ESTIMATING CHANGE POINT IN MULTIVARIATE PROCESSES VIA SIMULTANEOUS MEAN VECTOR AND COVARIANCE MATRIX

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy

Faculty of Mechanical Engineering
Universiti Teknologi Malaysia

FEBRUARY 2023

DEDICATION

This thesis is dedicated to my father, who taught me that the best kind of knowledge to have is that which is learned for its own sake. It is also dedicated to my mother, who taught me that even the largest task can be accomplished if it is done one step at a time.

ACKNOWLEDGEMENT

I contacted many people, researchers, academicians, and practitioners in preparing this thesis. They have contributed to my understanding and thoughts. I express my sincere appreciation to my thesis supervisor, Professor Dr. Noordin Mohd Yusof, and Ir Ts Dr. Nor Hasrul Akhmal Bin Ngadiman for their encouragement, guidance, criticism, and friendship. I am also very thankful to my co-supervisor, Professor Dr. Muhammad Hisyam Lee, for his guidance, advice, and motivation. Without their continued support and interest, this thesis would not have been the same.

I am also indebted to Universiti Teknologi Malaysia (UTM) for funding my Ph.D. study. Librarians at UTM also deserve special thanks for their assistance in supplying the relevant literature. I am grateful to all my family members, especially my father and mother.

ABSTRACT

In many industrial processes, several quality characteristics are inevitably related. In this situation, the mean vector and covariance matrix must be simultaneously monitored and controlled to determine whether a multivariate process is in control. With the increase in the number of variables, the performance of control charts is significantly reduced, and the time delay between the actual time of change in the process and the warning time of the control chart increases, which is one of the main challenges when using multivariable control charts. Between the real-time and the change time (called the change-point - CP), especially during the simultaneous monitoring and controlling of the parameters, the mean vector, and the covariance matrix cause problems such as delay or stoppage of the production lines or services, as well as inconsistent production of products or services. To improve this, a new way of estimating the CP will help statistical process control (SPC) professionals identify the cause(s) of out-of-control (OC) conditions, thus providing better feedback for process improvement. This study presented a new method based on an artificial neural network (ANN), which first examined the OC conditions for a multivariate process using the multivariate exponentially weighted moving average (MEWMA) and multivariate exponentially weighted mean square (MEWMS) control charts. Then, the ANN-fitting method was used to diagnose the cause(s) of OC conditions using the machine learning (ML)-classifier and estimating the length of delay time. Finally, the change point (CP) was estimated by integrating all these methods. The performance of the new approach was validated by comparing it with the results from another study. It also validated the proposed method developed by evaluating the accuracy and precision of this research. As a conclusion, the MEWMS chart was the best for detecting the OC condition while the support vector machines (SVM) gaussian model best to diagnoses the cause(s) of the OC condition. The model provided has estimated the change point on one sample with difference over 10,000 tested cases (simulated) with a probability of 99%, which is an accurate and reliable model for a practical approach.

