

Multivariate Charts for Multivariate  
Poisson-Distributed Data

by

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## ABSTRACT

There has been much research involving simultaneous monitoring of several correlated quality characteristics that rely on the assumptions of multivariate normality and independence. In real world applications, these assumptions are not always met, particularly when small counts are of interest. In general, the use of normal approximation to the Poisson distribution seems to be justified when the Poisson means are large enough. A new two-sided Multivariate Poisson Exponentially Weighted Moving Average (MPEWMA) control chart is proposed, and the control limits are directly derived from the multivariate Poisson distribution. The MPEWMA and the conventional Multivariate Exponentially Weighted Moving Average (MEWMA) charts are evaluated by using the multivariate Poisson framework. The MPEWMA chart outperforms the MEWMA with the normal-theory limits in terms of the in-control average run lengths.

An extension study of the two-sided MPEWMA to a one-sided version is performed; this is useful for detecting an increase in the count means. The results of comparison with the one-sided MEWMA chart are quite similar to the two-sided case. The implementation of the MPEWMA scheme for multiple count data is illustrated, with step by step guidelines and several examples. In addition, the method is compared to other model-based control charts that are used to monitor the residual values such as the regression adjustment. The MPEWMA scheme shows better performance on detecting the mean shift in count data when positive correlation exists among all variables.

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## Chapter 1

### INTRODUCTION

#### 1.1 Overview

The multivariate control charts are widely used to simultaneously monitor several quality characteristics for detecting the mean changes in manufacturing industries (i.e. the measurements in production lines or during the inspection). Various types of the multivariate charts have been explored and discussed extensively, including the Hotelling  $T^2$ , Multivariate Cumulative Sum (MCUSUM), and Multivariate Exponentially Weighted Moving Average (MEWMA) charts. Typically, the MEWMA scheme is used to detect a shift in the process means, especially for the small shift. The application of the MEWMA chart is not only limited to the manufacturing and service business, but has also been extended to public health and biosurveillance problems. For example, control charting has become more widespread for monitoring disease data and activity during recent years.

Two important assumptions (a multivariate normal distribution and the independence of observations) are made before applying the MEWMA scheme. In practice, the data are most likely observed as counts or number of events of interest, but sometimes the normal assumption is violated. The departure from normality can affect the statistical performance of the MEWMA chart. Rather than ignoring the normality violation, there is a need to investigate the MEWMA chart's performance and develop an appropriate way of monitoring multiple count data.

## **1.2 Statement of the Problem**

The objective of this research is applying the multivariate EWMA control chart to a specific problem in industry and syndromic surveillance, particularly for modeling counts or count rates from multiple sources. The situation can be found, for example, in monitoring several types of defects on a layer of wafer (e.g. particles, scratches, and pattern defects) during the fabrication process in the semiconductor industry. Indeed, the defects are considered to be count data and being monitored at very low level. Such data tend to follow the Poisson distribution and depart significantly from the assumption of normality.

The effect of violation of multivariate normality involving the MEWMA chart has not been intensively investigated, and therefore employing the traditional MEWMA scheme to monitor the changes in those defects becomes questionable. It could possibly result in a high early false alarm rate or a poor performance of detecting a shift in the means. In addition, the study of the robustness of the normal approximation to the Poisson distribution is too small, and it could be problematic for determining the appropriate mean value of the Poisson variable to properly approximate by the normal. Thus, an improvement of the traditional MEWMA chart is necessary to increase the accuracy of the detection performance by assuming a proper structure to those counts. A new MEWMA chart for monitoring the multiple correlated count data is proposed as an alternative method to the traditional one.

### **1.3 Potential Contributions**

This dissertation consists of three topics related to monitoring multivariate Poisson count data. Firstly, there has been some suspicion on the adequacy of using the MEWMA chart to monitor correlated counts from multiple sources. Since a Poisson distribution is commonly assumed in monitoring count data, the new type of the MEWMA chart that relies on the multivariate Poisson distributed-data is introduced to tackle this problem. The multivariate Poisson model is composed as a sum of two Poisson variables (one to represent the positive correlation among all variables). This new method is referred to as the Multivariate Poisson Exponentially Weighted Moving Average (or MPEWMA) control chart. The control limits are straightforwardly derived from Monte Carlo simulation results based on the multivariate Poisson distribution, instead of the usual the normality assumption.

A general framework for the construction and use of MPEWMA scheme to detect the mean changes in both upward and downward directions is presented. The statistical performance of the MPEWMA chart is examined through the run length distributions in terms of both the average and standard deviation. A comparison of the efficacy is made between the MPEWMA and traditional MEWMA charts at several combinations of the factors, such as the number of variables and the mean values. Besides understanding the effects on the MEWMA performance against the Poisson data, the result can help to clarify whether the use of the normal approximation to the Poisson distribution is appropriate or not and under what circumstances.

Secondly, an extension of the two-sided MPEWMA chart to the one-sided version is discussed for detecting any shift in a specified direction, an upward trend. In many situations, it is not necessary to monitor the mean count changes in both increasing and decreasing directions. For example in public health surveillance, one monitors the number of patients with respiratory disease visiting hospital emergency departments or the incidence rates of disease in various regions. It is desirable to detect only an increase in those counts because the downward shift indicates a better condition, i.e. people tend to become healthier or the spread of disease is not apparent. Hence, applying the two-sided MPEWMA scheme does not seem appropriate and useful since it should not be signaled by a decrease in the count (number of patients) or count rate (the incidence rates of disease).

The Poisson limits of the one-sided MPEWMA chart are again obtained through the same simulation procedure. The one-sided MPEWMA chart's performance is investigated and the results reported are the average and standard deviation of the run lengths. The performance comparison of the one-sided MPEWMA and one-sided MEWMA is examined under a variety of parameter conditions. The results could help to understand the robustness of the one-sided MEWMA chart to the multivariate Poisson distribution and determine when it is appropriate to use the normal approximation to the Poisson data.

For syndromic surveillance application, interpreting an out-of-control signal beyond the control limit as an out-of-control condition is considered to be uncertain. A claim that disease has dramatically increased is sometimes

overreacting if the out-of-control signal is truly a false alarm. However, waiting too long before making the claim can cause delay in the prevention of the disease when the disease rate has already increased. This is a trade-off between the detection time and the confidence in an increased rate of disease. In general, the time for detecting the mean shifts tends to be longer while waiting for more signals to occur to ensure an increase in the disease rate. To understand an effect of detection time delay on making the claim, the one-sided MPEWMA scheme's performance is examined not only in an individual out-of-control signal, but also a run of consecutive out-of-control signal (2, 3, 4, or 5 points in a row). The results are reported in terms of the detection time and the percentage of correct detection of the out-of-control state under each of the out-of-control condition described above. This would help determine whether the risks of making decisions affect the detection time or not and how big is the effect; therefore the user should be able to make a better decision on detecting a positive shift in the disease rate.

Thirdly, another type of control scheme called the model-based control chart has been utilized to monitor several correlated count data. The model-based control approaches embrace the process knowledge concept into the use of conventional control charts to improve their sensitivity and efficiency. There are several ways to implement process knowledge, but one implementation discussed in this study is fitting a model to gain more insights into the relationships of quality characteristics being monitored. The residuals after fitting the model will be plotted on the conventional control charts, and therefore it is sometimes



referred to as the residual-based control chart. The regression adjustment technique is chosen and used in conjunction with the univariate EWMA scheme. The EWMA scheme is selected for study because it is known to be an effective method of detecting a small mean shift.

The performances of those model-based control charts are investigated for several combinations of the parameters including mean values, number of variables, and various sizes of shift. The average run length (ARL) performances are reported and then compared with the two-sided MPEWMA chart. The results are discussed in more detail to explain how well the regression analysis works with multiple correlated counts, i.e. the performance in removing the correlation and the ability to transform data into an approximately normal distribution. Moreover, a comparison of the ARL results can assist in determining whether the proposed MPEWMA scheme is more useful for early detection of the count changes than those model-based control methods.

## Chapter 2

### BACKGROUND LITERATURE

#### 2.1 Background

A Multivariate Exponentially Weighted Moving Average (MEWMA) chart is one type of multivariate control charts involving a simultaneous monitoring of several correlated quality characteristics. The MEWMA scheme was firstly introduced by Lowry *et al.* (1992) as a multivariate version of the univariate EWMA chart for detecting a shift in the mean vectors. In general, the MEWMA scheme is applied to monitor the process changes in the manufacturing industries. Testik and Borrer (2004) have recommended the use of MEWMA to detect small and moderate shifts in the process means. Typically, a smaller smoothing weight ( $\lambda$ ) is used in favor of detection of a smaller size of shift. Bersimis *et al.* (2006) suggested that the MEWMA scheme outperforms the multivariate Shewhart chart, and for many practitioners it is easier to implement than a multivariate cumulative sum control chart (Fricker, Knitt, and Hu, 2008).

#### 2.2 Statistical Performance of the MEWMA chart

The statistical performance of the MEWMA chart is computed and reported in terms of the run length properties. There are three different methods of calculation. The first method is the simulation technique. Both Average Run Length (ARL) and the standard errors of the ARL are derived from simulation over 6,000 times. If all variables have equal interest in monitoring the changes, the ARL performance will be based on a function of the noncentrality parameter ( $\delta$ ) or the shift size (Lowry *et al.*, 1992). If the quality characteristics being

monitored are not of equal interest (assuming unequal smoothing weight), the ARL will depend on the direction of the shift and can be obtained through the regression adjustment method (Hawkins, 1991).

The second method is using an integral equation. The integral and double-integral equations are developed to approximate the ARL values. The ARL for the in-control case can be estimated by solving a single integral equation whereas the ARL for the out-of-control case is computed by solving a double integral equation (Rigdon, 1995a; and Rigdon, 1995b). The third method involves the Markov Chain approach. The Markov chain model has been extended to estimate the ARL. The MEWMA chart's performance is presented in two conditions: the 'zero-state' and 'steady-state' ARL. The 'zero-state' ARL is obtained as the process starts at the normal condition. The 'steady-state' ARL is calculated by assuming a shift has been introduced after the normal operating process runs for a certain period of time. The ARLs are also reported in terms of a quantity of shift size for several parameter combinations (Prabhu and Runger, 1997; Runger and Prabhu, 1996).

### **2.3 Robustness to non-normal data**

The basic assumptions of independence and multivariate normality significantly affect the adequacy of the MEWMA method. Few articles have appeared concerning the MEWMA scheme and its performance when it is applied to non-normal data. The performances of the MEWMA chart were investigated using the multivariate t and gamma distributions with various values of skewness and kurtosis up to ten variables (Stoumbos and Sullivan, 2002) and up to twenty

variables (Testik, Runger, and Borrór, 2003). The MEWMA chart's performance is found to be better than Chi-square ( $\chi^2$ ) chart in terms of both larger in-control and smaller out-of-control ARL values. In both works the MEWMA scheme relies on the asymptotic covariance. Stoumbos and Sullivan (2002) mentioned that the use of an exact covariance matrix in calculating the MEWMA statistics can actually decrease the robustness against the non-normal data. The MEWMA scheme with a large number of data points and a range of the smoothing weight (between 0.02 and 0.05) is sufficient to ensure a central limit theorem and hold for robustness. For the high dimensional case, a smaller value of the smoothing weight ( $\lambda$ ) is recommended for increasing robustness to a non-normal distribution. However, a significant chance of having early false alarm leads to a departure from the multivariate normality, and therefore the robustness becomes an issue.

