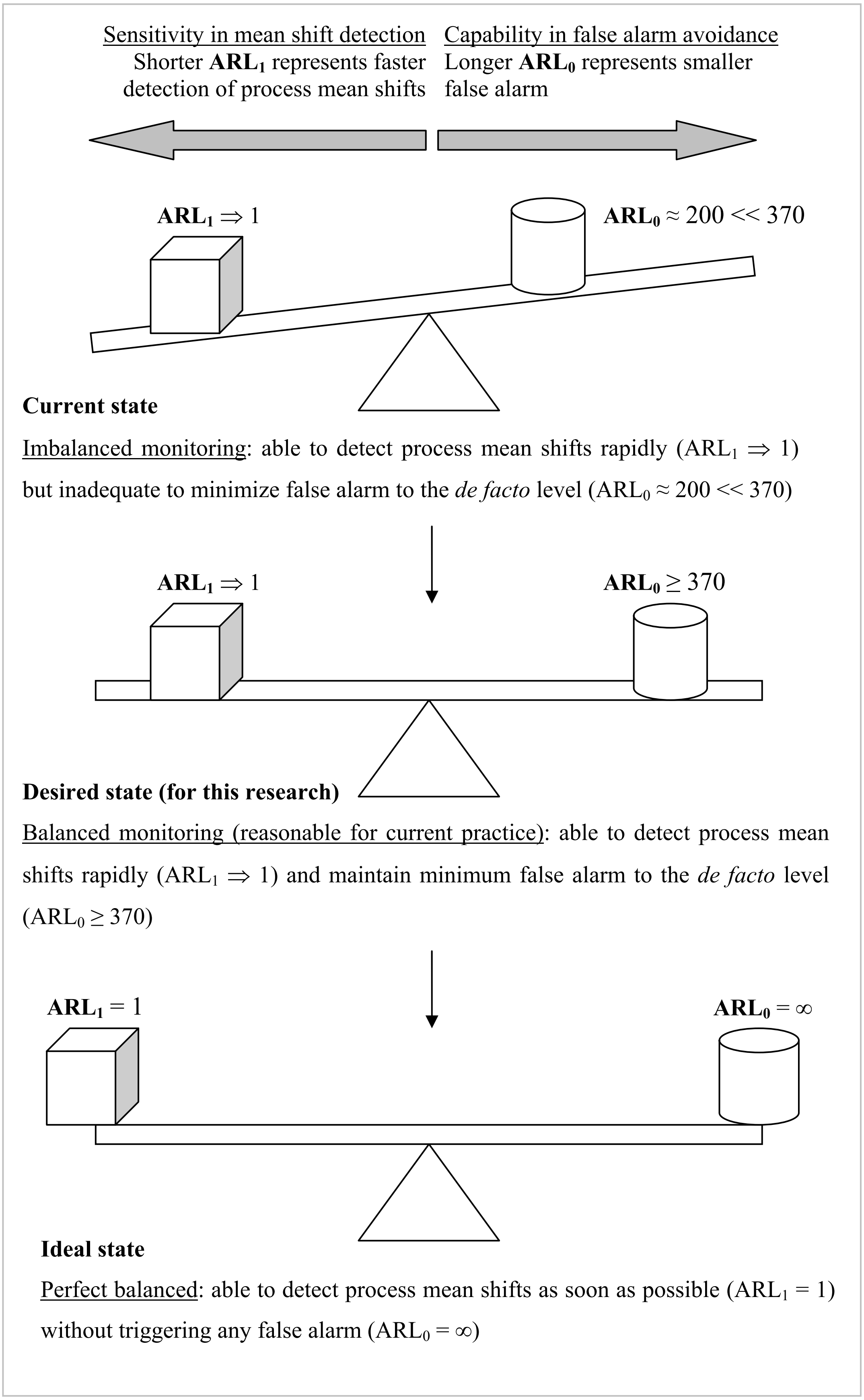


Figure 1.3 : Current state and desired state towards balanced monitoring

1.2 Statement of the Problem

In manufacturing industries, monitoring and diagnosis of process variation is necessary towards continuous quality improvement. It will be more challenging when involving two or more dependent variables (multivariate), whereby an appropriate scheme is required to perform joint monitoring and diagnosis. It is important that the multivariate process variation be rapidly and correctly identified with minimum false alarm. Failure to avoid false alarm and incorrect diagnosis could lead to wrong decision making. The existing multivariate pattern recognition schemes are mainly inadequate to fulfill these requirements. Such schemes mainly show imbalanced monitoring, which is only effective to detect mean shifts rapidly but inadequate to maintain minimum false alarm to the *de facto* level as for univariate SPC ($ARL_0 \geq 370$). Additionally, they are also lacking to accurately identify the sources of variation particularly when dealing with small mean shifts. In order to improve these limitations, it is necessary to investigate a scheme for enabling “balanced monitoring and accurate diagnosis”.

1.3 Purpose of the Research

The purpose of this research is to design, develop and test runs a scheme for enabling balanced monitoring and accurate diagnosis of bivariate process mean shifts. The desirable characteristics for the intended scheme are applicable for (i) bivariate process (correlated data streams) and (ii) on-line situation (dynamic data streams). The desirable monitoring-diagnosis performances are capable to: (i) rapidly detect process mean shifts ($ARL_1 \Rightarrow 1$), (ii) minimize false alarms to the *de facto* level for univariate SPC charting schemes ($ARL_0 \geq 370$), and (iii) accurately identify the sources of variation in mean shifts (recognition accuracy, RA > 95%).

1.4 Objectives

The objectives of this research are:

(i) To design and develop a baseline scheme for enabling on-line monitoring and diagnosis of bivariate process mean shifts.

