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

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To Minah binti Husein, Zaiton binti Adil, Siti Fatimah, Siti Safura
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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).

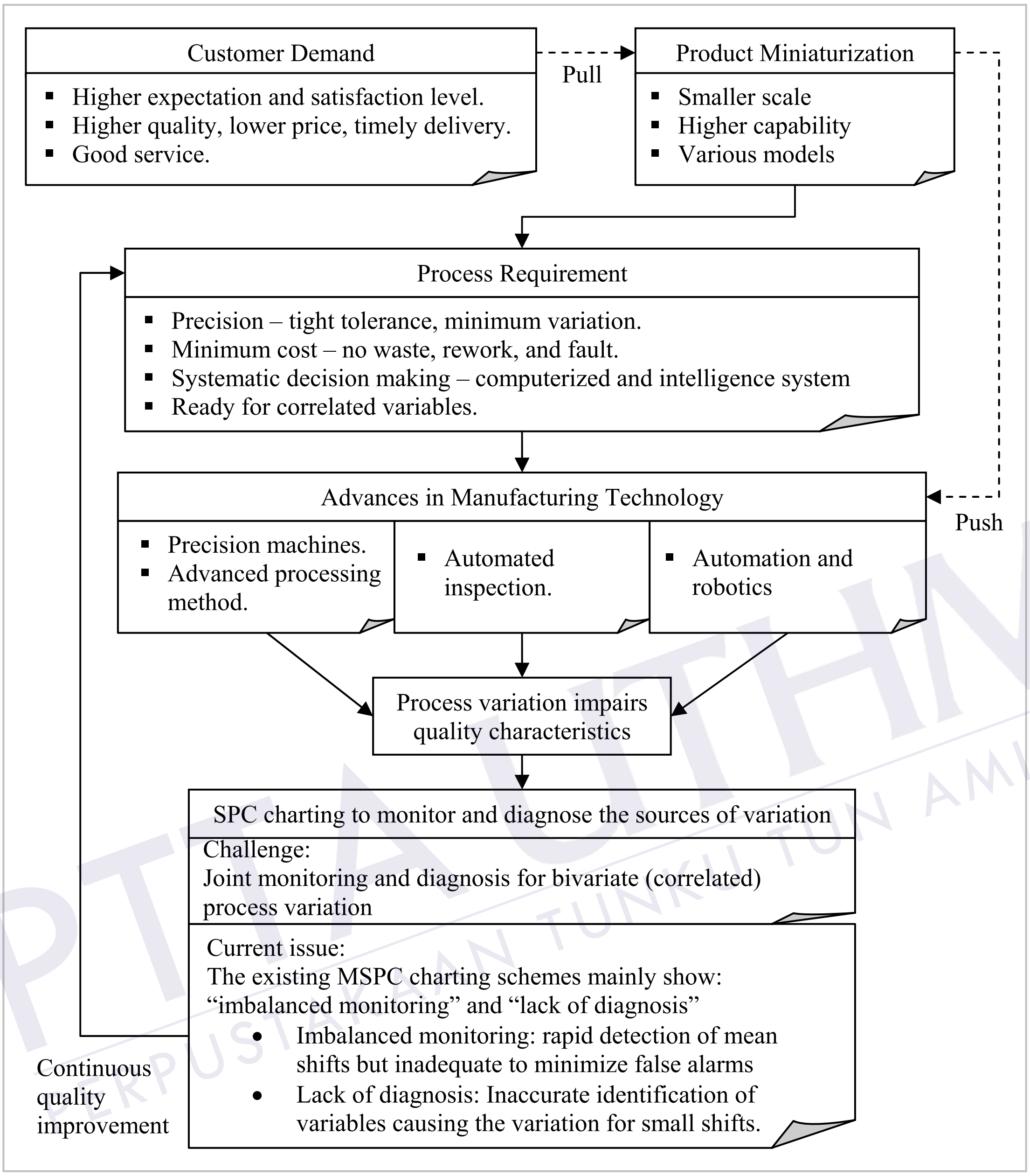


Figure 1.1 : Scenario leading to the current research issue

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.