Testik, Runger, and Borrór (2003) state that the in-control performance may be decreased in monitoring non-normal data, that is, the false alarm rate is likely to increase. Generally, the MEWMA chart with the weight constant of 0.05 is recommended due to its good performance in detecting the changes and robustness under non-normal conditions, similarly to Testik and Borrór (2004). Testik and Borrór (2004) noted that the smaller  $\lambda$  value can provide greater robustness, but it also delays the detection time when the MEWMA vectors go in the opposite direction relative to the occurrence of a shift. It is referred to as the inertia problem. For more details of this problem and solutions, see Lowry *et al.*, 1992; Niaki and Abbasi, 2005; Woodall and Mahmoud, 2005. Unfortunately,

there was no further study on the robustness again multivariate Poisson data for the MEWMA scheme.

In fact, the MEWMA chart is also employed to monitor Poisson counts by assuming normality. Typically, the normal approximation for Poisson data will suffice for the large mean counts. For the univariate and multivariate control charts, several authors have suggested that a good approximation to the Poisson distribution with a normal distribution can be obtained if the Poisson mean is 5 or more (Xie, Goh, and Kuralmani, 2002), the Poisson mean is greater than 10 (Joner *et al.*, 2008), the Poisson mean exceeds 12 (Box, Luceño, and Paniagua-Quiñones, 2009) and the Poisson mean is at least 15 (Montgomery, 2009). Moreover, Testik, Runger, and Borror (2003) advised that the central limit theorem can be applied to the MEWMA if the number of samples is large enough. However, there has been no clear cut-off values for the mean and appropriate sample sizes to provide more accurate approximation to the Poisson.

Since those earlier reviews do not provide much information about the efficiency of the traditional MEWMA scheme to Poisson-distributed data, the use of the MEWMA chart with the normal-theory limits in such a scenario remains in doubt due to the accuracy of the normal approximation. In our study, we introduce a new MEWMA scheme based on the multivariate Poisson distribution. The simulation method is used to calculate the appropriate control limits and estimate the performance of the proposed chart. Details on the multivariate Poisson model and parameter estimation are described in Section 2.4. In Section 2.5, a review of the multivariate control charts that rely on the multivariate

Poisson assumption are discussed. In Section 2.6, an extension of the MEWMA scheme to the one-sided test is presented. A discussion of other control chart techniques for dealing with multivariate data is provided in Section 2.7.

## 2.4 Multivariate Poisson Distribution

### 2.4.1 Multivariate Poisson Random Variables

The multivariate Poisson distribution was introduced in two different forms. Kawamura (1979) presented the multivariate Poisson model in terms of the sum of  $p$  independent random Poisson variates. Johnson, Kotz, and Balakrishnan (1997) proposed a structure of a multivariate Poisson distribution involving the correlated Poisson variates. For the control chart application in this research, the multivariate Poisson distribution is based on the work of Johnson, Kotz, and Balakrishnan (1997). The  $p$  multivariate Poisson random variables are defined as

$$X_i = Y_i + Y, \text{ for } i = 1, 2, \dots, p \quad (1)$$

where  $Y$  and  $Y_i$  are independent Poisson random variables with means  $\theta$  and  $\theta_i$ , respectively and  $X_i$  are Poisson random variables with means  $\theta + \theta_i$  for  $i = 1, 2, \dots, p$ . The variance-covariance matrix of  $X_1, \dots, X_p$  has diagonal elements,  $Var(X_i) = \theta + \theta_i$  and off-diagonal elements,  $Cov(X_i, X_j) = \theta$ . Elements of the variance-covariance matrix are

$$Var(X_i) = \theta + \theta_i, \quad i = 1, 2, \dots, p \quad (2)$$

$$Cov(X_i, X_j) = \theta, \quad j = 1, 2, \dots, p \text{ and } i \neq j \quad (3)$$

The fixed parameter,  $\theta$ , corresponds to an event or mean common to all  $p$  random variables. Let's use the previous scenario where monitoring three

types of defects (particles, scratches, and pattern defects) as an example. The particle defects on the layer of the wafer ( $X_1$ ) are the combination of the effect of particle defects on the layer ( $Y_1$ ) (such as etching process) and the effect of original wafer quality ( $Y$ ). The quality of the original wafer can also affect other types of defects; in other words, the scratch defects on the layer of the wafer ( $X_2$ ) are the combination of the effect of scratch defects on the layer ( $Y_2$ ) (such as polishing process and handling equipment) and, again, the effect of original wafer quality ( $Y$ ). Thus, the effect of original wafer quality is considered as the common relationships among all types of defects. Skinners, Runger, and Montgomery (2006) have recommended using this model for monitoring several types of defects per unit of product (such as defects in assembly automobiles) or defects per area of product (such as defects in paper or cloth products).

The estimation of all parameters, especially the fixed parameter, is an important issue, if it is not assumed to be known. We provide a brief description of the various methods for obtaining  $\theta_i$  and  $\theta$  as follows.

#### **2.4.2 Theta Parameter Estimation Methods**

Holgate (1964) compared two ways of estimating the parameter  $\theta$  for the bivariate Poisson distribution: 1) the maximum-likelihood estimation and 2) the method of moments. The method of moments is considered efficient with two uncorrelated variables. If the correlation increases, the efficiency of the method of moments tends to decrease whereas the maximum-likelihood method provide more precise due to the reduction in variance of maximum-likelihood estimator. Karlis (2003) used an EM algorithm to approximate the parameters  $\theta_i$

of multivariate Poisson distributions. The E-step is used to calculate the estimates (or pseudo-values). The estimates are then updated by the M-step. One restriction is to pick the initial values for  $\theta_i$  in the feasible range such as  $\theta_i > 0$ , otherwise the final values will not be in the admissible range.

Jost *et al.* (2006) proposed a new approach based on the composite likelihood concept of Lindsay (1988) to estimate parameters. The optimal composite likelihood estimator can be derived by using an iterative approach to solve the equation relating a pairwise log-likelihood function below

$$\sum_{u=1}^{m-1} \sum_{v=u+1}^m w_{uv} \frac{\partial l_{uv}(\theta)}{\partial \theta} \Big|_{\theta=\hat{\theta}} = 0 \quad (4)$$

where  $m$  is the number of variables and  $w_{uv}$  is the weight where in general  $w_{uv}=1$  for  $1 \leq u < v \leq m$ , and  $l_{uv}(\theta)$  is the bivariate marginal log-likelihood function between two variables  $X_u$  and  $X_v$ .

This new method is more effective than the method of moments, and requires less computational effort than the maximum-likelihood method. He also mentioned the disadvantage of Karlis (2003) that the computation becomes more complicated as the multivariate Poisson distribution involves a large number of variables (eight or more).

## 2.5 Multivariate charts for the multivariate Poisson distribution

There have been many articles involved in introducing the new types of multivariate charts that relied on the multivariate Poisson distribution. The first control chart for the multivariate Poisson distribution was presented by Patel (1973). The ‘G-statistic’, similar to the Hotelling T-square statistic, is calculated



and plotted on the chi-square control chart. The control scheme discussed in Patel (1973) has not been used in practice because of the complexity of obtaining the 'G-statistic'. Skinners, Runger, and Montgomery (2006) proposed two types of schemes to detect the change in the means of multiple Poisson counts. Firstly, the Deleted-Y chart based on the moment estimator is recommended for only one or two variables shifted when the all mean counts are assumed equal. Secondly, the  $\bar{Y}$  chart computed from the sample mean is proposed to detect a change in all variables. Since both Deleted-Y and  $\bar{Y}$  statistics are plotted on  $p$  individual Shewhart charts, they may not be easy to use for the higher-dimensional problems.

Chiu and Kuo (2008) studied two new types of control charts for monitoring multivariate Poisson counts with correlated variables: 1) the multivariate Poisson (MP) chart and 2) a Shewhart-type chart. The control limits of the MP chart can be obtained by either the exact distribution based on the sum of all Poisson variates or a multiple linear regression method (Kuo and Chiu, 2008). The control limits of the Shewhart-type scheme are derived from the normal approximation to the Poisson distribution. The result shows that using the normal approximation to the Poisson distribution is good for a mean count of five or larger. It can be seen that the MP chart performs better than the Shewhart-type in terms of the in-control ARL, but the out-of-control ARL performance is sensitive to an increase in the coefficient of correlation. One limitation of the result is that the authors only examined the run length performance for two and three variable problems, not in the higher-dimensional case. In addition, it is

restricted to the case of positive correlation among the variables being monitored because the multivariate Poisson model used in this work is expanded from the bivariate Poisson model proposed by Holgate (1964).

## **2.6 MEWMA chart and its extension to the one-sided version**

The MEWMA chart is generally applied to monitor both positive and negative changes in the process means. In addition to the industrial and business applications, the quality control method also has great potential for use in the area of public health-care and bioterrorism surveillance. An increasing number of papers have studied the outcome from applying the control chart to detect and monitor diseases in public health surveillance. The implementation of the MEWMA chart for public-care and bioterrorism monitoring has been recently discussed by many authors (Burkom *et al.*, 2005; Yan, Chen, and Zeng, 2008; and Woodall, 2006). Rolka *et al.* (2007) addressed the MEWMA chart as one of several techniques for detecting events of bioterrorism-related outbreak. However, it is necessary to improve the outcome and avoid false alarm triggered by unrelated events. Fricker, Knitt and Hu (2008) found a similar performance between the directional MCUSUM and MEWMA charts in biosurveillance application. However, the MEWMA scheme is preferred based on practical reasons for selecting parameters.

A review of statistical methods in modern biosurveillance, describing a variety of control charts including the MEWMA chart, is given by Shmueli (2009). The author outlines some concerns with applying traditional multivariate charts to syndromic data. One concern is the data most often do not follow a

multivariate normal distribution nor is the independence assumption satisfied. It is difficult to justify that bio-surveillance data follow a multivariate normal distribution since the variety of data sources come from widely diverse environments (Shmueli and Fienberg, 2006). Fricker (2009) also noted that the natural occurrence of autocorrelated data cannot be well monitored by standard SPC techniques used in manufacturing. Another concern is related to the covariance structure for standard multivariate SPC techniques. The covariance structure is often assumed to be constant across time. Empirical evidence has shown that when the data is syndromic, the covariance structure changes over time. Therefore, applying the standard multivariate charts in these situations should be done with caution since the covariance structure departs from its intended application and original setting. Finally, it is more reasonable to detect only when an increase in syndromic data has occurred. Consequently, the standard control charts must be modified so that they are more sensitive to certain directional shifts. For example, one-sided monitoring techniques modified for surveillance of syndromic data will often result in better detection performance than two-sided monitoring methods (Lotze and Shmueli, 2008).

Discussions of the design of MEWMA control chart are extended to a one-sided MEWMA for detecting only an increase in the mean shift. The one-sided MEWMA scheme has been studied and appears in many literatures. Fassò (1999) modified the multivariate EWMA chart for the bivariate case by using a restricted maximum likelihood estimator (MLE) to the MEWMA statistics. The resulting one-sided MEWMA control chart is designed to monitor an upward shift in at

least one quality characteristic when no variables have a decreased rate. Unfortunately, this approach has not been extensively used because of the method's complexity and the restrictive assumptions.