ABSTRAK

Dalam banyak proses perindustrian, beberapa situasi berkaitan ciri kualiti tidak dapat dielakkan. Dalam keadaan ini, vektor min dan matriks kovarian mesti dipantau dan dikawal secara serentak untuk menentukan sama ada proses multivariat berada dalam kawalan. Dengan peningkatan dalam bilangan pembolehubah, prestasi carta kawalan akan berkurangan dengan ketara, dan kelewatan masa antara masa sebenar perubahan dalam proses serta masa amaran carta kawalan akan meningkat, dimana ia merupakan salah satu cabaran utama apabila menggunakan carta kawalan pelbagai pembolehubah. Antara masa nyata dan masa perubahan (dipanggil titik perubahan - CP), terutamanya semasa pemantauan dan kawalan serentak parameter; vektor min dan matriks kovarians menyebabkan masalah seperti kelewatan atau pemberhentian talian pengeluaran atau perkhidmatan, serta pengeluaran produk atau perkhidmatan yang tidak konsisten. Sebagai penambahbaikan, cara baru untuk menganggarkan CP akan membantu profesional statistical process control (SPC) mengenal pasti punca keadaan luar kawalan (OC), sekali gus memberikan maklum balas yang lebih baik untuk penambahbaikan proses. Kajian ini membentangkan kaedah baharu berdasarkan rangkaian saraf tiruan (ANN), yang terlebih dahulu mengkaji keadaan OC untuk proses multivariate menggunakan carta kawalan multivariate exponentially weighted moving average (MEWMA) and multivariate exponentially weighted mean square (MEWMS) control charts. Kemudian, kaedah pemasangan ANN digunakan untuk mendiagnosis punca keadaan OC menggunakan pengelasan pembelajaran mesin (ML) dan menganggarkan tempoh kelewatan masa. Akhirnya, titik perubahan (CP) dianggarkan dengan menyepadukan semua kaedah ini. Prestasi pendekatan baharu telah disahkan dengan membandingkannya bersama keputusan daripada kajian lain. Ia juga mengesahkan kaedah yang dicadangkan untuk dibangunkan dengan menilai ketepatan dan kejituan penyelidikan ini. Sebagai kesimpulan, carta MEWMS adalah yang terbaik untuk mengesan keadaan OC, manakala model support vector machines (SVM) gaussian adalah baik untuk mendiagnosis punca keadaan OC. Model yang disediakan telah menganggarkan CP bagi satu sampel dengan perbezaan daripada 10,000 kes yang diuji (simulasi) dengan kebarangkalian 99%, di mana ia merupakan model yang tepat dan boleh dipercayai untuk pendekatan praktikal.

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LIST OF ABBREVIATIONS

ANNs	-	Artificial Neural Networks
ARL	-	Average Run Length
BP	-	Backpropagation
BR	-	Bayesian Regularization
CP	-	Change Point
CUSUM	-	Cumulative Sum
CI	-	Confidence Interval
EWMA	-	Exponentially Weighted Moving Average
GP	-	Gaussian Process
KNN	-	Kernel Neural Network
LM	-	Levenberg-Marquardt
MEWMA	-	Multivariate Exponentially weighted Moving Average
MEWMS	-	Multivariate Exponentially weighted Mean Square
MCUSUM	-	Multivariate Cumulative Sum
ML	-	Machine Learning
MLE	-	Maximum Likelihood Estimator
MSPC	-	Multivariate Statistical Process Control
OC	-	Out of Control
PDF	-	Probability Density Function
QC	-	Quality Control
SPC	-	Statistical Process Control
SVM	-	Support Vector Machine

LIST OF SYMBOLS

α	-	Type I error rate
μ	-	Mean
σ	-	Variance
ρ	-	Correlation Coefficient
Σ	-	Covariance Matrix
δ	-	Sigma
ν	-	Degrees of Freedom
λ	-	Probability Distribution
τ	-	Real CP
$\hat{\tau}$	-	Estimate CP
I	-	Input
M	-	Mean Vector
T^2	-	T Square (Hotelling Control Chart)
$\chi 2$	-	Chi-Square
R^2	-	R-Square (Training)

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CHAPTER 1

INTRODUCTION

1.1 Background of Study

Statistical process control (SPC) is a powerful set of quality control (QC) tools used in the industrial and services sector that effectively improves the processes and increases efficiency by reducing variability and errors. One of the main goals of SPC is to detect process changes by getting an out-of-control (OC) signal from the process so that the causes of such changes can be investigated and identified quickly. Then, a related corrective action taken by experts could eliminate that cause(s). The reason (s) for change are generally divided into two categories: common (natural) causes and assignable (special) causes. The common causes have to do with the innate nature of the process. They can never be eliminated without changing the process, for example, lighting, noise, pollution, temperature, and ventilation. The assignable causes of variation interfere with the process. They are not difficult to detect and should be eliminated. However, seeing these causes also requires procedure for detect them involving experts in during process, for example, operator error and device malfunction (Montgomery, 2020).