(ii) To improve the performance of the scheme towards achieving "balanced monitoring and accurate diagnosis", that is, effective in rapidly detecting process mean shifts with minimum false alarm, and accurately identifying the sources of variation in mean shifts.

1.5 Scope and Key Assumptions

The scopes of this research are:

(i) Bivariate process variables are dependent to each other based on linear cross correlation (ρ). In particular, focus is given to positive data correlation ($\rho > 0$).

(ii) In a statistically out-of-control process state, predictable bivariate patterns are limited to sudden shifts (upward shift and downward shift) in the component variables.

(iii) Bivariate process variation is limited to changes in mean shifts at specified data correlation, or changes in data correlation at specified mean shifts.

(iv) Magnitudes of mean shifts in the component variables are limited within $\pm$ 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.

(vi) The Baseline scheme is developed based on artificial neural network (ANN) recognizer and raw data-based input representation.

1.6 Importance of the Research

The research is significant in theoretical and real world perspectives. In theoretical perspective, implementation of balanced monitoring and accurate diagnosis scheme in MQC would be useful for minimizing errors through computerized decision making. In real world perspective, an intended scheme would be effective towards realizing precision (minimum variation, tight tolerance), minimum cost (minimum waste, rework, fault) and systematic decision making (computerized, intelligence system) in today's manufacturing environment.

1.7 Research Approach

The solution concept for addressing imbalanced monitoring and lack of accurate diagnosis of bivariate process mean shifts was investigated through extensive computer simulation-experiments. Broadly, the investigation was divided into four phases. In initial phase, the Baseline scheme was designed and developed for enabling on-line monitoring and diagnosis of bivariate process mean shifts. In the following phases, further investigation was focused on improved input representation, improved recognizer design and integration between monitoring and recognition. As such, three alternative enhanced schemes, namely, Statistical Features-ANN, Synergistic-ANN and Integrated MEWMA-ANN schemes were designed and developed towards achieving balance monitoring and accurate diagnosis performances. Details methodology adopted in this research are presented in Chapters 3 to 5.

1.8 Definition of Terms

The following terms are important and frequently used in this research:

(a) On-line process

On-line process refers to in-process environment in manufacturing industries, that is, during manufacturing operation is running. Based on individual samples, continuous data streams patterns will be produced through automated measuring and inspection devices. An in-control process is represented by random/normal patterns, while an out-of-control process is represented by gradual trend or sudden shift pattern.

(b) Process monitoring and diagnosis

Process monitoring refers to the identification of process status either it is running within a statistically in-control or has become a statistically out-of-control. Process diagnosis refers to the identification of sources of variation in relation to a statistically out-of-control process.

(c) Sources of variation

Source of variation refers to a component variable or group of component variables that indicate a bivariate process has become out-of-control. In this research, it is focused on sudden shift in process mean (process mean shifts). This information is useful towards diagnosing the root cause error.

(d) Balanced monitoring

Balanced monitoring refers to the desirable monitoring performance, that is, effective to detect bivariate process mean shifts rapidly and maintain the minimum false alarms to the *de facto* level ($ARL_0 \geq 370$).

(e) Imbalanced monitoring

Imbalanced monitoring refers to the undesirable monitoring performance, that is, only effective to rapidly detect bivariate process mean shifts but inadequate to minimize false alarms to the *de facto* level ($ARL_0 \geq 370$).

(f) *De facto* level (*de facto* monitoring level)

De facto level refers to a widely acceptable average run length value for the first false alarms to occur in monitoring process variables or quality characteristics. Specifically, it refers to $ARL_0 \geq 370$ based on the traditional univariate SPC charting schemes such as Shewhart, CUSUM and EWMA control charts.

(g) Accurate diagnosis

Accurate diagnosis refers to a desirable diagnosis performance, that is, effective to correctly identify the sources of variation with high recognition accuracy (> 95%).

(h) Control chart patterns (CCPs)

Control chart patterns refer to the patterns of univariate process data streams that can be indicated graphically using Shewhart control chart.

(i) Bivariate patterns

Bivariate patterns refer to the unified patterns that are able to indicate the linear correlation between two dependent variables. In this research, these patterns are represented graphically using scatter diagrams.

(j) Pattern recognition

Pattern recognition is an operation of extracting information from an unknown process data streams or signals, and assigning it to one of the prescribed classes or categories (Haykin, 1999). In this research, it deals with bivariate patterns.

(k) Pattern recognition scheme

Pattern recognition scheme refers to a set of related procedures formulated and presented in a unified manner for addressing the problem of control chart pattern recognition (Hassan, 2002).

1.9 Research Contributions

The contributions for this research can be summarized in a hierarchical form as shown in Figure 1.4. The main contribution is a concept to improve monitoring-diagnosis performances of the MSPC charting scheme. In order to proof this concept, philosophy for improvement, namely, “balanced monitoring and accurate diagnosis” was implemented in developing the proposed scheme that is effective to detect bivariate process variation (mean shifts) rapidly with minimum false alarms and accurately identify the sources of variation (mean shifts). The supporting contribution is the design strategy towards developing an intended scheme. It involves application of the existing procedure and investigation on improved and new procedures. The existing procedure includes modeling of bivariate process samples and patterns, which is less reported in this field. The improved procedures involve modification on the statistical features input representation and the Synergistic-ANN recognizer that have been applied in univariate process monitoring and diagnosis. The new procedure investigated is two-stage monitoring and diagnosis using the integrated MEWMA – ANN scheme.