Testik and Runger (2006) extended the one-sided MEWMA proposed by Fassò (1999) for use in a higher dimensional problem. Another control method is proposed for the case where at least one variable shifts either upward or downward (one-sided test for some variables) and others move in any direction (two-sided test for the remaining variables). The new approach is referred to as the partial one-sided control chart. Fassò and Locatelli (2007) also developed an asymmetric MEWMA chart that is similar to the partial one-sided chart by Testik and Runger (2006) which allows the remaining quality characteristics to change in both upward and downward direction. Testik and Runger (2006) and Fassò and Locatelli (2007) obtained the MEWMA statistics by quadratic programming. The slight difference between the two methods is that the control chart statistics of the asymmetric MEWMA is computed using the asymptotic covariance matrix, but is not necessary for the partial one-sided chart.

Sonesson and Frisén (2005) recommended applying an individual upper CUSUM limit to the MEWMA chart introduced by Lowry *et al.* (1992). The proposed method can detect an upward shift in some quality characteristics without being affected by the downward shifts of other quality characteristics. Stoto *et al.* (2006) modified the multivariate CUSUM (MCUSUM) chart to detect positive shifts by limiting the MCUSUM statistics to be positive values only.

Note that each of the methods given above is based on the multivariate normality assumption.

Joner *et al.* (2005) and Joner *et al.* (2008) presented a new one-sided MEWMA chart to detect a small upward shift in the incidence rates of disease. This one-sided MEWMA scheme is built up from two works - Sonesson and Frisén (2005) and Stoto *et al.* (2006). One good feature of the new control method is that it should not take too long to detect an abrupt increase when there is evidence of a continuing decrease in the incidence rates before. This is a result of placing a 'barrier' (or zero) within the equation of MEWMA statistics calculation to prevent the negative results. Consequently, the decrease does not greatly affect the next computation for detecting the upcoming increase in the incidence rates. This approach relies on the assumption that the normal approximation to the true underlying distribution (such as the Poisson) is appropriate (means greater of 10 or more). There are, however, some situations where the normal approximation to the Poisson distribution is not necessarily true. In particular, when the process mean is quite small. In these situations, an adequate mean for using the normal approximation is still an issue in the multivariate case and, therefore monitoring techniques based directly on the Poisson distribution are recommended.

Recently, there has been a review of the robustness of the one-sided MEWMA chart to multivariate Poisson data. Yahav and Shmueli (2010) investigated the performance of the Hotelling T-square and two types of one-sided MEWMA charts (modified Follmann (1996) and Testik and Runger (2006)'s work) under a simulated multivariate Poisson distribution. The

multivariate Poisson model is generated by the work of Yahav and Shmueli (2009). The mean rates (from 1, 5, 10, and 20) are tested and the variance-covariance matrix is assumed to be known. Two extended one-sided MEWMA charts show superior performance to the Hotelling T-square based on the in-control ARL. This finding is similar to the result that the two-sided MEWMA chart is more robust to the multivariate t and gamma distributions than the Hotelling T-square, as previously discussed by Stoumbos and Sullivan (2002).

## **2.7 Other control chart techniques**

Control chart methods are normally employed on the raw data. A new method has been developed by combining other modeling techniques with the quality control monitoring of multivariate data. In the other words, this new method consists of two steps in data monitoring: 1) a pre-process step and 2) a control step. The first step is transforming the multivariate data to gain more insights into a diagnosis such as applying regression analysis. Once the model has been found, the residuals are calculated and used in the next step. The second step is monitoring these residuals on control chart for detecting the mean changes. Thus, the method is called the model-based control chart, or sometimes it is referred to as the residual-based control chart.

There have been many papers recently that developed the model-based control charts (see Hawkins, 1991; 1993; Healy, 1987; Mandel, 1969; Skinner, Montgomery, and Runger, 2003; and Zhang, 1984). The model-based control technique was firstly introduced by Mandel (1969). The Regression control chart was aimed to monitor the varying mean by using the conventional control chart in

conjunction with the regression method. The idea of Mandel (1969) has been extended to a cause-selecting chart (Zhang, 1984) for monitoring two process steps. The outgoing variable is monitored by applying regression to adjust for the effect of an incoming variable. One good feature is that it can help determine which subprocess goes out of control. Healy (1987) expanded a CUSUM control method to detect the mean shift in the multivariate case. The proposed CUSUM chart based on a linear combination of the variables is recommended if shifts in a known direction are expected. If the shifts are expected in more than one direction, the CUSUM of orthogonal linear combinations is needed to assure independence.

Two types of regression adjustment are proposed by Hawkins (1991; 1993). The first method involves the problem of correlated variables and expecting a shift in the mean of a single variable does not affect the remaining variables. Hawkins (1991) recommended applying the  $Z$  transformation to the data rescaled to zero mean and unit variance for further improving the Hotelling T-squared chart. The control chart based on the  $Z$  scaled residuals are obtained from regressing each variable on all others (e.g. regression  $X_j$  on  $X_1, X_2, \dots, X_{j-1}, X_{j+1}, \dots, X_p$ ) and plotting them in multiple univariate control charts, such as CUSUM charts. The second method relates to a process having a natural ordering, and therefore a shift can affect some or all subsequent variables, not the prior variables. It is referred to as a cascade process. Hawkins (1993) introduced other ways to transform the  $X$  scale to the vector  $Y$  and  $W$  scales by firstly standardizing variables to zero mean and unit standard deviation. The  $Y$  scaled

residuals are computed from regression each variable on all preceding variables (e.g. regression  $X_j$  on  $X_1, X_2, \dots, X_{j-1}$ ). The vector  $W$  is defined by scaling vector  $X$  using principal components. The  $W$  scale will work reasonably if a shift has occurred in the direction of one of the principal components. It is considered less useful than other scales due to a restriction that shifts of the mean should be in a direction along one of the principal components axes. However, it is not obvious that  $Y$  or  $Z$  scales give a better performance. Those decomposition approaches can be extended for use with other schemes, including the univariate and multivariate EWMA charts.

Besides the regression adjustment, another regression technique is proposed for situations where the data are obtained from a biosurveillance system. Burkom *et al.* (2004) discussed the concept of sliding buffers under the baseline period for aggregated data. He suggested applying the control chart method to normalized data (i.e. the residuals of linear or Poisson regression) if the raw data show systematic behaviors. The comparison results indicate that using a multiple EWMA chart with the baseline length obtained from the empirical test provides better performance than the Hotelling T-square chart with the residuals of Provider-count regression. Fricker, Knitt, and Hu (2008) applied the “adaptive regression model with a sliding baseline” presented by Burkom *et al.* (2004) and Burkom, Murphy, and Shmueli (2007) to remove the systematic components in the biosurveillance data. The residuals are plotted on the directional multivariate CUSUM and EWMA charts.



To effectively eliminate the systematic components, there is a need to determine the appropriate values of parameters used in the adaptive regression such as forms of the regression model (linear and quadratic models) and the length of the sliding baseline. Pre-processing is also suggested to remove deviation from the normality assumption and autocorrelation (Lotze, Murphy, and Shmueli, 2008; and Yahav and Shmueli, 2010). Those residuals that go through the pre-process will satisfy the control chart requirements, and then they are applicable for the quality control methods.

Lotze, Murphy, and Shmueli (2008) pointed out that the preconditioning (e.g. linear regression, log regression, and differencing) can reduce the seasonality impact in the syndromic data. Since there may be many explainable patterns in the data, a failure to remove all those patterns could have a remarkable effect on the results of the control charting methods. In particular, biosurveillance data with extremely low counts significantly departs from the normality assumption. Hence, using the control chart on the unprocessed data may lead to failure of detection of the presence of an outbreak or an increasing numbers of false alarm rates. The preprocessing methods used before applying the CUSUM chart to the actual data have shown improvements by removing variation from other irrelevant sources.

The ordinary least square regression technique above is limited to the normally distributed data. For non-normal data, the generalized linear model-based control charts were initiated to monitor counts (Skinner, Montgomery, and Runger, 2003) and over-dispersed counts (Skinner, Montgomery, and Runger, 2004) from multiple sources. The deviance residuals are calculated by using the

predicted value obtained from fitting the generalized linear model with an appropriate link. The deviance residuals used in conjunction with the  $C$  chart show superior performance to the  $C$  chart itself in both univariate and bivariate cases. The link for the model should be selected with care, since it could result in bad predictions. Lewis, Montgomery, and Myers (2001) investigated the confidence interval coverage of the mean response when the incorrect link is assumed. The result demonstrated that a misspecified link has an impact on the model performance, especially for Poisson data. Precision is reduced and the confidence interval coverage is degraded by the misspecified link. In addition, the normal probability plot of the deviance residuals also showed the possible insufficiency of the fit model.

## Chapter 3

### TWO-SIDED MEWMA CONTROL CHART

#### 3.1 Introduction

A Multivariate Exponentially Weighted Moving Average (MEWMA) control chart is generally used to simultaneously monitor several correlated quality characteristics for many applications in manufacturing and business. The implementation of the MEWMA chart requires an assumption of a multivariate normal distribution. In real world situations, there has been interest in monitoring a small change in the count or count rate of occurrence of an event. A few simple examples of quantities that are monitored are the number of defects found at inspection stations, the number of car accidents that occurred at major junctions during peak traffic periods, and the number of customer complaints about service quality to service providers. These sample counts are usually assumed to follow a Poisson distribution. Since no extension of the MEWMA chart is developed for the multivariate Poisson distribution, the normal approximation to the Poisson can be used for applying the MEWMA chart.

There has been no extensive assessment of the MEWMA control scheme performance for monitoring multiple Poisson-distributed variables when the assumption of the normal approximation to the Poisson distribution is not necessarily valid. The adequacy of the normal-distribution model for traditionally Poisson-distributed data is an issue of concern, particularly if the process means are small (say 5 or less). In addition, control chart performance, which corresponds to the normal approximation assumption, is often evaluated assuming

the covariance structure does not change along with a shift or change in the process mean. This is not true for the Poisson distribution because an upward shift in the mean also results in an increase in the variance. If the covariance matrix remains constant after a shift in the mean has occurred, then it could affect the shift size calculation and probably lead to an incorrect summary of the run length distribution.

A new type of multivariate EWMA chart that relies on the multivariate Poisson distribution has been studied and proposed to properly handle this problem. It can be referred to as the multivariate Poisson Exponentially Weighted Moving Average (MPEWMA) control chart. Monte Carlo simulation is utilized to obtain the appropriate control limits which correspond to an in-control Average Run Length (ARL) of 200. The statistical performance of the MPEWMA chart is reported in the form of ARL and Standard Deviation of the Run Length (SDRL). In addition, comparison of the proposed MPEWMA and the traditional MEWMA chart's performance is made in terms of the ARLs.

In Section 3.2, we assess the normality of the multivariate Poisson distribution. Section 3.3 describes the MEWMA chart. Section 3.4 discusses the details of simulation method. Section 3.5 presents and summarizes the ARL and SDRL results. Section 3.6 develops the general equation to estimate the control chart's performance. Section 3.7 compares the performance of the traditional MEWMA and MPEWMA charts. Section 3.8 illustrates an example of using the MPEWMA scheme.