A control chart is one of the SPC's most powerful and useful tools compared to other tools. A control chart contains the measures and detects if the fundamental probability distribution remains stable over time. In 1921, Control charts were presented by Walter Shewhart in Bell Telephone Laboratories. The Shewhart control chart, exponentially weighted moving average (EWMA), and cumulative sum (CUSUM) are popular control charts used to monitor and control univariate processes (Hahs-Vaughn and Lomax, 2020; Park and Jun, 2015).

Subsequently, many researchers started to employ multivariate quality control involving several dependent quality characteristics for many industrial and service operations. In multivariate methods, the process's two or more quality characteristics are monitored and controlled simultaneously. Hence, the quality characteristics of the multivariate process are correlated and cannot be monitored independently and individually. Therefore, the multivariate statistical process control (MSPC) offers an approach that simultaneously monitors several quality characteristics of the process. In 1947, Hotelling identified the MSPC procedure to monitor the mean vector of multivariate processes by applying the (T^2) T-square statistics for the first time (Ajadi et al., 2020).

MSPC has different types, including Hotelling (T^2) charts, Chi-square (χ^2) charts, multivariate exponentially weighted moving average (MEWMA) charts, and multivariate cumulative sum (MCUSUM) as the most important well-known control charts in the field of multivariate process monitoring. Control charts monitor the process and detect cause deviations before many nonconforming products are produced (Gunaratne, 2018). Notably, monitoring of deviations is important on the control charts. The mission of the control charts has been to distinguish common causes from assignable causes. Normally, the assignable cause is the reason for the OC condition in control charts, So this is a problem in the production process in the QC system. Thus, it should be found and remove the reason for the OC condition before any defective products and poor services are rendered (Sogandi et al., 2018).

Each of these control charts, in addition to being sensitive to the number of variables, is also sensitive to each parameter. Therefore, need to :

a) Monitor the mean vector of the process (sensitive to mean vector).

b) Analyze the covariance matrix of the process (sensitive to variation).

For example, the MEWMA control chart is sensitive to the mean vector. In the last decade, some researchers used another control chart called MEWMS (multivariate exponentially weighted mean square). This chart is sensitive to variance.

One of the other problems in quality control, the control chart detects deviations with a time delay from real-time. One of the most efficient ways to identify the sources of the defect in the process is to identify the real-time deviation causing the change in the process. The exact real-time change in the process is called a change point (CP) . The estimated CP helps manufacturing engineers search within a shorter period to discover the assignable cause(s) and remove them by taking corrective action to improve quality (Ahmadzadeh, 2018; Atashgar and Rafiee, 2020; Yeganeh et al., 2021).

In the last 20 years, most research has focused on developing different CP estimating methods for monitoring shifts in the process mean. For example, it can find some reviews of these developments in Atashgar (2013), Shadman (2015), Lu (2016), Ahmadzadeh (2018), and Amiri (2018). However, this research also includes reviews on estimating CP multivariate processes for monitoring shifts in a covariance matrix, and their development has been limited. Accordingly, several control charts, such as MEWMS chart , have been developed to monitor the covariance matrix of multivariate processes. This issue indicates the importance of controlling the variability of qualitative characteristics in the process. It is noteworthy that the covariance matrix and the mean vector should be monitored in multivariate techniques and simultaneously estimate the CP (Gunaratne, 2018). Many researchers have studied different methods for estimating CP, but most research has been done in multivariate processes related to estimating CP, considering only the mean vector (Amiri and Allahyari, 2012).

The change point estimation in the control charts was examined by Nishina, (1992) using two control charts, CUSUM and EWMA control charts. Although the two control charts previously mentioned were used initially to detect OC conditions, they have also been used to estimate the change point of the process after receiving a warning from the control chart. However, in recent years, researchers have shown that control charts are inefficient for accurate CP estimation because of the control chart limitations, including the increase of shifts, increased variables, and the sensitivity of each control chart on each parameter mean vector and variety (Atashgar, 2015).