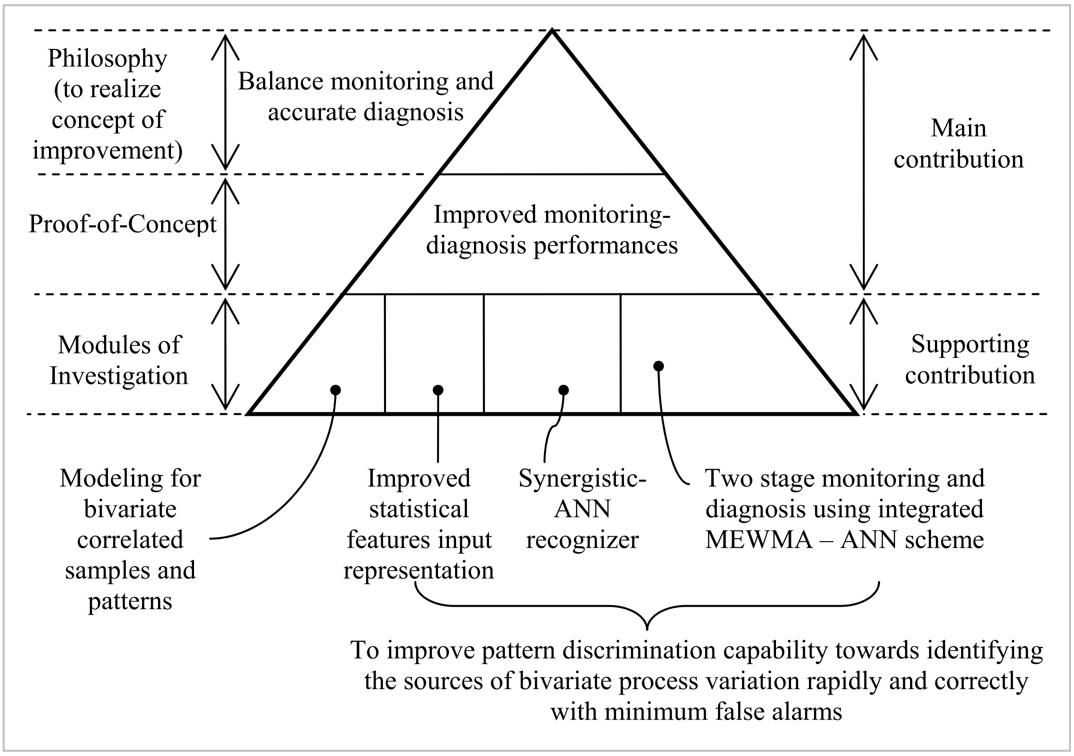


Figure 1.4 : Hierarchy of research contributions

1.10 Organization of the Thesis

Organization of this thesis is summarized in Figure 1.5. The first chapter describes the foundation of the research. This is followed by an extensive literature review in Chapter 2 that provides background information in the related fields and research trends leading to the current issue addressed in this research. Chapter 3 then presents the research methodology adopted for solving the focused issue. In Chapters 4 and 5, the proposed methodologies were then applied into design, development and testing for the Baseline scheme and Enhanced schemes towards achieving balanced monitoring and accurate diagnosis performances. Overall discussion on the research findings are provided in Chapter 6. The conclusions of this research, list of publications, knowledge contribution and practical impact, limitations, and suggestions for further research are highlighted in the final chapter.