### 3.2 Normality test on the Poisson distribution

The adequacy of the normal approximation to multivariate Poisson-distributed data is examined by performing the Anderson-Darling normality test. We illustrate an example of testing the normality on a four-variate Poisson distribution,  $X = [X_1, X_2, X_3, X_4]$ . Suppose all four means ( $\theta_1 + \theta$ ,  $\theta_2 + \theta$ ,  $\theta_3 + \theta$ ,  $\theta_4 + \theta$ ) are assumed equal. We consider five multivariate Poisson distributions with mean 5, 15, 25, 30, and 35, respectively. Each sample data ( $X_1, X_2, X_3$ , and  $X_4$ ) is randomly generated from each of these five distributions with various  $\theta$  values (0, 0.0005, 0.05, and 1) for a minimum sample size ( $n$ ) of 100 to 200 observations. The Normal probability plots are constructed and the resulting  $p$ -values from the Anderson-Darling test were calculated. The  $p$ -values of the first two variables ( $X_1$  and  $X_2$ ) are reported in Table 1 below.

**Table 1** Summary of the  $p$ -values from the Anderson-Darling Test ( $n = 100$ -200)

Mean	$\theta = 0$		$\theta = 0.0005$		$\theta = 0.05$		$\theta = 1$	
	$X_1$	$X_2$	$X_1$	$X_2$	$X_1$	$X_2$	$X_1$	$X_2$
5	< 0.005	< 0.005	< 0.005	< 0.005	< 0.005	< 0.005	< 0.005	0.006
15	0.024	0.028	< 0.005	< 0.005	< 0.005	0.11	0.015	0.067
25	0.226	0.018	0.308	0.16	0.005	0.109	0.065	0.085
30	0.193	0.017	0.053	0.048	0.466	0.021	0.098	0.229
35	0.021	0.384	0.131	0.191	0.389	0.115	0.057	0.332

It can be seen that the normal approximation is not always valid, particularly when the mean of the Poisson process is small (e.g., means of 5 and

15). As a result, control charts based on the assumption of normal-theory limits may not be appropriate when monitoring Poisson data. Thus, there is a need for monitoring techniques based on the true underlying distribution of the data.

### 3.3 The Multivariate Poisson Exponentially Weighted Moving Average (MPEWMA) Control Chart

The new type of the MEWMA scheme is developed based on the traditional multivariate EWMA chart. Lowry *et al.* (1992) proposed the MEWMA as an extension to the univariate EWMA chart. The MEWMA scheme takes into account recent past data which often results in quicker detection of the shifts in the process mean. Let's say that  $p$  quality characteristics are being monitored simultaneously. The MEWMA statistic is given by

$$\mathbf{Z}_t = \mathbf{R}\mathbf{X}_t + (\mathbf{I} - \mathbf{R})\mathbf{Z}_{t-1} \quad (5)$$

where  $\mathbf{Z}_t$  is the  $t^{\text{th}}$  MEWMA statistics vector,  $\mathbf{X}_t$  is the  $t^{\text{th}}$  observation vector for  $t = 1, 2, \dots, n$  and  $\mathbf{Z}_0 = \mathbf{0}$ . The vector  $\mathbf{R}$  consists of weights assigned to past observations in each of the  $p$  quality characteristics being monitored and  $\mathbf{I}$  is the  $p \times p$  identity matrix. Specifically, let  $r_j$ , represent the weight assigned to the  $j^{\text{th}}$  quality characteristic, then  $\mathbf{R} = \text{diag} (r_1, r_2, \dots, r_p)$ , where  $0 < r_j \leq 1$  and  $j = 1, 2, \dots, p$ . If equal weight is assigned to each random variable so that  $r_1 = r_2 = \dots = r_p = \lambda$ , then

$$\mathbf{Z}_t = \lambda\mathbf{X}_t + (1 - \lambda)\mathbf{Z}_{t-1} \quad (6)$$

The covariance matrix for the random variable  $\mathbf{Z}_t$  is

$$\Sigma_{\mathbf{z}_t} = \left\{ \frac{\lambda [1 - (1 - \lambda)^{2t}]}{2 - \lambda} \right\} \Sigma \quad (7)$$

where  $\Sigma$  is the covariance matrix for the  $p$  random variables and is assumed to be known. (Assuming a known covariance matrix is common when evaluating monitoring techniques). If the covariance matrix is unknown, then it can be estimated using a number of possible methods (see, e.g., Sullivan and Woodall, 1995; and Williams *et al.*, 2006). As  $t \rightarrow \infty$ , the asymptotic covariance matrix can be written as

$$\Sigma_{\mathbf{z}_t \rightarrow \infty} = \left\{ \frac{\lambda}{2 - \lambda} \right\} \Sigma \quad (8)$$

The MEWMA control chart statistic is given by

$$T_t^2 = \mathbf{Z}_t' \Sigma_{\mathbf{z}_t}^{-1} \mathbf{Z}_t \quad (9)$$

An out-of-control signal will occur if  $T_t^2 > H$ , where  $H > 0$  is a threshold limit selected in order to achieve a desired in-control ARL. The choices of the parameters  $H$  and  $\lambda$  can have significant effects on the performance of the MEWMA chart and should be selected with care.

Since all  $p$  random variables being monitored truly follow a multivariate Poisson distribution, the data are generated from the multivariate Poisson model, as earlier discussed in Section 2.4.1, using Monte Carlo simulation. The MPEWMA statistic is obtained simply through the same steps for calculating the MEWMA statistics (from Equation (5) – Equation (9)). The asymptotic covariance matrix as shown in Equation (8) is used as the covariance matrix of the MPEWMA chart. We also consider two additional factors (the mean value and

the thetafix parameter) in determining the control limits of the MPEWPA chart. We will present results for various combinations of these parameters in order to obtain in-control ARL of interest.

### 3.4 Data Simulation

The proposed control chart is called the multivariate Poisson exponentially weighted moving average (or MPEWMA) chart. In this simulation study, the means  $\theta + \theta_1, \dots, \theta + \theta_k$  generated from the Poisson distribution to be investigated are 3, 5, 8, 10, and 15. Two smoothing weights ( $\lambda = 0.05$ , and 0.1) are selected for  $p = 4, 6, 8$ , and 10 variables. To simplify the study, the means of all variables are assumed equal. As previously mentioned, the chosen values of  $\lambda$  have been shown to be effective in detecting small shifts in the process mean. Values of  $\theta$  were arbitrarily chosen to be 0.5 and 1. The MPEWMA control chart is studied under the “steady-state” condition. A “steady-state” control chart is defined as a control chart that operates in statistical control for some period of time. To simulate the steady-state condition and then a shift in the process mean, we allow the control chart to run under normal conditions for one-hundred time periods before a shift in the process is introduced at time period 101. The simulation continues until either the first out-of-control signal is found or the simulation routine reaches 100,000 iterations. Each simulation is replicated 50,000 times to provide more accurate results.

We are interested in the capability of the monitoring scheme to detect the increase in the mean (shifts) for one or more of the variables. The scenario of interest is limited to a permanent upward shift, or a long-lasting increase in the



means. The performance of the MPEWMA scheme is evaluated using various sizes of the mean shifts such as increases of one up to four units in one or more variables. Table 2 displays a list of all shifts that we applied to the four-variable and then the six-variable cases. To illustrate how to interpret the notation in Table 2, suppose we have four Poisson processes with equal means that are being monitored simultaneously and a shift of 2 units has occurred in only one of the processes, say process 3. This can be represented by the notation  $[0, 0, 2, 0]$ , which can be interpreted as no shift in the mean for the first two processes, a two unit shift in mean for the third process, and no shift in the mean for the fourth process.

**Table 2** Shift matrix for four-variable and six-variable cases

No. of Shift matrix	Variable shift	
	$X_1, X_2, X_3, X_4$	$X_1, X_2, X_3, X_4, X_5, X_6$
1	0,0,0,0	0,0,0,0,0,0
2	1,0,0,0	1,0,0,0,0,0
3	0,1,0,0	0,1,0,0,0,0
4	2,0,0,0	2,0,0,0,0,0
5	0,2,0,0	0,2,0,0,0,0
6	1,1,0,0	1,1,0,0,0,0
7	2,2,0,0	2,2,0,0,0,0
8	1,0,1,0	1,0,1,0,0,0
9	0,0,2,0	0,0,2,0,0,0
10	1,0,0,1	1,0,0,1,0,0
11	0,0,0,2	0,0,0,2,0,0
12	1,1,1,1	1,0,0,0,1,0
13	2,2,2,2	0,0,0,0,2,0
14	3,3,3,3	1,0,0,0,0,1
15	4,4,4,4	0,0,0,0,0,2
16		1,1,1,1,1,1
17		2,2,2,2,2,2
18		3,3,3,3,3,3
19		4,4,4,4,4,4

The shift size or ‘noncentrality parameter’ ( $\delta$ ) is based on Lowry *et al.*’s work (1992) and defined as

$$\delta = [(\boldsymbol{\mu} - \boldsymbol{\mu}_0)' \boldsymbol{\Sigma}^{-1} (\boldsymbol{\mu} - \boldsymbol{\mu}_0)]^{1/2} \quad (10)$$

where  $\boldsymbol{\mu}_0$  represents the mean vector for an in-control process,  $\boldsymbol{\mu}$  represents the mean vector after a shift has occurred, and  $\boldsymbol{\Sigma}$  is the variance-covariance matrix. It can be noted that equation (10) is also referred to as the Mahalanobis’ distance. As shown in equation (10), the shift size is related to changes in both the mean and covariance matrix.

For the multivariate Poisson model, an increase in any element of the variance-covariance matrix,  $\boldsymbol{\Sigma}$ , corresponds to a shift in one or more means,  $\theta + \theta_i$ , which are diagonal elements of the covariance matrix. In other words, we take into account the effect of the mean shifts on the variance-covariance matrix to obtain a better estimate of the MPEWMA statistics in equation (9) and the shift size calculation in equation (10). Table 3 displays the shift size calculation assuming the means of all four variables are 3 with two values of  $\theta$  ( $\theta = 0.5$ , and 1). For example, the shift size using equation (10) for the case of  $[0, 0, 2, 0]$  would be  $\delta = 0.912$  (for  $\theta = 0.5$ ) and  $\delta = 0.953$  (for  $\theta = 1$ ). It is important to note that shifts in the process means will not always result in the same overall shift size ( $\delta$ ). For example,  $[0, 0, 2, 0]$  and  $[1, 1, 0, 0]$  both represent a total two-unit shift in the process. However,  $\delta = 0.912$  for  $[0, 0, 2, 0]$  and  $\delta = 0.689$  for  $[1, 1, 0, 0]$  when  $\theta = 0.5$ . Therefore, there can be slightly different resulting shift sizes for any two processes that may have the same total *unit* shift.

**Table 3** Examples of the shift size calculation on four-variable case

No. of Shift matrix	Variable shift $X_1, X_2, X_3, X_4$	shift size ( $\delta$ )	
		Mean = 3 $\theta = 0.5$	Mean = 3 $\theta = 1$
1	0,0,0,0	0	0
2	1,0,0,0	0.512	0.542
3	0,1,0,0	0.512	0.542
4	2,0,0,0	0.912	0.953
5	0,2,0,0	0.912	0.953
6	1,1,0,0	0.689	0.707
7	2,2,0,0	1.239	1.265
8	1,0,1,0	0.689	0.707
9	0,0,2,0	0.912	0.953
10	1,0,0,1	0.689	0.707
11	0,0,0,2	0.912	0.953
12	1,1,1,1	0.853	0.756
13	2,2,2,2	1.569	1.414
14	3,3,3,3	2.191	2.000
15	4,4,4,4	2.744	2.309

### 3.5 Results

The statistical performance of the proposed MPEWMA chart is investigated by assessing the run length distribution, including the average run length (ARL) and standard deviation of the run length (SDRL). The control limit ( $H$ ) was chosen to provide the in-control ARL of 200. The appropriate control limits to achieve the steady-state in-control ARL of 200 are summarized in Table 4. The ARL performance for different smoothing weights ( $\lambda$ ) and various number of quality characteristics ( $p$ ) are presented in Tables 5 and 6 for  $\theta = 0.5$  and  $\theta = 1$ , respectively.