Another method of estimating the change point is to use the maximum likelihood estimator (MLE). This method was introduced by Samuel et al. (1998) to evaluate the CP in the mean of the normal process. The use of MLE is one of the most popular methods of assessing the change point. In addition to the methods as mentioned above, researchers have studied other techniques, including learning-based methods, clustering, decision tree, and artificial neural networks (ANNs). Some researchers also have estimated CP with two methods and then comparison together. For example, Ahmadzadeh (2018) and Amiri et al. (2018) have estimated CP using two models, ANN and MLE. After comparing these models, the result of the ANN model was quickly and more accurate than the MLE method in detecting CP.

1.2 Statement of Problem

The increasing practice of SPC in various industrial and service sectors demanded the use more effective methods that can detect changes in quality level quickly. The quality characteristics of the multivariate process must be correlated, and they cannot be monitored independently and individually. Previous studies found that changes in the mean do not affect the covariance, while changes in the covariance matrix affect the mean vector. Lack of this type of control and monitoring system leads to the production of non-conforming goods, production line downtime or service waste time, energy loss, and high costs to processes, especially multivariate processes, and this is because there has been a correlation between parameters. Therefore, multivariate statistical process control (MSPC) offers methods that simultaneously monitor several quality parameters of the process. Hotelling, Chi-square, MCUSUM, MEWMA, and MEWMS are among the popular control charts for multivariate process monitoring (Gunaratne, 2018).

As mentioned in the background of the study, each of these control charts is sensitive to a specific parameter. For example, Figure 1.1 compares two different control charts (MEWMA and MEWMS) with the correlated quality parameters and 1000 simulation samples data, with $\rho=0.5$ as the correlation coefficient, where the OC condition is different. The MEWMA chart did not show any signal and looked nearly perfect. In contrast, the MEWMS chart shows an OC signal at around two hundred.

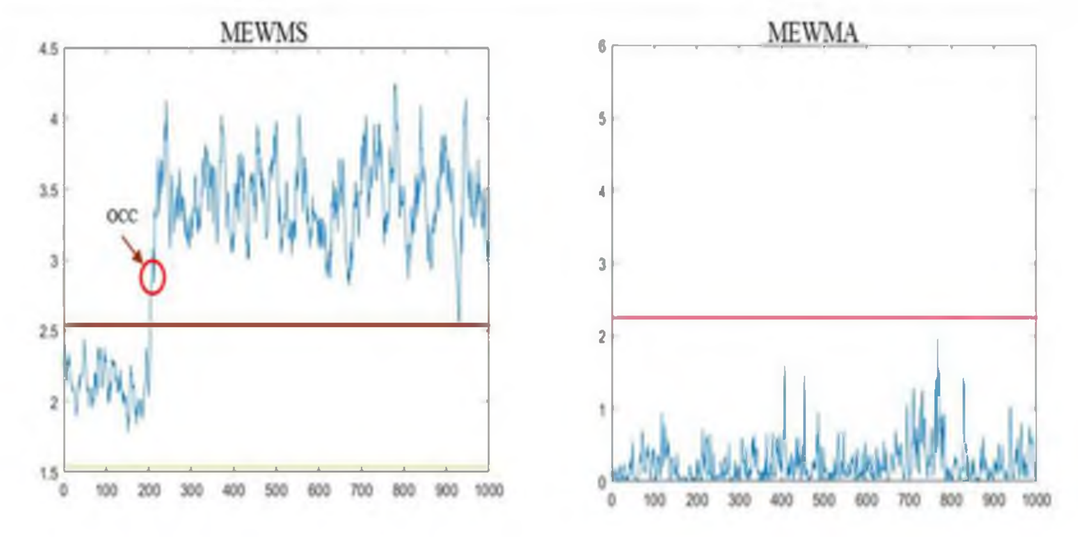

Figure 1.1 Multivariate control charts (MEWMA and MEWMS) , ρ=0.5 and simulation 1000 samples data.