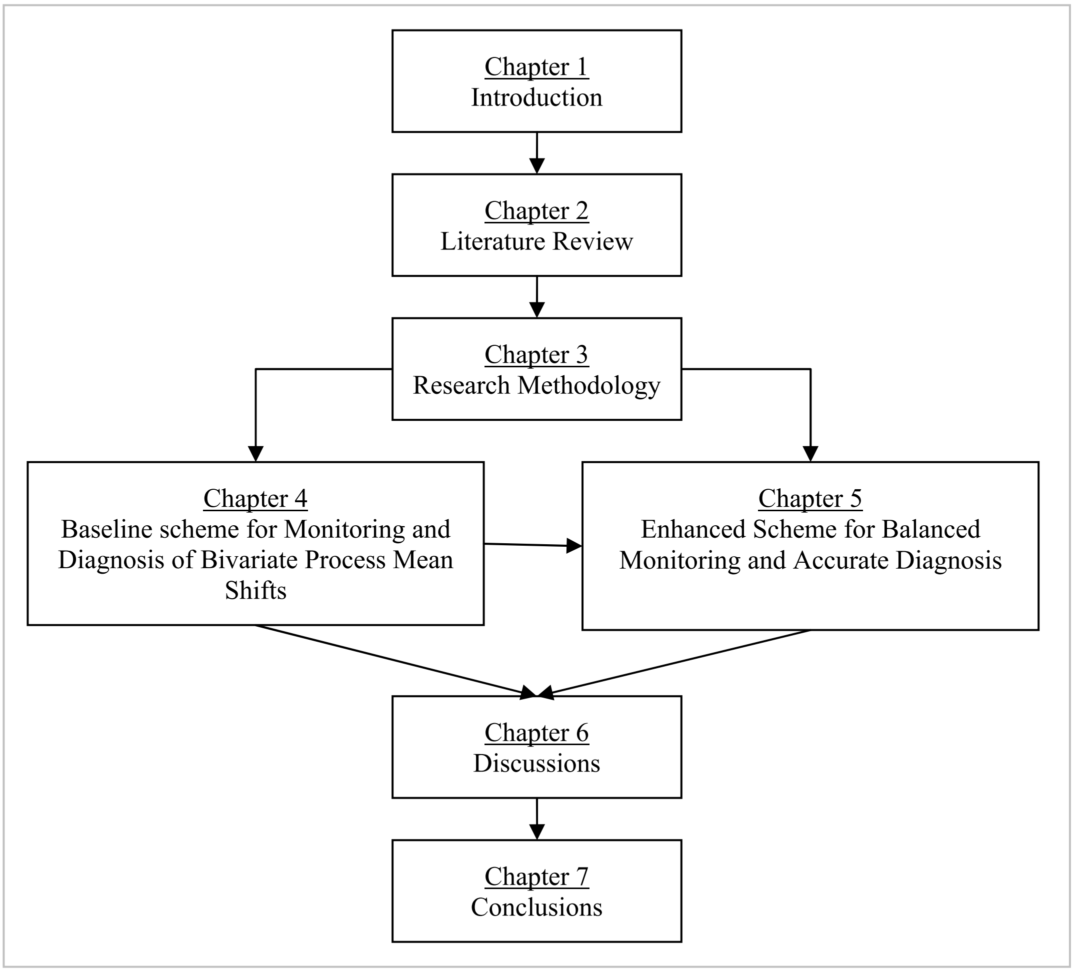


Figure 1.5 : Organization of the thesis

1.11 Summary

This chapter has provided an essential introduction to this research through the statement of problem, purpose, objectives, scopes and key assumptions, and importance of the research. A brief note of research approach is then provided, important terms are defined, research contributions are summarized and organization of the thesis is outlined.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter provides a review on the existing researches related to the subject of this thesis. This includes a general review on multivariate quality control (MQC) and research works in multivariate statistical process control (MSPC), and a specific review on statistical process control pattern recognition (SPCPR) schemes. The need for joint monitoring of two dependent variables has led to the extensive researches in the area of MSPC. Issues in development of the SPCPR schemes and limitations of the existing multivariate pattern recognition (MPR) schemes are reviewed. This chapter is organized as follows: Section 2.2 describes the fundamental concept of joint monitoring of bivariate process variation, which is supported with an industrial example. Section 2.3 focuses on the designs of MSPC charting schemes. Section 2.4 then presents the advances in SPCPR schemes. This is followed by further discussions on issues through out the development stages of the SPCPR schemes in Section 2.5. Section 2.6 discusses the limitations of existing MPR schemes. Finally, the summary of the review is outlined in Section 2.7.

2.2 Monitoring of Bivariate Process Variation

In manufacturing industries, it is commonly known that process variation such as wear and tear, machine vibration, inconsistent material and lack of human operators, among others has become a major source of poor quality. It can be monitored and diagnosed using the statistical process control (SPC) charting tools.

In monitoring and diagnosis of univariate process variation in mean shifts, the traditional SPC charting schemes such as Shewhart (Nelson, 1984; 1985; 1989), cumulative sum (CUSUM) (Hawkin, 1981; 1993) and exponentially weighted moving average (EWMA) (Crowder, 1989; Lucas and Saccucci, 1990) control charts remains among the most important tools for maintaining process stability. The key feature of control chart is the promising technique to differentiate between a statistically in-control and an out-of-control state of a running process or quality characteristic.

In practice, many processes or quality characteristics comprised of two or more dependent (correlated) variables, whereby they are need to be monitored-diagnosed jointly. This scenario, which is sometimes called multivariate quality control (MQC) (Montgomery, 2005) can be observed in machining of counterbore feature in hard disc drive (HDD) component as shown in Figure 2.1. The counterbore features namely, the counterbore hole and the counterbore head are the critical features for component assembly. It is machined using different tools that are: the counterbore hole is machined using boring tool, whereas the counterbore head is machined using endmill tool. The positioning of counterbore hole and the concentricity of counterbore head are two dependent process variables (bivariate) that need for joint monitoring and diagnosis. This bivariate process is the simplest case in MQC. Automation system is applied for handling and loading the work piece into the machine, and it is hold using pneumatic fixture for machining.