**Table 4** The chosen control limit obtained by simulation to achieve an in-control ARL of 200

Mean	$\hat{\lambda}$	4 variables		6 variables		10 variables		15 variables	
		$\theta = 1$	$\theta = 0.5$	$\theta = 1$	$\theta = 0.5$	$\theta = 1$	$\theta = 0.5$	$\theta = 1$	$\theta = 0.5$
3	0.1	13.02	13.01	16.68	16.65	23.20	23.17	30.65	30.62
	0.05	11.49	11.49	14.95	14.93	21.19	21.17	28.41	28.39
5	0.1	12.95	12.95	16.56	16.54	23.03	23.04	30.49	30.49
	0.05	11.48	11.48	14.92	14.90	21.14	21.15	28.34	28.34
8	0.1	12.92	12.91	16.50	16.50	22.98	22.98	30.41	30.40
	0.05	11.47	11.47	14.91	14.89	21.13	21.14	28.32	28.31
10	0.1	12.90	12.90	16.50	16.48	22.94	22.95	30.38	30.36
	0.05	11.46	11.46	14.91	14.89	21.13	21.13	28.31	28.30
15	0.1	12.89	12.89	16.48	16.49	22.94	22.91	30.35	30.33
	0.05	11.46	11.46	14.90	14.90	21.12	21.12	28.30	28.30

**Table 5** ARLs for the MPEWMA Control Chart when  $\theta = 0.5$

p	Mean														
	3			5			8			10			15		
	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$
4	11.49	13.01	0.00	11.48	12.95	0.00	11.47	12.91	0.00	11.46	12.90	0.00	11.46	12.89	0.00
	200.124	200.012	0.56	200.114	199.771	0.46	199.806	200.234	0.57	199.200	198.817	0.49	199.549	199.811	0.57
	28.843	32.322	1.05	25.287	27.1677	0.88	33.0807	37.142	1.09	24.971	25.576	0.93	30.681	34.584	1.09
	13.115	12.491	1.37	10.964	10.033	1.70	13.801	13.017	1.58	10.505	9.378	1.36	12.826	11.886	1.58
	6.858	5.708	1.95	7.951	6.775	2.18	6.062	4.995	2.03	6.618	5.518	1.77	7.912	6.753	2.03
	4.569	3.607	2.95	5.196	4.172	2.63	4.486	3.532	2.46	4.847	3.877	2.16	5.713	4.656	2.46
	3.478	2.657	0.00	3.143	2.378	0.00	3.573	2.749	0.00	3.845	2.977	0.00	4.488	3.551	0.00
6	14.93	16.65	0.00	14.90	16.54	0.00	14.89	16.50	0.00	14.89	16.48	0.00	14.9	16.49	0.00
	200.023	199.591	0.41	199.306	200.009	0.46	199.670	199.801	0.42	199.214	199.801	0.42	200.150	200.066	0.42
	31.746	36.831	0.77	43.168	51.347	0.88	36.643	42.586	0.81	42.204	49.655	0.81	34.287	39.700	0.81
	14.015	13.896	1.05	18.188	18.535	1.39	15.045	14.597	1.29	16.973	16.805	1.11	21.478	22.381	1.29
	9.588	8.559	1.59	11.943	11.002	2.00	8.590	7.388	1.87	9.366	8.191	1.62	11.274	10.152	1.87
	6.509	5.326	2.27	7.330	6.147	2.57	5.515	4.43	2.41	5.951	4.830	2.11	7.006	5.829	2.41
	4.328	3.350	0.00	4.802	3.775	0.00	4.058	3.142	0.00	4.372	3.411	0.00	5.078	4.051	0.00
10	21.17	23.17	0.00	21.15	23.04	0.00	21.14	22.98	0.00	21.13	22.95	0.00	21.12	22.91	0.00
	200.104	199.268	0.42	199.475	200.122	0.47	199.927	199.828	0.42	199.332	200.06	0.42	199.441	199.469	0.42
	36.169	43.709	0.98	49.796	61.486	1.66	66.215	50.685	1.56	48.818	59.331	1.36	39.676	47.551	1.56
	13.747	12.783	1.86	15.491	14.796	2.41	17.002	16.873	2.27	19.333	19.708	2.00	23.809	25.45	2.27
	10.628	9.517	2.68	6.966	5.667	3.11	7.837	6.559	2.94	8.433	7.136	2.61	9.845	8.592	2.94
	6.374	5.1	3.44	4.534	3.483	3.11	5.031	3.933	2.812	5.355	4.253	2.61	6.174	4.98	2.812
	4.226	3.201	0.00	3.407	2.522	0.00	3.735	2.812	0.00	3.947	2.996	0.00	4.476	3.477	0.00
15	28.39	30.62	0.00	28.34	30.49	0.00	28.31	30.40	0.00	28.30	30.36	0.00	28.30	30.33	0.00
	199.862	199.034	0.42	200.025	200.182	0.47	199.650	199.478	0.42	199.677	199.244	0.42	200.098	200.112	0.42
	40.647	50.393	0.77	56.139	70.966	0.97	47.175	58.461	0.91	54.607	68.097	0.81	44.790	55.192	0.91
	17.875	18.304	1.07	23.031	25.069	1.88	17.252	16.940	1.78	18.531	18.507	1.58	21.820	22.693	1.78
	11.514	10.561	2.07	15.233	14.138	2.74	7.549	6.192	2.60	8.003	6.655	2.32	9.105	7.757	2.60
	6.515	5.138	3.00	6.869	5.542	3.55	4.854	3.745	3.38	5.090	3.961	3.04	5.724	4.541	3.38
	4.307	3.217	0.00	4.486	3.403	0.00	3.599	2.660	0.00	3.763	2.807	0.00	4.167	3.171	0.00

**Table 6** ARLs for the MPEWMA Control Chart when  $\theta = 1$

p	Mean														
	3			5			8			10			15		
	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$
4	11.49	13.02	0.00	11.48	12.95	0.00	11.47	12.92	0.00	11.46	12.90	0.00	11.46	12.90	0.00
	199.031	199.730	0.00	199.142	200.252	0.00	199.309	200.236	0.00	200.141	200.059	0.00	200.141	200.059	0.00
	26.558	29.416	0.56	25.254	27.102	0.46	33.638	37.845	0.53	27.063	29.124	0.49	27.063	29.124	0.49
	12.349	11.641	1.04	11.029	10.024	1.11	10.352	9.155	1.03	11.288	10.205	0.89	11.288	10.205	0.89
	7.833	6.653	1.26	8.857	7.672	1.60	6.529	5.431	1.50	7.048	5.921	1.31	7.048	5.921	1.31
	5.141	4.133	1.81	5.691	4.646	2.07	4.789	3.812	1.94	5.165	4.138	1.71	5.165	4.138	1.71
6	3.885	2.988	2.31	4.252	3.319	2.50	3.800	2.948	2.36	4.059	3.166	2.09	4.059	3.166	2.09
	14.95	16.68	0.00	14.92	16.56	0.00	14.91	16.50	0.00	14.91	16.50	0.00	14.91	16.50	0.00
	199.747	200.020	0.00	199.905	199.622	0.00	199.439	199.093	0.00	200.111	198.872	0.00	200.111	198.872	0.00
	29.068	33.037	0.43	41.300	49.471	0.46	36.722	42.578	0.42	42.481	50.155	0.49	42.481	50.155	0.49
	13.404	12.852	1.07	11.740	10.76	0.88	15.061	14.517	0.80	17.153	16.935	0.68	17.153	16.935	0.68
	7.836	6.538	1.41	8.579	7.291	1.26	9.67	8.459	1.18	10.418	9.216	1.04	10.418	9.216	1.04
10	5.111	4.014	2.04	5.508	4.403	1.84	6.143	4.973	1.73	6.545	5.402	1.53	6.545	5.402	1.53
	3.836	2.916	2.62	4.093	3.146	2.38	4.513	3.513	2.25	4.79	3.765	2.00	4.79	3.765	2.00
	21.19	23.20	0.00	21.14	23.03	0.00	21.13	22.98	0.00	21.13	22.94	0.00	21.13	22.94	0.00
	199.484	199.341	0.00	199.739	199.64	0.00	200.081	199.334	0.00	200.194	198.783	0.00	200.194	198.783	0.00
	32.922	38.808	0.43	47.399	58.248	0.47	41.389	49.981	0.43	48.300	58.690	0.49	48.300	58.690	0.49
	14.984	14.719	1.10	12.889	12.056	0.89	16.741	16.680	0.81	19.058	19.381	0.68	19.058	19.381	0.68
15	8.168	6.754	1.58	8.581	7.224	1.45	9.322	8.010	1.38	9.852	8.514	1.24	9.852	8.514	1.24
	5.317	4.101	2.30	5.513	4.318	2.12	5.914	4.710	2.02	6.196	4.995	1.83	6.196	4.995	1.83
	3.965	2.945	2.98	4.095	3.074	2.76	4.352	3.327	2.64	4.525	3.502	2.39	4.525	3.502	2.39
	28.41	30.65	0.00	28.34	30.49	0.00	28.32	30.41	0.00	28.31	30.38	0.00	28.31	30.38	0.00
	200.047	199.953	0.00	199.949	199.448	0.00	199.995	200.083	0.00	199.587	199.686	0.00	199.587	199.686	0.00
	36.455	44.795	0.44	52.785	67.044	0.48	46.022	57.209	0.43	53.747	67.435	0.49	53.747	67.435	0.49