Therefore, according to the above problem, the question arises whether there is a need for a new approach that can identify the OC conditions when using the mentioned control charts, according to the sensitivity of each one on a parameter? Because this problem in multivariable industries will be making non-conforming products during production, at the same time, the system is still under control. Thus, a new efficient method is needed to quickly find the point as the assignable cause that caused this problem to the OC condition in the process.

As noted in the background of the study, the main problem is the use of multivariate control charts for simultaneous monitoring of the covariance matrix and the mean vector for estimating CP. In the CP estimation problems, according to Gunaratne (2018) nad Rahimi et al.(2019), and in addition to the mean vector, the variability of the covariance matrix is important for evaluating whether the process is in control. Especially, as the number of variables becomes larger, the time required for the simulation increases, and the multivariate quality charts could not accurately CP estimation when monitoring the covariance matrix and the mean vector simultaneously. For example,

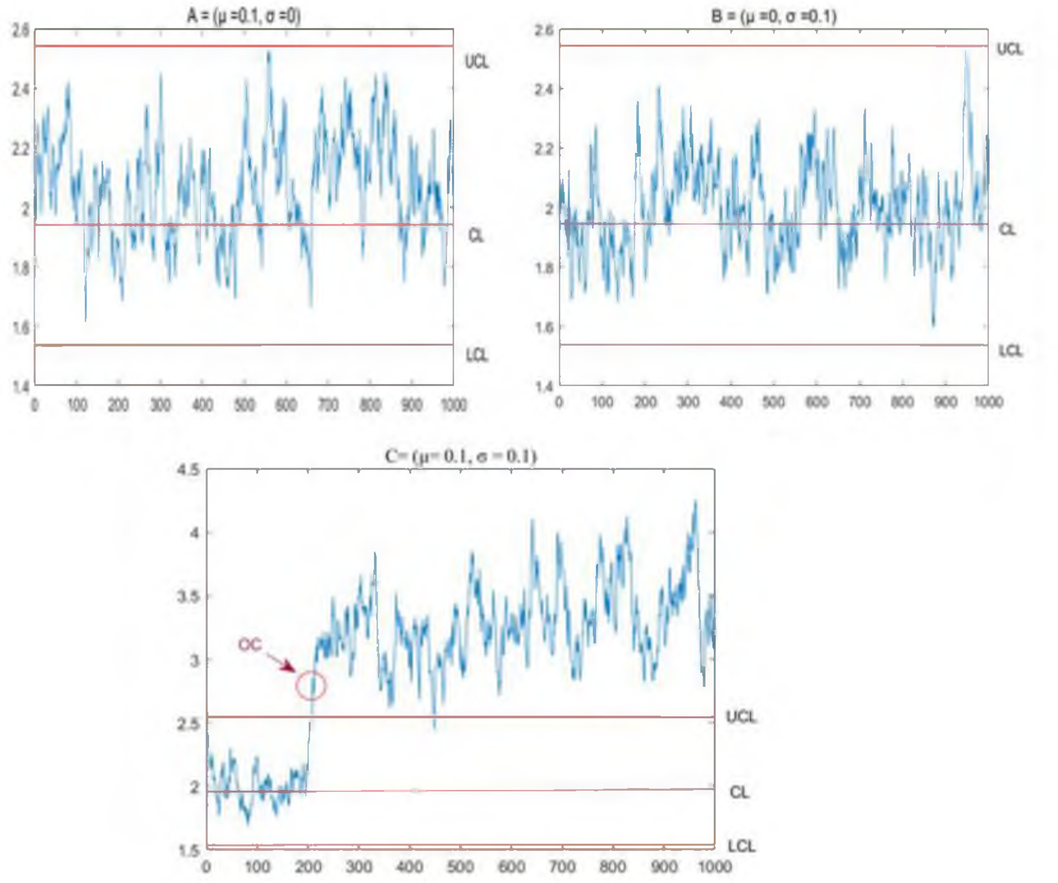