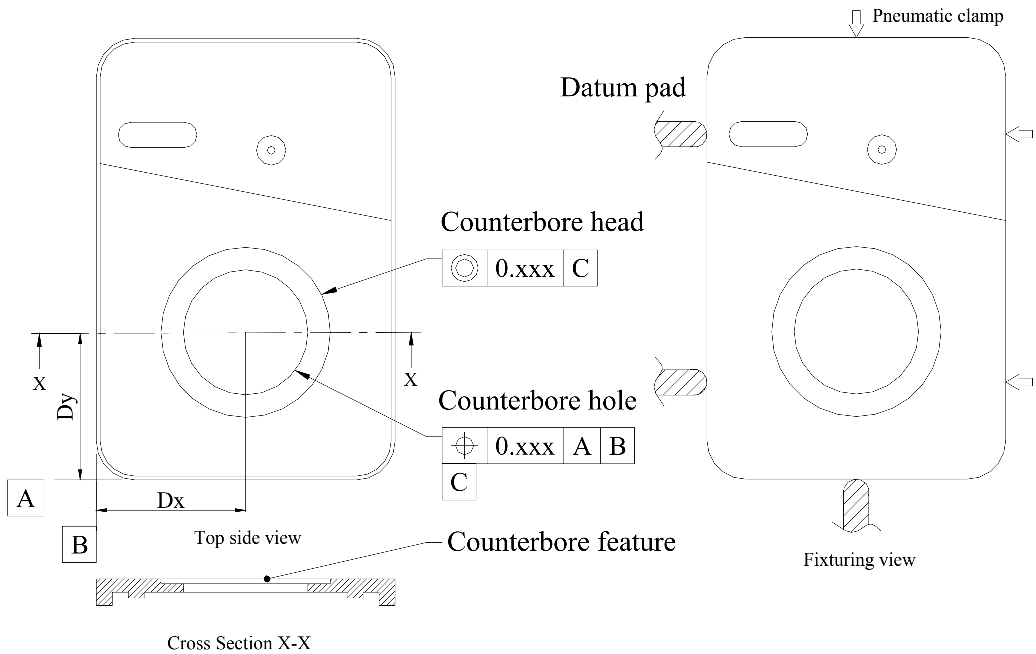


Figure 2.1 : Positioning and concentricity of counter-bore feature

Unnatural variation in bivariate process could exist due to "loading error" and "offsetting tool" as illustrated in Figure 2.2. Loading error occurred when metal chips or hard particles sticked at the datum pad of pneumatic fixture. Consequently, the positioning (P) of counter-bore hole would be suddenly increased (upward shift), whereas the concentricity (C) of counter-bore head remains in-control (normal pattern). Offsetting tool occurred when metal burr sticked inside the cutting tool holder. In this case, both quality characteristics (P and C) would be suddenly increased (upward shift). The related sources of variation are summarized in Table 2.1. Notation '1' represents shifted variable, while notation '0' represents normal variable. Bivariate in-control process is represented by (0, 0), whereby both quality characteristics (Positioning, Concentricity) in normal patterns. Bivariate out-of-control processes are represented by (1, 0), (0, 1) or (1, 1), whereby one or both quality characteristics in shift pattern.

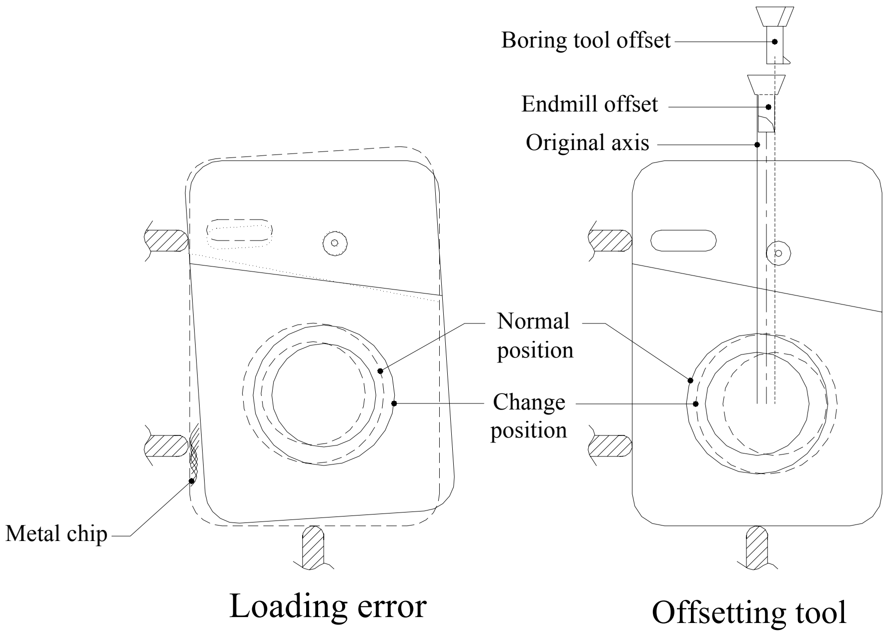
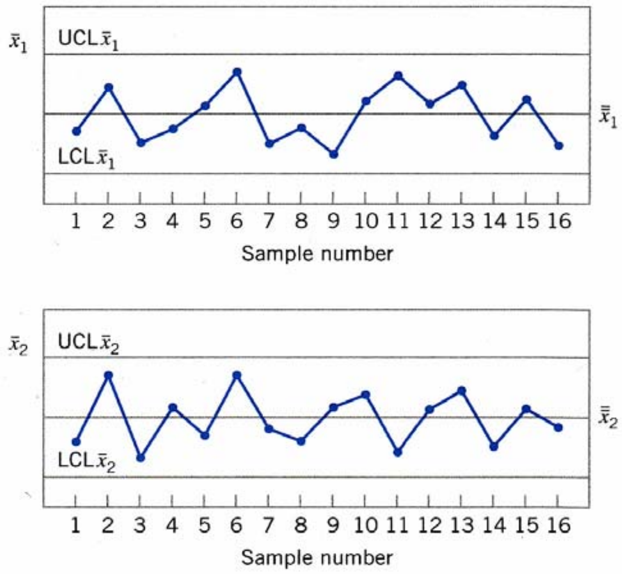


Figure 2.2 : Process variation due to loading error and offsetting tool

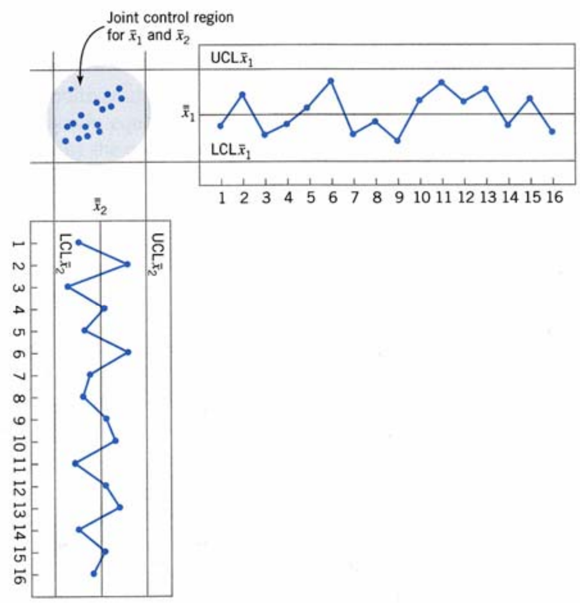
Table 2.1: Sources of variation in bivariate process

	In-control (0, 0)	Loading error (1, 0)	Offsetting tool (1, 1)
Positioning (P)	Normal	Upward Shift	Upward Shift
Concentricity (C)	Normal	Normal	Upward Shift

Based on common sense, one may think that the bivariate process variation as described above should be easily monitored and diagnosed independently (separately) using several Shewhart control charts. In certain situation as illustrated in Figure 2.3, however, this assumption could be inefficient and leading to erroneous decision making. In the presence of data correlation, an unusual sample with respect to the other samples can be identified using joint monitoring approach (based on joint control region) rather than using independent monitoring approach (based on different Shewhart control charts). This situation also indicates that the unusual sample could be deviate based on data correlation structure. Montgomery (2005) noted that univariate SPC charting schemes is nearly impossible to detect an assignable cause in the presence of bivariate correlated samples.