**Table 7** SDRRLs for the MPEWMA control chart when  $\theta = 0.5$

p	Mean														
	3			5			8			10			15		
	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$
4	11.49	13.01	0.00	11.48	12.95	0.00	11.47	12.91	0.00	11.46	12.90	0.00	11.46	12.89	0.00
	201.330	201.809	0.51	200.489	200.438	0.56	201.513	201.147	0.46	200.473	200.082	0.57	200.473	200.082	0.49
	19.132	25.756	0.91	16.089	20.775	0.88	23.128	30.656	0.88	15.324	20.253	0.93	15.324	20.253	0.93
	6.608	7.461	1.57	5.267	5.568	1.37	7.231	7.971	1.70	5.056	5.147	1.58	5.056	5.147	1.36
	2.762	2.594	2.19	3.465	3.328	1.95	2.554	2.287	2.18	2.841	2.618	2.03	2.841	2.618	1.77
	1.693	1.471	2.74	2.059	1.811	2.95	1.793	1.518	2.63	1.981	1.707	2.46	1.981	1.707	2.16
	1.220	1.041	14.93	1.140	0.950	16.54	1.375	1.149	14.89	1.516	1.281	14.89	1.516	1.281	14.9
6	14.93	16.65	0.00	14.90	16.54	0.00	14.89	16.50	0.00	14.89	16.48	0.00	14.89	16.48	0.00
	202.741	200.140	0.52	200.880	200.923	0.41	200.194	201.853	0.46	200.153	200.417	0.42	200.153	200.417	0.49
	21.313	29.153	0.93	32.147	44.941	0.77	25.956	35.852	0.88	31.258	43.152	0.81	31.258	43.152	0.68
	6.750	8.234	1.26	10.049	12.450	1.05	7.764	9.101	1.39	9.148	10.969	1.29	9.148	10.969	1.11
	4.221	4.308	1.79	5.744	6.164	1.59	3.734	3.589	2.00	4.181	4.153	1.87	4.181	4.153	1.62
	2.454	2.252	2.52	2.980	2.801	2.27	2.153	1.868	2.57	2.407	2.138	2.41	2.407	2.138	2.11
	1.487	1.274	21.17	1.768	1.528	23.04	1.520	1.273	21.14	1.683	1.413	21.14	1.683	1.413	21.12
10	21.17	23.17	0.00	21.15	23.04	0.00	21.14	22.98	0.00	21.13	22.95	0.00	21.13	22.95	0.00
	202.254	200.787	0.52	200.668	202.111	0.42	200.902	201.510	0.47	200.966	201.003	0.42	200.966	201.003	0.49
	24.965	36.515	1.08	38.094	54.956	0.98	30.552	43.745	0.89	37.096	52.683	0.81	37.096	52.683	0.70
	6.135	6.998	1.28	7.502	8.722	1.86	8.817	10.639	1.66	10.555	13.171	1.56	10.555	13.171	1.36
	4.623	4.802	2.05	2.581	2.366	2.68	3.126	2.918	2.41	3.485	3.274	2.27	3.485	3.274	2.00
	2.197	1.972	2.93	1.527	1.287	3.44	1.822	1.554	3.11	1.990	1.739	2.94	1.990	1.739	2.61
	1.309	1.104	28.39	1.095	0.900	30.49	1.282	1.056	28.31	1.403	1.152	28.31	1.403	1.152	28.30
15	28.39	30.62	0.00	28.34	30.49	0.00	28.31	30.40	0.00	28.30	30.36	0.00	28.30	30.36	0.00
	201.321	200.938	0.52	201.462	201.443	0.42	200.514	200.623	0.47	200.975	201.435	0.42	200.975	201.435	0.49
	28.583	43.190	0.93	44.097	64.634	0.77	35.018	51.605	0.97	42.622	61.689	0.91	42.622	61.689	0.81
	9.120	11.565	1.29	13.029	17.766	1.07	8.561	10.305	1.88	9.527	11.835	1.78	9.527	11.835	1.58
	5.044	5.398	2.24	6.971	8.121	2.07	2.813	2.594	2.74	3.089	2.871	2.60	3.089	2.871	2.32
	2.071	1.849	3.22	2.384	2.156	3.00	1.638	1.368	3.55	1.774	1.498	3.38	1.774	1.498	3.04
	1.230	1.031	1.230	1.395	1.174	1.174	1.150	0.935	1.150	1.244	1.016	1.150	1.244	1.016	1.206

**Table 8** SDRLs for the MPEWMA control chart when  $\theta = 1$

p	Mean														
	3			5			8			10			15		
	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$	$\lambda = 0.05$	$\lambda = 0.1$	$\delta/H$
4	11.49	13.02	0.00	11.48	12.95	0.00	11.47	12.92	0.00	11.46	12.90	0.00	11.46	12.89	0.00
	200.534	202.437	0.54	200.347	202.086	0.56	200.577	201.463	0.46	201.088	202.059	0.53	201.088	202.1212	0.49
	17.088	22.958	0.95	25.254	20.765	1.04	23.548	31.484	1.11	17.600	22.721	1.03	17.600	22.721	0.89
	6.068	6.752	1.41	11.029	5.572	1.26	4.900	4.941	1.60	5.501	5.685	1.50	5.501	5.685	1.31
	3.249	3.128	2.00	8.857	3.846	1.81	2.759	2.521	2.07	3.067	2.842	1.94	3.067	2.842	1.71
	1.932	1.706	2.53	5.691	2.039	2.31	1.929	1.658	2.50	2.120	1.847	2.36	2.120	1.847	2.09
	1.381	1.170	14.95	4.252	1.375	14.92	1.486	1.246	14.91	1.621	1.358	14.91	1.621	1.358	14.90
	14.95	16.68	0.00	14.92	16.56	0.00	14.91	16.5	0.00	14.91	16.50	0.00	14.91	16.48	0.00
	200.636	200.901	0.55	201.829	202.104	0.43	202.657	200.512	0.46	201.069	199.387	0.42	201.069	204.029	0.49
	18.914	26.116	0.97	30.244	42.729	1.07	26.022	35.892	0.88	31.583	43.567	0.80	31.583	32.678	0.68
	6.552	7.483	1.55	5.565	5.913	1.41	7.815	8.956	1.26	9.285	11.035	1.18	9.285	11.035	1.04
	3.016	2.884	2.22	3.574	3.449	2.04	4.297	4.291	1.84	4.731	4.850	1.73	4.731	4.850	1.53
	1.786	1.546	2.83	2.061	1.814	2.62	2.465	2.169	2.38	2.672	2.410	2.25	2.672	2.410	2.00
	1.270	1.070	21.19	1.446	1.217	21.14	1.693	1.426	21.13	1.850	1.577	21.13	1.850	1.577	21.12
	21.19	23.2	0.00	21.14	23.03	0.00	21.13	22.98	0.00	21.13	22.94	0.00	21.13	22.94	0.00
	200.799	201.361	0.56	201.164	200.237	0.43	201.381	200.540	0.47	202.238	200.292	0.43	202.238	200.826	0.49
	31.4404	31.4404	0.98	35.670	51.263	1.10	29.843	43.042	0.89	36.632	52.183	0.81	36.632	40.026	0.68
	4.32852	4.32852	1.69	6.053	6.683	1.58	8.698	10.500	1.45	10.376	12.891	1.38	10.376	14.588	1.24
	2.77813	2.77813	2.45	3.290	3.168	2.30	3.854	3.771	2.12	4.181	4.154	2.02	4.181	4.154	1.83
	1.4507	1.4507	3.16	1.876	1.635	2.98	2.165	1.897	2.76	2.343	2.060	2.64	2.343	2.060	2.39
	0.98221	0.98221	28.41	1.314	1.089	28.34	1.500	1.248	28.32	1.602	1.352	28.31	1.602	1.352	28.30
	28.41	30.65	0.00	28.34	30.49	0.00	28.32	30.41	0.00	28.31	30.38	0.00	28.31	30.35	0.00
	200.324	202.701	0.57	200.396	201.100	0.44	201.743	202.246	0.48	199.869	200.416	0.43	199.869	200.128	0.49
	37.468	37.468	0.98	40.432	60.442	1.11	33.894	50.238	0.91	41.730	60.927	0.82	41.730	47.477	0.71
	10.076	10.076	1.37	10.324	13.399	1.48	11.839	11.839	1.58	11.517	15.070	1.52	11.517	15.070	1.39
	4.734	4.734	1.78	6.586	7.578	2.48	3.653	3.545	2.32	3.916	3.853	2.24	3.916	3.853	2.05
	2.772	2.772	2.60	1.805	1.563	3.23	2.023	1.763	3.04	2.183	1.897	2.93	2.183	1.897	2.70
	1.416	1.416	1.635	1.253	1.035	1.416	1.398	1.165	1.416	1.489	1.245	1.398	1.489	1.245	1.706



The results show that the out-of-control ARLs can be quite different for processes that have the same number of unit shifts. For example, a shift of two units in a single mean such as  $[2, 0, 0, 0]$  (or  $\delta = 0.912$ ) with  $\lambda = 0.1$  and  $\theta = 0.5$  has an ARL of 12.491 (see Table 5), while a two-unit shift in two variables such as  $[1, 1, 0, 0]$  (or  $\delta = 0.689$ ) has an approximate ARL of 19.648 (again with  $\lambda = 0.1$  and  $\theta = 0.5$ ). Both are a “shift” of 2 units, but the ARLs and the shift-size of the mean are fairly different. However, the out-of-control ARLs are similar when the same number of variables shifts by the same amount. For example, the ARL for a shifted process such as  $[1, 1, 0, 0]$  is roughly the same as the ARL for the resulting process of  $[1, 0, 1, 0]$  or the process of  $[1, 0, 0, 1]$  for the same value of  $\lambda$ .

For a complete investigation of the performance of the proposed MPEWMA chart, the standard deviation of each scenario is calculated and summarized in Tables 7 and 8. The pooled standard deviations are applied within the same shift size. Moreover, the accuracy of the true mean of the population can be evaluated by calculating the standard error of the ARL ( $SE_{ARL}$ ). The formula of the  $SE_{ARL}$  is given by

$$SE_{ARL} = \frac{S}{\sqrt{n}} \quad (11)$$

where  $S$  is the standard deviation, and  $n$  is the number of replicates. A total of 50,000 replications is used for each scenario. Thus, the standard error of the mean is comparatively small due to the large sample size. The maximum value of  $SE_{ARL}$  is around 0.91 whereas the minimum value is approximately 0.005. A smaller

value of  $SE_{ARL}$  implies a more accurate estimate of the true mean of the run length, and therefore the sample mean is close to the population mean of the run length. The results clearly demonstrate that the  $SE_{ARL}$  decreases monotonically with an increase of the shift size. The  $SE_{ARL}$  computed from a large shift size tends to be small and one obtains a better estimate of the true mean than for a small size of shift.

### **3.6 General Equation of the Average Run Length**

Since the simulation study is limited to the certain values of the parameter combination as discussed in Section 3.4, the average run length performance of the proposed MPEWMA control chart could be further extended to include other values of those parameters by performing a multiple regression. We fit both the multiple linear regression and Generalized Linear Models (GLM) to the ARL values. The five possible variables considered affecting the out-of-control ARL values are the shift size ( $\delta$ ), the fixed common mean ( $\theta$ ), the smoothing weight ( $\lambda$ ), the number of variables being monitored ( $p$ ), and the process mean of interest which is assumed to be equal among all process means ( $\mu$ ). Cases of no shift ( $\delta = 0$ ) related to an in-control ARL are removed to provide a more accurate model. The preliminary results show that the GLM with the exponential distribution provides a better fit to the ARL performance of the MPEWMA scheme as the ARL values tend to decrease exponentially with increasing the size of shift. The SAS output indicates that only four parameters ( $p$ ,  $\delta$ ,  $\lambda$ , and  $\mu$ ) are statistically significant (p-value < alpha level of 0.05) as shown in Table 9. The fixed common mean,  $\theta$ , is not significant and dropped from the fitted model. Table 10 reports the

output of fitting the model without the fixed common mean variable ( $\theta$ ) in SAS.

Thus, the fitted model is

$$\hat{y} = \frac{-1}{0.007 + 0.0008 p - 0.0004 \mu + 0.0547 \lambda - 0.0840 \delta} \quad (12)$$

**Table 9** The SAS output of fitting the GLM with the exponential distribution to the ARL values obtained from simulation.