Figure 1.2 MEWMS chart, ρ=0.5 and simulations 1000 samples data, for different shifts for μ and δ shows three shifts for the different quality parameters as change. Part A shows that the mean has shifted, and variability has been constant. As shown in this section, despite the problem in the system, the charts does not offer any OC conditions. In Part B, the covariance shifted, and the mean was no shift. Despite the problem and the upward trend of the system to near the upper control, it still does not show the control chart OC condition. In Part C, both quality parameters shifted simultaneously and got a warning condition.

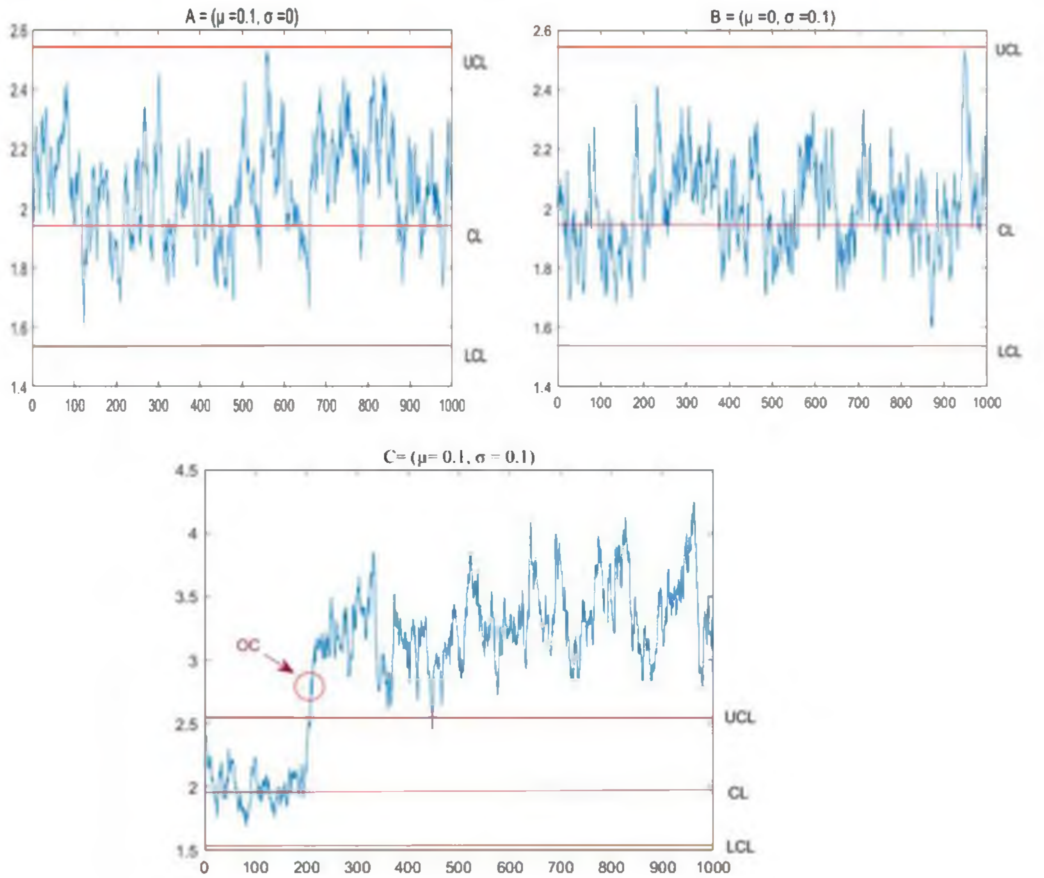

Figure 1.2 MEWMS chart, ρ=0.5 and simulations 1000 samples data, for different shifts for μ and δ

The example above shows the importance of monitoring the mean and covariance simultaneously in multivariate processes. According to the above examples and previous studies (Amiri et al,2018 and Ahmadzadeh,2018), it is clear that multivariable control charts have problems accurately diagnosing OC conditions and finding the cause(s) of OC conditions. In addition, each of the μ and σ parameters, alone or simultaneously, will create different patterns, causing many errors in detecting delay-time (Yeganeh et al., 2021; Atashgar and Rafiee, 2020).