<u>Independent monitoring (based on different Shewhart control charts)</u>



<u>Joint monitoring (based on joint control region)</u>

Figure 2.3 : Independent and joint monitoring (Montgomery, 2005)

2.3 Researches in Multivariate Statistical Process Control (MSPC)

The need for joint monitoring-diagnosis as described in Section 2.2 has become the basis for investigation in multivariate statistical process control (MSPC). Previous researches have focused on design and application of the MSPC charting schemes.

2.3.1 Design of MSPC Charting Schemes

Advances in design of MSPC charting schemes have focused towards achieving better monitoring and diagnosis capabilities as shown in Figure 2.4. The T^2 control chart (Hotelling, 1947) that is developed based on logical extension of univariate SPC chart (Shewhart control chart) was claimed as an original work in MSPC. Initially, it was applied for joint monitoring of multivariate process of bombsight data during World War II (Montgomery, 2005). Nevertheless, it was found to be effective only for detecting mean shift in large magnitudes ($\geq$ 1.5 standard deviations). In order to improve capability for detecting mean shift in smaller magnitudes ($<$ 1.5 standard deviations), the multivariate cumulative sum (MCUSUM) (Crosier, 1988; Pignatiello and Runger, 1990) and the multivariate exponentially weighted moving average (MEWMA) (Lowry et al., 1992; Prabhu and Runger, 1997) control charts were developed based on logical extension of univariate CUSUM and EWMA control charts respectively. These multivariate control charts are commonly known as the traditional MSPC charting schemes.