The GENMOD Procedure							
Model Information							
Data Set	WORK.ALLDATA						
Distribution	Gamma						
Link Function	Power(-1)						
Dependent Variable	ARL						
	Number of Observations Read						1900
	Number of Observations Used						1900
Criteria For Assessing Goodness Of Fit							
Criterion	DF	Value		Value/DF			
Deviance	1894	37.8351		0.0200			
Scaled Deviance	1894	1906.2848		1.0065			
Pearson Chi-Square	1894	32.5436		0.0172			
Scaled Pearson X2	1894	1639.6761		0.8657			
Log Likelihood		-5132.6491					
Full Log Likelihood		-5132.6491					
AIC (smaller is better)		10279.2981					
AICC (smaller is better)		10279.3573					
BIC (smaller is better)		10318.1454					
Algorithm converged.							
Analysis Of Maximum Likelihood Parameter Estimates							
Parameter	DF	Estimate	Standard Error	Wald 95% Confidence Limits		Chi-Square	Wald Pr > ChiSq
Intercept	1	-0.0068	0.0006	-0.0079	-0.0056	129.39	<.0001
Var	1	-0.0008	0.0000	-0.0008	-0.0007	1576.43	<.0001
Mean	1	0.0004	0.0000	0.0003	0.0004	225.06	<.0001
Lambda	1	-0.0547	0.0031	-0.0608	-0.0486	308.19	<.0001
Shiftsize	1	0.0840	0.0005	0.0830	0.0851	24258.5	<.0001
Thetafix	1	-0.0003	0.0003	-0.0009	0.0003	1.08	0.2996
Scale	1	50.3840	1.6293	47.2897	53.6807		
NOTE: The scale parameter was estimated by maximum likelihood.							

**Table 10** The SAS output after dropping the fix common mean variable from the model

```

                                The GENMOD Procedure
                                Model Information
Data Set                        WORK.ALLDATA
Distribution                     Gamma
Link Function                    Power(-1)
Dependent Variable              ARL      ARL
      Number of Observations Read      1900
      Number of Observations Used      1900

                                Criteria For Assessing Goodness Of Fit
Criterion                        DF          Value      Value/DF
Deviance                        1895          37.8565      0.0200
Scaled Deviance                 1895          1906.2884      1.0060
Pearson Chi-Square              1895          32.5559      0.0172
Scaled Pearson X2              1895          1639.3756      0.8651
Log Likelihood                  -5133.1867
Full Log Likelihood             -5133.1867
AIC (smaller is better)        10278.3734
AICC (smaller is better)       10278.4178
BIC (smaller is better)       10311.6711
Algorithm converged.

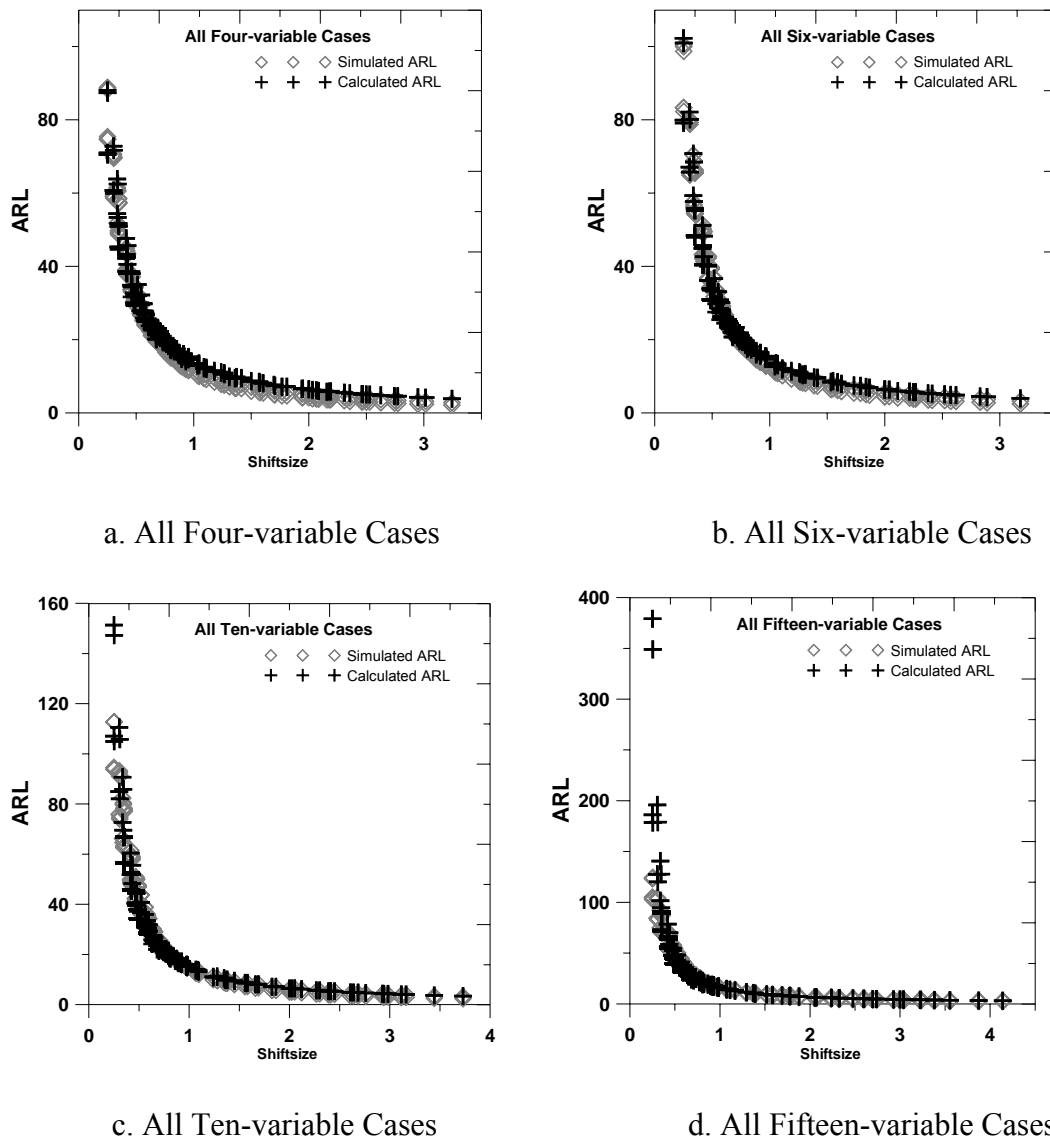
                                Analysis Of Maximum Likelihood Parameter Estimates
Parameter  DF   Estimate  Standard  Wald 95% Confidence  Wald  Pr > ChiSq
              Error  Limits  Chi-Square
Intercept    1   -0.0070   0.0006   -0.0081  -0.0059    157.61  <.0001
Var          1   -0.0008   0.0000   -0.0008  -0.0007   1574.78  <.0001
Mean        1    0.0004   0.0000    0.0003   0.0004    224.29  <.0001
Lambda      1   -0.0547   0.0031   -0.0608  -0.0485    307.95  <.0001
Shiftsize   1    0.0840   0.0005    0.0830   0.0851   24266.2  <.0001
Scale       1   50.3557   1.6284   47.2631   53.6505
NOTE: The scale parameter was estimated by maximum likelihood.

```

A comparison between the simulated and fitted ARL from the above equation is provided in Figure 1. Figure 1 displays the plot of the out-of-control ARL values of the simulation and those from the fitted model for all cases as a function of  $\delta$ . However, using the general equation gives a slightly larger out-of-control ARL than the simulation method. It can be noted that the general equation may not provide good approximations for the small shift size and large number of variables. We can see from Figure 1.d, when the size of shift is around 0.25 with fifteen-variables, the out-of-control ARL based on equation (12) is approximately

380, with the simulated value being close to 125. Thus, it can be noted that one should use the general equation with caution to approximate the out-of-control ARL value for the small shift size (say less than 0.3) and large number of variables (ten or more).

**Figure 1** The comparison of the simulated and calculated ARL plots separated by the number of variables.



### 3.7 Effect of Changing the Common Variable

In Section 3.5, we discussed the statistical performances of the MPEWMA chart with two thetafix values ( $\theta = 0.5$ , and 1). The ARL values reported in Table 5 – 6 are calculated by assuming the mean of the common variable ( $\theta$ ) remains the same. However, sometimes both the mean of the common variable and other variables (i.e.  $\theta_i$ ) increase simultaneously. Thus, we extend the investigation of the proposed MPEWMA scheme into the case of monitoring the mean shift in the common variable ( $X$ ). Five mean values of the common variable are tested ( $\theta = 0.5, 1, 1.5, 2, \text{ and } 2.5$ ). The smoothing weight of 0.05 is selected in this study. Table 11 shows the ARL performances of the MPEWMA chart when the common variable and one of the other variables shift together. For two variables shifted and all variables shifted, please see Table 12 and 13, respectively.

It can be seen that an increase in the common variable has an effect on the in-control ARL for the mean of 3, but there is a little or none for the mean of 5 or larger. The out-of-control ARL values show a significant decrease in case of one or two variables shifted (Table 11 - 12), particularly for a small unit of shift matrix. It is worthy to note that the combination of increase in both common variable and all variable means could cause a dramatic increase in the out-of-control ARL values (see Table 13). This corresponds to the small shift size ( $\delta$ ) computed from Equation (10). An increase in the mean of the common variable can result in a large covariance matrix, and produce the small shift size.

**Table 11** The ARL performance of the MPEWMA chart for detecting the mean shift in one variable when varying  $\theta$

$\theta$	Number of variable (p)														
	4 (H = 11.48)			6 (H = 14.93)			10 (H = 21.17)			15 (H = 28.39)					
Mean Shift matrix	(0,0,0,0)	(1,0,0,0)	(2,0,0,0)	(0,0,0,0)	(1,0,0,0)	(2,0,0,0)	(0,0,0,0)	(1,0,0,0)	(2,0,0,0)	(0,0,0,0)	(1,0,0,0)	(2,0,0,0)	(0,0,0,0)	(1,0,0,0)	(2,0,0,0)
3	0.5	200.899	29.082	13.2	200.303	31.984	14.41	201.338	36.47	16.223	199.065	40.688	17.967	199.065	40.688
	1	199.975	26.672	12.392	199.957	28.987	13.404	199.19	32.722	15.014	199.155	36.719	16.565	199.155	36.719
	1.5	201.616	23.733	11.374	199.355	25.659	12.305	196.607	28.811	13.759	197.186	31.953	15.164	197.186	31.953
	2	198.211	20.396	10.276	197.622	21.852	11.073	194.4	24.491	12.349	194.223	27.097	13.644	194.223	27.097
	2.5	192.625	16.421	8.954	189.496	17.638	9.725	184.353	19.763	10.916	184.593	21.962	12.03	184.593	21.962
5	$\theta$	4 (H = 11.48)			6 (H = 14.9)			10 (H = 21.15)			15 (H = 28.39)				
	0.5	203.365	39.066	16.616	200.739	43.543	18.281	200.868	50.151	20.799	199.901	56.135	23.038	199.901	56.135
	1	201.421	37.545	16.103	199.229	41.576	17.592	201.805	47.368	19.849	199.312	53.626	21.978	199.312	53.626
	1.5	200.763	35.745	15.474	200.49	38.849	16.659	201.581	44.286	18.763	200.611	49.101	20.709	200.611	49.101
	2	201.773	33.223	14.532	199.294	36.007	15.775	199.91	40.448	17.543	197.88	44.811	19.373	197.88	44.811
	2.5	198.748	30.548	13.692	198.194	32.852	14.653	197.967	36.886	16.345	199.281	41.03	18.03	199.281	41.03
8	$\theta$	4 (H = 11.47)			6 (H = 14.89)			10 (H = 21.14)			15 (H = 28.31)				
	0.5	201.058	51.889	21.304	199.038	57.542	23.544	199.441	67.08	27.079	199.901	74.77	30.091	199.901	74.77
	1	201.337	50.981	20.957	199.146	56.781	23.079	200.657	65.22	26.18	199.599	72.481	29.221	199.599	72.481
	1.5	200.735	50.029	20.543	200.124	55.053	22.441	200.394	62.689	25.456	201.379	69.929	28.295	201.379	69.929
	2	202.275	48.248	20.042	199.421	52.925	21.689	199.258	60.062	24.394	200.633	67.131	27.086	200.633	67.131
	2.5	200.318	46.437	19.188	198.62	50.895	20.82	200.982	57.328	23.284	200.836	64.091	25.845	200.836	64.091
10	$\theta$	4 (H = 11.46)			6 (H = 14.89)			10 (H = 21.13)			15 (H = 28.3)				
	0.5	200.526	59.933	24.217	200.501	66.497	26.918	201.528	76.53	30.751	199.439	84.578	34.564	199.439	84.578
	1	200.119	58.798	23.895	201.651	65.197	26.429	201.571	74.724	30.246	200.96	83.475	33.82	200.96	83.475
	1.5	200.409	58.061	23.632	198.849	63.842	25.881	201.211	73.064	29.413	199.343	81.214	32.869	199.343	81.214
	2	199.177	56.667	22.99	200.793	62.369	25.263	200.28	70.894	28.737	200.137	78.585	31.783	200.137	78.585
	2.5	199.768	55.344	22.512	200.472	60.506	24.44	199.337	68.726	27.549	201.232	75.538	30.437	201.232	75.538
15	$\theta$	4 (H = 11.46)			6 (H = 14.9)			10 (H = 21.12)			15 (H = 28.3)				
	0.5	199.361	74.765	30.755	200.394	83.528	34.659	202.492	94.707	40.03	200.783	104.669	45.072	200.783	104.669
	1	200.78	74.995	30.538	199.645	82.837	34.103	201.015	94.489	39.423	200.466	104.326	44.396	200.466	104.326
	1.5	199.96	74.662	30.466	200.647	82.247	33.986	199.99	92.543	38.785	200.009	102.403	43.607	200.009	102.403
	2	199.545	73.663	29.986	201.459	81.225	33.18	201.115	91.802	38.058	200.4	100.586	42.759	200.4	100.586
	2.5	200.377	72.989	29.761	199.867	79.958	32.746	200.54	90.295	37.251	199.495	99.43	41.852	199.495	99.43