Now the question arises, which of these two parameters is the cause of out-of-control conditions? Because of in the proposed method, according to the change of patterns in different shifts in μ and σ, there is a need for ways that can detect causes of the OC condition. In addition, is there a need for a new method to find the length of the delay time of change in the assumed model? Furthermore, considering the two proposed models for detecting OC conditions and their cause (s) and estimating the delay length, there is a need for a one-to-one model that can do all the above automatically to calculate the CP.

Similarly, considering the two proposed models for detecting OC conditions and their cause (s) and estimating the delay length, there is a need for a one-to-one model that can do all the above automatically to calculate the CP. After estimating the CP using the new approach involving the mean and covariance simultaneously, the developed model's effectiveness needs to be verified and validated.

1.3 Research Questions

The following questions have been followed to investigate the statement of problems:

1) According to the initial problem, is there a need for a new approach to identify the OC conditions when using the mentioned control charts (MEWMA and MEWMS), according to the sensitivity of each one on a parameter?

2) the second question arises, which of these two parameters (μ and σ) is the cause(s) of OC conditions? Because of the proposed method, according to the change of patterns in different shifts in μ and σ, there is a need for ways that can detect the causes of the OC condition. In addition, is there a need for a new method to find the length of the delay time of change in the assumed model?

3) Considering the two proposed models for detecting OC conditions and their cause (s) and estimating the delay length, there is a need for a one-to-one model that can do all the above automatically to calculate the CP ?

4) After estimating the CP with the new proposed model involving the mean and covariance simultaneously, how does the developed model's effectiveness needs to be verified and validated?

1.4 Objectives of Research

This research aims to develop a new CP estimating procedure for multivariate processes. The following objectives have been conformed to investigate the main aim and research questions:

1) To design a simulation algorithm by comparing two types of multivariate control charts: MEWMA and MEWMS, towards best performance to determine OC conditions quickly and accurately.

2) To design new methods for diagnosing the cause(s) of OC conditions using the machine learning (ML)-classifier and estimate the length of delay time using the ANN-fitting method.

3) To integrate the methods developed to determine OC condition as well as ANN(fitting)-ML(classifier) algorithm for CP estimation by considering the mean vector and covariance matrix parameters simultaneously.

4) To validate the proposed method developed by evaluating the accuracy and precision and benchmark their accurateness with the results from another study.

1.5 Scope of Study

The scope for this dissertation is as follows:

1) The process understudy has a multivariate normal distribution.

2) The studies have been performed in phase II. Since the parameters of the quantitative characteristics of the process have a normal distribution, the covariance matrix and mean vector are known based on the results of the phase I analysis.

3) The Monte-Carlo (MC) simulation is used to investigate and evaluate the performance of our proposed estimator.

4) For simplicity, the simulation research settings are constructed for the bivariate and will be examined these performance indicators.

5) This study correlates quantitative characteristics of the multivariate normal distribution and the value of the correlation between the quantitative characteristics of the process is constant over time.

6) The neural network-based method was utilised to estimate the CP where the characteristics and the changes in the process covariance variance matrix and the mean vector simultaneously occur. The type of change made in the research is a single-step change.

7) MATLAB 2018b used for simulation and developing algorithm.