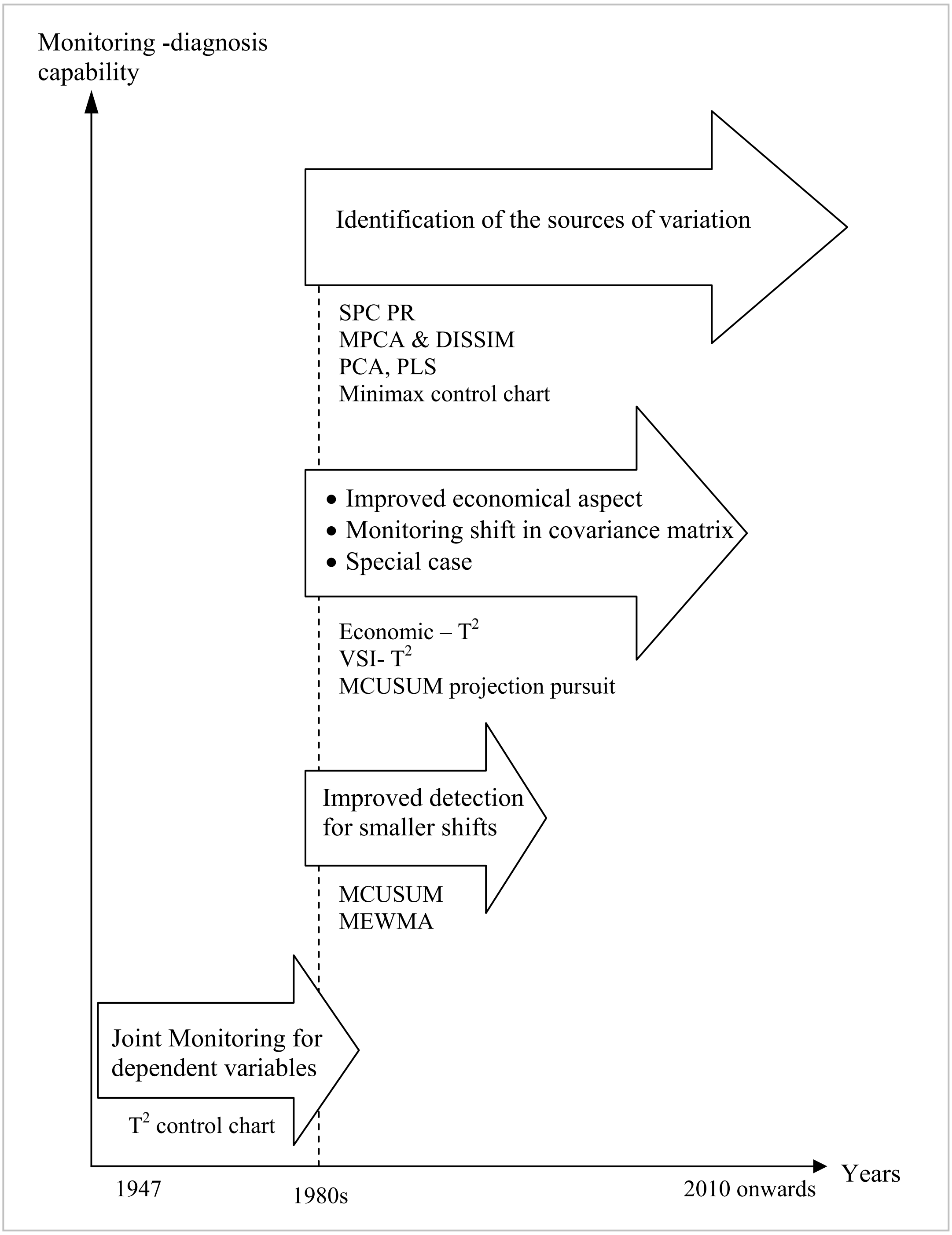


Figure 2.4 : Advances in MSPC charting schemes

The monitoring capability of the traditional MSPC charting schemes particularly the T^2 control chart was then enhanced for dealing with economical aspect, variable sampling interval (VSI), process dispersion (shift in covariance matrix), mean vector and covariance matrix, autocorrelated process, and specific situation, among others. Montgomery and Klatt (1972) proposed an economic T^2

charting scheme by including cost model into the multivariate charting procedures. Chen (1995) investigated the additional statistical constrains into the T^2 control charting procedures. Aparisi and Haro (2001) proposed the T^2 control chart for variable sampling interval (VSI) to improve sensitivity in detecting mean shifts. Chou *et al.*, (2003) proposed the economic-statistical design of the multivariate control chart for monitoring the mean vector and covariance matrix simultaneously. Chou *et al.*, (2006) and Chen (2007) applied genetic algorithm (GA) into the economic design of VSI-T^2 charting schemes. Chou *et al.*, (2006) utilized GA for searching the optimal design parameters of the VSI-T^2 control chart (sample size, long sampling interval, short sampling interval, warning limit and control limit) towards minimizing the expected total cost. Chen (2007) used Markov Chain approach in designing the cost model, whereas GA was utilized to determine the optimal design parameters towards minimizing the cost function. Khoo and Quah (2003) developed a multivariate control chart for monitoring shifts in the covariance matrix based on individual observations. Alwan and Alwan (1994), Apley and Tsung (2002), and Jiang (2004) investigated the application of T^2 control chart for monitoring mean shifts in univariate autocorrelated processes. Wei Jiang (2004) focused on the global properties of the T^2 test in a situation where mean shift information is unknown. Ngai and Zhang (2001) proposed the MCUSUM control chart based on projection pursuit to deal with a specific situation, that is, the process mean is already shifted at the time the control charting begins. The extensive literature review based on the international journal papers as cited above revealed that there is a strong interest in the fields of economical and VSI designs of the T^2-based control chart for monitoring multivariate process mean and dispersion.

The traditional MSPC charting schemes are only effective for monitoring (detecting) mean shifts but they are unable to diagnose (identify) the sources of variation in mean shifts. In other word, it is unable to provide diagnosis information for a quality practitioner towards finding the root cause errors and solution for corrective action. Therefore, besides research in the fields of economical and VSI designs, major attention was also focused for improving capability in identifying the sources of variation, particularly variation in mean shifts. Among others, the Shewhart control charts with Bonferroni control limits (Alt, 1985), Shewhart control charts with an exact simultaneous control interval (Hayter and Tsui, 1994), principle component analysis (PCA) (Jackson, 1980; 1991), T^2-decomposition (Mason *et al.*, 1995; 1996; 1997), Minimax control chart (Sepulveda and Nachlas, 1997), multivariate profile chart (Fuchs and Benjamini, 1994), dynamic Gabriel biplot (Spark *et al.*, 1997), T^2 with ratio charts (Maravelakis *et al.*, 2002; Bersimis *et al.*, 2005) and Andrews curves (Maravelakis and Bersimis, 2005) are several methods proposed for solving this issue. Further discussions on these schemes can be referred in (Lowry and Montgomery, 1995; Kourti and MacGregor, 1996; Mason *et al.*, 1997; Bersimis *et al.*, 2007).

The review also reveals that there are other schemes or procedures have been proposed in the recent years towards improving the capability to identify the sources of variation. They included the moving principle component analysis (MPCA) and dissimilarity index (DISSIM) (Kano *et al.*, 2002), vector autoregressive residual (VAR) (Pan and Jarrett, 2007), and pattern recognition (PR) (Chih and Rollier, 1994; 1995; Wang and Chen, 2001; Zorriassatine *et al.*, 2003; Chen and Wang, 2004; Niaki and Abbasi, 2005; Guh, 2007; Cheng and Cheng, 2008; Guh and Shuie, 2008; Hwarng, 2008; Cheng and Cheng, 2008; Yu and Xi, 2009; Yu *et al.*, 2009; El-Midany *et al.*, 2010; Hwarng and Wang, 2010), among others. The MPCA and DISSIM scheme, as enhancement from the PCA method, can be used to identify the sources of mean shifts by monitoring the direction of principle components and the dissimilarity index. The VAR scheme was designed for monitoring multivariate process in the presence of serial correlation. The PR schemes were designed for monitoring and diagnosis of bivariate process variation based on automated recognition of data streams patterns. This technique coupled with knowledge of manufacturing processes and quality characteristics would result in very effective information for diagnosis and corrective action purposes. In this research, further investigation was focused on these schemes since it was found as one of the advanced techniques in the MSPC charting designs and showed significant improvement in overall monitoring-diagnosis capabilities. As such, further discussions on PR schemes are provided in the next section.

Briefly, the design of MSPC charting schemes as discussed above can also be classified as in Figure 2.5.