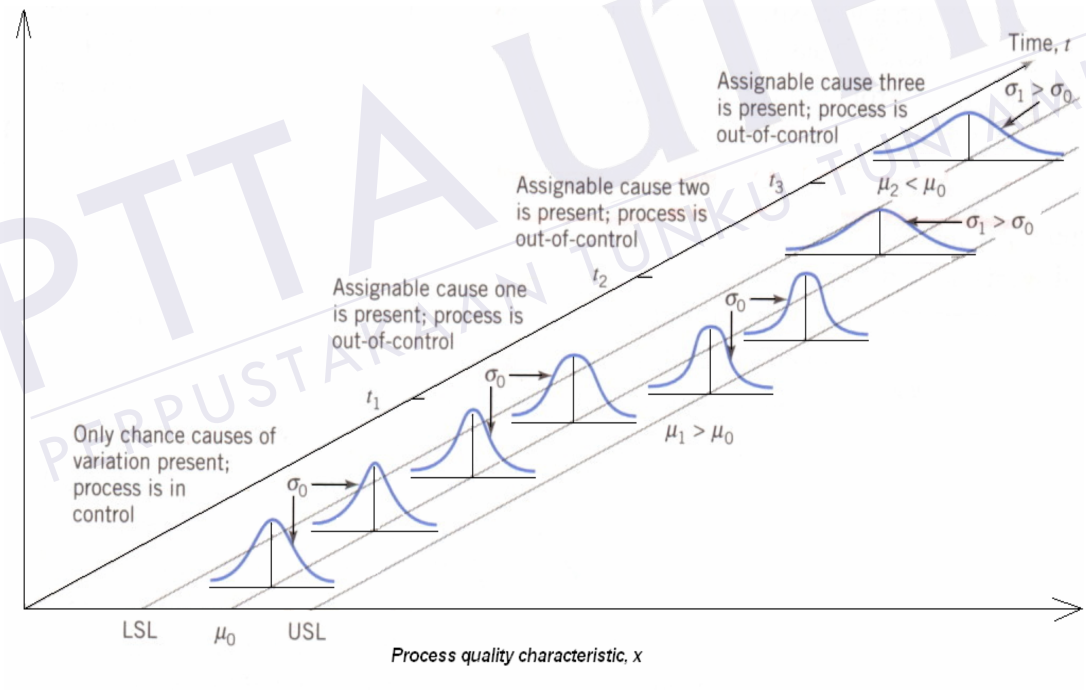


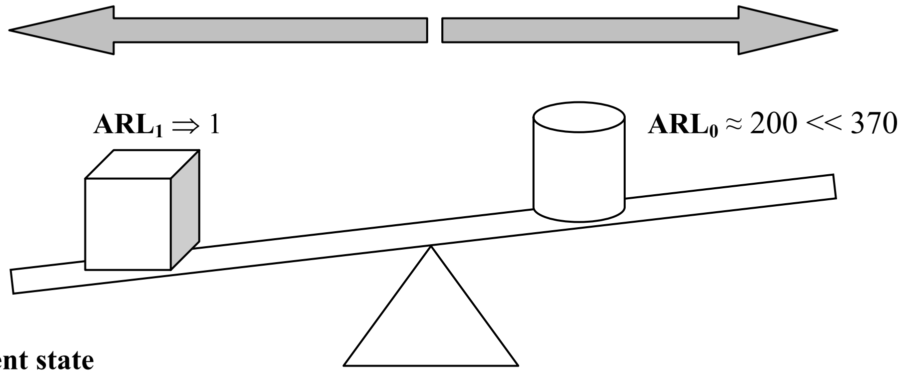
Figure 1.2 : Process variation (Montgomery, 2005)

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 ≥ 95%).

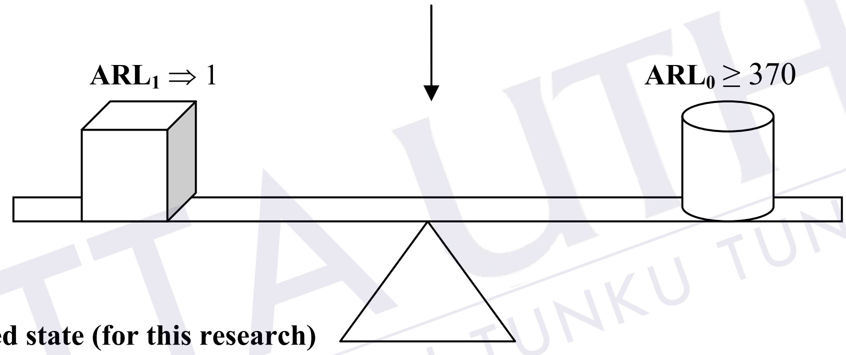
Sensitivity in mean shift detection
Shorter **ARL$_1$** represents faster detection of process mean shifts

Capability in false alarm avoidance
Longer **ARL$_0$** represents smaller false alarm



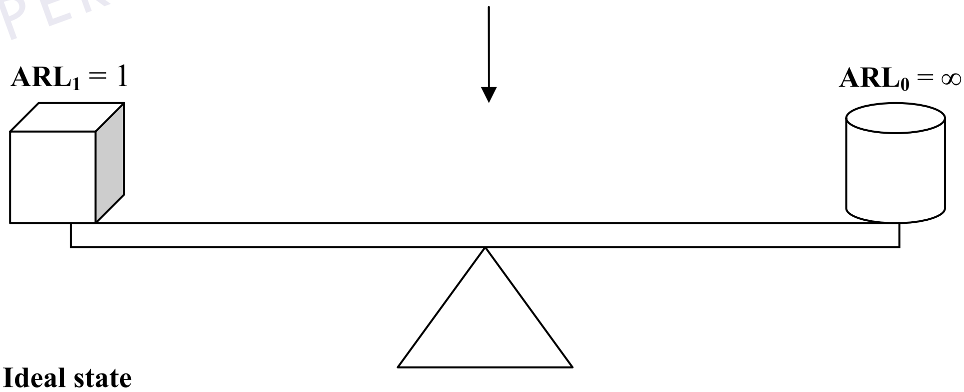
Current state

Imbalanced monitoring: able to detect process mean shifts rapidly (ARL$_1$ $\Rightarrow$ 1) but inadequate to minimize false alarm to the *de facto* level (ARL$_0$ $\approx$ 200 << 370)



Desired state (for this research)

Balanced monitoring (reasonable for current practice): able to detect process mean shifts rapidly (ARL$_1$ $\Rightarrow$ 1) and maintain minimum false alarm to the *de facto* level (ARL$_0$ $\geq$ 370)



Ideal state

Perfect balanced: able to detect process mean shifts as soon as possible (ARL$_1$ = 1) without triggering any false alarm (ARL$_0$ = ∞)

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%).

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