1.6 Significance and Contribution of Study

Multivariate processes involve more than one variable. Hence, if there is a change in process parameters, the process analysis, monitoring, and controlling variables will be more difficult compared to the univariate process. There is no clear picture of which variable caused the OC condition. This study focuses on a new ANN-based supervised learning approach to detect the point of change with the covariance matrix and the mean vector simultaneously for the multivariate process in normal distribution. In addition, estimating the CP can also see the variable causing the deviation. The contribution of the proposed method consists of three parts that can detect such things as follow:

1) Detection uncontrolled conditions with multivariate control charts to detect OC conditions. The importance of this part of the research is to quickly show the OC conditions in the system that the control charts could not offer and may cause disruption in the production system and the product in the continuation of production.

2) Determining the variables that caused the change with training classifier in Machine Learning (ML) algorithm, Also ANN-fitting for the estimated length of CP. The importance of this part is to show which parameter(s) cause OC condition in the process, also estimate delay time.

3) Estimating the CP in the multivariate process with mean vector and covariance matrix simultaneously, which helps quality engineers, will be done quickly and precisely in corrective action for this situation in the future.

This research covers three significant areas: engineering and services, statistics, and computer science:

1) Providing multivariate process control to industrial plants and other organizations by comparing engineering and service viewpoints. An industrial plant will be able to monitor production better, identify CP to multivariate control processes more effectively, and reduce production costs and waste.

2) A new statistical method will be introduced to estimate the real-time in a multivariate normal process. The CP diagnostic statistics can help reduce the search time required to diagnose a control chart signal and reduce the cost of unnecessary experiments or adjustments to the process, thus saving valuable resources. The combination of ANN and is one of the Machine learning (ML) applications that have a significant ability to derive meaning from complex data. Therefore, this integrate model is appropriate to extract patterns and identify complex or imperceptible trends, to estimating delay time, saves both time and cost in the calculation.

3) As part of the research in the computer sciences aspect, a new ANN algorithm will be adopted. Thus, this study may be beneficial academically for students and researchers concerned with statistical process control. Research institutes can also use statistical process calibration and control. Alternatively, the proposed method can be used in industries and service sectors to describe the quality and performance of any product.

1.7 Organization of Thesis

This research is divided into five chapters:

1) The first chapter includes a brief introduction to quality control tools, the multivariate control process, and CP estimation problems. Research gaps, problem statements and the research objectives are then discussed. Finally, the research scope is defined to describe and analyse the significance and contribution of the study.

2) The second chapter covers the literature review of this study. It consists of a brief introduction to statistical process control (SPC), multivariate control chart, artificial neural network (ANN), and support vector machine (SVM) as one of the models of classifier. Subsequently, the performance of previous

research in estimating CP was reviewed, and their efficiency was compared.

1) The third chapter described the full methodology of the study, including the method process and characterisation techniques for the proposed approach. First, it will explain the method for simulation and OC conditions. Then, the following will interpret the new method of CP estimation by monitoring the mean vector and covariance matrix simultaneously with the proposed model. After that, how they evaluate this study's proposed methods' performance can be explained.

2) The fourth chapter explains the proposed ANN-classifier method for the CP estimation of multivariate process by simultaneously considering the mean vector and covariance matrix. The accuracy and perception model were then evaluated and compared with the previous study. Finally, a discussion and an illustrated example are provided.

3) The fifth chapter provides a general conclusion based on the current study results. Several recommendations for future studies were presented to continue this investigation.

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LIST OF PUBLICATIONS

1- Firouzi, A., Yusof, N. M., Lee, M. H., & Bashiri, R. (2022). Theoretical and experimental investigation of estimating change point in multivariate processes via simultaneous covariance matrix and mean vector. *Jurnal Teknologi*, *84*, 85-96.

2- Firouzi, A., Yusof, N. B. M., & Lee, M. H. (2020, July). Multivariate Change Point Estimation in Covariance Matrix Using ANN. In IOP Conference Series: Materials Science and Engineering (Vol. 884, No. 1, p. 012101). IOP Publishing.