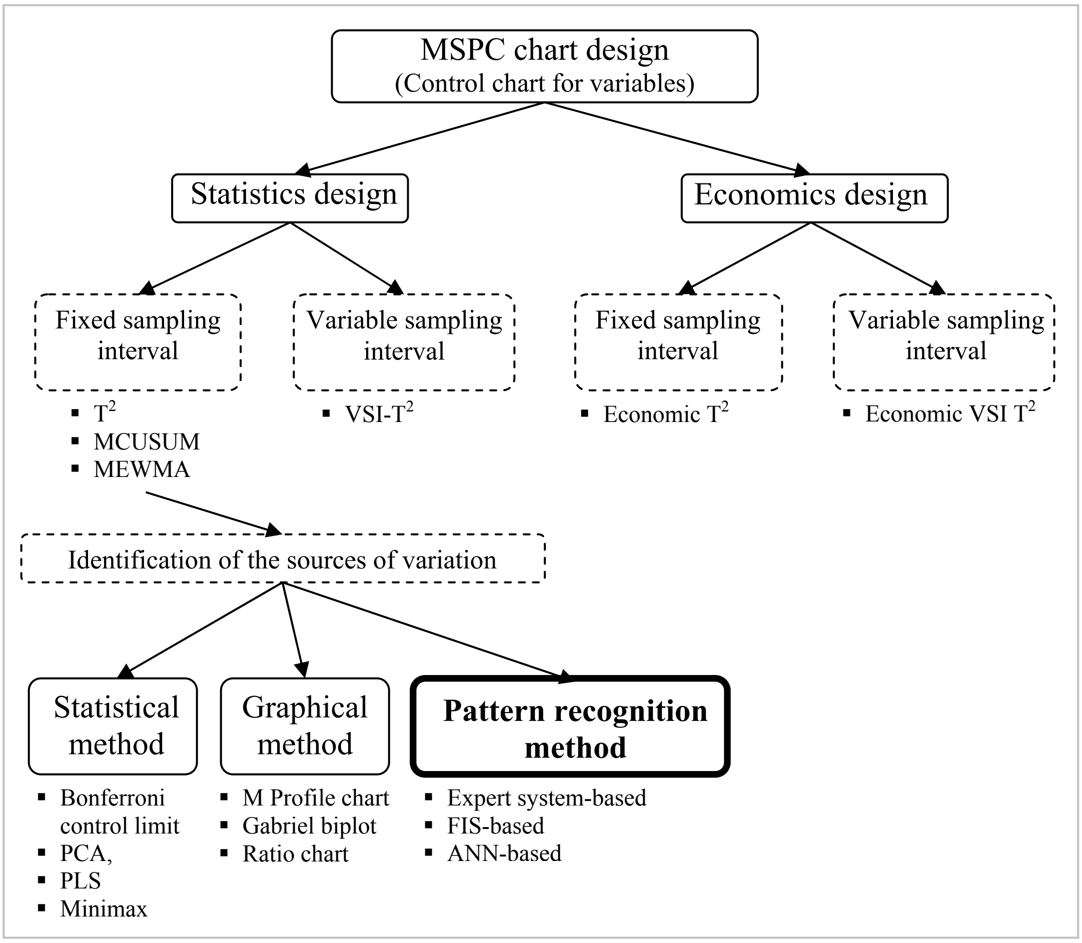


Figure 2.5 : Classification of MSPC charting schemes

Basically, the MSPC charting schemes for variables can be categorized to: (i) statistical design, and (ii) economical design. Both design categories can be further classified to fixed sampling interval (FSI) and variable sampling interval (VSI). The traditional MSPC charting schemes that are T^2, MCUSUM and MEWMA control charts were designed based on statistical consideration for dealing with FSI. In the same level, the T^2 charting procedures were enhanced to deal with VSI (VSI-T^2), economical consideration (economic-T^2), and joint VSI-economic consideration (economic VSI-T^2). Based on the diagnosis issue of the T^2 charting scheme, various schemes designed towards identifying the sources of mean shifts can be classified to (i) statistical method (such as PCA, PLS, MPCA and DISSIM, and VAR, among others) (ii) graphical method (such as M-profile chart, Gabriel biplot and ratio charts, among others), and (iii) pattern recognition method (such as expert systems (ES), neural-fuzzy (ANFIS), artificial neural network (ANN), support vector machine (SVM) and decision tree (DT), among others.

2.3.2 Application of MSPC Charting Schemes

Advances in automated inspection, data acquisition, computerized SPC, and their integration systems have enabled the application of MQC in manufacturing industries. Satisfy applications of T^2 control chart have been reported in Flores *et al.* (1995), Mason *et al.* (2001), Parra and Loziza (2003; 2004), and Williams *et al.* (2006), among others. In semiconductor manufacturing, T^2 control chart was used to monitor six quality parameters for achieving optimal micro-lithographic performance. Such parameters provided effects to the wafer grid-staging error (Flores *et. al.*, 1995). In spatialty plastic polymer manufacturing, T^2 control chart was used to monitor seven chemical compositions for achieving rigid chemical formulation. The chemical formulation is necessary for mould release when the spatialty plastic polymer has completely transformed into a product (Mason *et al.*, 2001). In drug manufacturing, T^2 control chart with T^2 decomposition procedures was used to control seven major organic impurities profile that constitutes an identifier of a particular drug substance (Parra and Loziza, 2003; 2004). Then, the used of T^2 distribution based on 'successive differences estimator' was presented by Williams *et al.* (2006).

Singh and Gilbreath (2002) and Milatec *et al.* (2004), among others, have reported effective application of principal components analysis (PCA) and partial least square (PLS) schemes in chemical industries. In developing a real-time control system prototype, PCA was utilized for monitoring process performance and product characteristics (Singh and Gilbreath, 2002). Milatec *et al.* (2004) reported the development of an on-line monitoring system for multivariate processes, which involve system design, integration, performance evaluation with on-line systems,

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