**Table 12** The ARL performance of the MPEWMA chart for detecting the mean shift in two variables when varying  $\theta$

Mean Shift matrix	Number of variable ( $p$ )														
	4 ( $H = 11.49$ )			6 ( $H = 14.93$ )			10 ( $H = 21.17$ )			15 ( $H = 28.39$ )					
$\theta$	(0,0,0,0)	(1,1,0,0)	(2,2,0,0)	(0,0,0,0)	(1,1,0,0)	(2,2,0,0)	(0,0,0,0)	(1,1,0,0)	(2,2,0,0)	(0,0,0,0)	(1,1,0,0)	(2,2,0,0)	(0,0,0,0)	(1,1,0,0)	(2,2,0,0)
3	0.5	200.899	19.291	8.997	200.303	20.834	9.611	201.338	23.062	10.643	199.065	25.422	11.588	199.155	22.901
	1	199.975	18.573	8.693	199.957	19.339	9.153	199.19	21.074	9.922	199.155	22.901	10.829	197.186	20.125
	1.5	201.616	16.972	8.136	199.355	17.376	8.43	196.607	18.521	9.126	197.186	20.125	8.887	194.223	17.128
	2	198.211	14.688	7.352	197.622	14.767	7.558	194.4	15.851	8.242	194.223	17.128	8.945	184.593	14.038
	2.5	192.625	11.691	6.308	189.496	11.906	6.593	184.353	12.851	7.227	184.593	14.038	7.911	184.593	14.038
5	$\theta$	4 ( $H = 11.46$ )	6 ( $H = 14.9$ )	10 ( $H = 21.15$ )	15 ( $H = 28.39$ )										
	0.5	203.365	25.364	11.05	200.739	27.632	11.982	200.868	31.505	13.445	199.901	34.836	14.721	199.901	34.836
	1	201.421	25.444	11.068	199.229	27.147	11.797	201.805	29.934	12.985	199.312	33.054	14.098	199.312	33.054
	1.5	200.763	24.725	10.883	200.49	25.726	11.35	201.581	28.135	12.311	200.611	30.577	13.346	200.611	30.577
	2	201.773	23.47	10.492	199.294	24.117	10.748	199.91	26.084	11.623	197.88	28.24	12.516	197.88	28.24
	2.5	198.748	22.041	9.935	198.194	22.219	10.097	197.967	23.687	10.853	199.281	25.565	11.706	199.281	25.565
8	$\theta$	4 ( $H = 11.47$ )	6 ( $H = 14.89$ )	10 ( $H = 21.14$ )	15 ( $H = 28.31$ )										
	0.5	201.058	33.17	13.856	199.038	36.731	15.13	199.441	42.53	17.058	199.901	47.496	18.857	199.901	47.496
	1	201.337	33.744	13.919	199.146	36.705	15.145	200.657	41.882	16.82	199.599	46.155	18.441	199.599	46.155
	1.5	200.735	33.678	13.921	200.124	36.229	14.911	200.394	40.363	16.361	201.379	44.243	17.78	201.379	44.243
	2	202.275	33.446	13.881	199.421	35.164	14.47	199.258	38.785	15.871	200.633	42.627	17.247	200.633	42.627
	2.5	200.318	32.583	13.618	198.62	33.969	14.086	200.982	36.971	15.264	200.836	40.37	16.475	200.836	40.37
10	$\theta$	4 ( $H = 11.46$ )	6 ( $H = 14.89$ )	10 ( $H = 21.13$ )	15 ( $H = 28.3$ )										
	0.5	200.526	37.926	15.523	200.501	42.361	17.122	201.528	48.657	19.295	199.439	54.924	21.404	199.439	54.924
	1	200.119	38.845	15.717	201.651	42.712	17.088	201.571	48.478	19.204	200.96	54.215	21.102	200.96	54.215
	1.5	200.409	38.886	15.793	198.849	42.135	17.006	201.211	47.404	18.921	199.343	52.575	20.6	199.343	52.575
	2	199.177	38.574	15.742	200.793	41.426	16.803	200.28	46.339	18.415	200.137	50.897	20.023	200.137	50.897
	2.5	199.768	38.227	15.538	200.472	40.63	16.422	199.337	44.585	17.879	201.232	49.065	19.42	201.232	49.065
15	$\theta$	4 ( $H = 11.46$ )	6 ( $H = 14.9$ )	10 ( $H = 21.12$ )	15 ( $H = 28.3$ )										
	0.5	199.361	48.029	19.483	200.394	54.725	21.545	202.492	63.201	24.45	200.783	71.011	27.651	200.783	71.011
	1	200.78	49.802	19.78	199.645	54.979	21.83	201.015	63.152	24.555	200.466	70.635	27.381	200.466	70.635
	1.5	199.96	50.062	19.891	200.647	55.602	21.735	199.99	62.764	24.426	200.009	70.303	27.001	200.009	70.303
	2	199.545	50.273	19.916	201.459	54.948	21.674	201.115	62.095	24.094	200.4	69.062	26.556	200.4	69.062
	2.5	200.377	50.35	19.851	199.867	54.785	21.402	200.54	61.221	23.702	199.495	67.45	26.085	199.495	67.45



**Table 13** The ARL performance of the MPEWMA chart for detecting the mean shift in all variables when varying  $\theta$

Mean Shift matrix	Number of variable (p)														
	4 (H = 11.49)			6 (H = 14.93)			10 (H = 21.17)			15 (H = 28.39)					
	(1,1,1,1)	(2,2,2,2)	(3,3,3,3)	(1,1,1,1)	(2,2,2,2)	(3,3,3,3)	(1,1,1,1)	(2,2,2,2)	(3,3,3,3)	(1,1,1,1)	(2,2,2,2)	(3,3,3,3)	(1,1,1,1)	(2,2,2,2)	(3,3,3,3)
3	0.5	14.712	6.85	4.569	13.984	6.467	4.327	13.801	6.373	4.227	14.054	6.511	4.309	15.254	6.867
	1	17.436	7.859	5.149	17.463	7.859	5.116	18.353	8.166	5.301	19.668	8.71	5.647	20.519	8.885
	1.5	19.817	8.791	5.707	20.716	9.078	5.856	22.622	9.833	6.309	24.83	10.66	6.85	26.326	10.69
	2	22.408	9.695	6.263	23.864	10.275	6.561	26.885	11.383	7.227	29.894	12.573	7.981	30.035	12.409
	2.5	24.898	10.617	6.781	27.145	11.45	7.26	31.125	12.928	8.161	35.06	14.44	9.079	34.422	14.042
5	0.5	17.891	7.984	5.175	16.448	7.371	4.803	15.485	6.971	4.552	15.254	6.867	4.5	15.254	6.867
	1	20.308	8.842	5.704	19.686	8.569	5.507	19.787	8.554	5.51	20.519	8.885	5.711	20.519	8.885
	1.5	22.539	9.744	6.235	22.61	9.682	6.166	23.714	10.063	6.404	25.326	10.69	6.803	25.326	10.69
	2	24.892	10.518	6.7	25.498	10.788	6.806	27.521	11.42	7.261	30.035	12.409	7.821	30.035	12.409
	2.5	27.071	11.346	7.149	28.299	11.77	7.414	31.339	12.85	8.069	34.422	14.042	8.791	34.422	14.042
8	0.5	22.511	9.522	6.069	20.028	8.631	5.513	17.985	7.849	5.05	17.258	7.54	4.851	17.258	7.54
	1	24.592	10.345	6.544	22.942	9.699	6.133	22.166	9.36	5.911	22.184	9.36	5.944	22.184	9.36
	1.5	26.613	11.129	6.966	25.64	10.731	6.725	25.904	10.727	6.733	26.757	11.035	6.946	26.757	11.035
	2	28.677	11.819	7.399	28.326	11.679	7.307	29.398	12.012	7.463	31.079	12.631	7.87	31.079	12.631
	2.5	30.531	12.577	7.839	31.043	12.648	7.85	32.902	13.301	8.222	35.286	14.065	8.768	35.286	14.065
10	0.5	25.088	10.552	6.63	22.173	9.414	5.953	19.742	8.45	5.368	18.531	7.988	5.106	18.531	7.988
	1	27.269	11.298	7.054	25.077	10.468	6.548	23.613	9.854	6.191	23.407	9.752	6.144	23.407	9.752
	1.5	29.238	12.05	7.449	27.809	11.452	7.098	27.276	11.155	6.984	27.806	11.349	7.113	27.806	11.349
	2	31.254	12.739	7.919	30.311	12.344	7.658	30.771	12.405	7.71	32.084	12.869	7.99	32.084	12.869
	2.5	33.185	13.402	8.3	32.971	13.256	8.181	34.137	13.622	8.41	36.424	14.322	8.808	36.424	14.322
15	0.5	31.598	12.886	7.924	27.526	11.348	7.027	23.981	9.883	6.187	21.912	9.129	5.74	21.912	9.129
	1	33.276	13.494	8.335	30.13	12.23	7.525	27.542	11.183	6.914	26.363	10.738	6.681	26.363	10.738
	1.5	35.437	14.139	8.689	32.66	13.157	8.037	30.982	12.377	7.601	30.784	12.261	7.579	30.784	12.261
	2	37.172	14.87	9.066	35.227	13.95	8.522	34.268	13.553	8.306	34.885	13.687	8.377	34.885	13.687
	2.5	38.95	15.47	9.412	37.73	14.871	9.032	37.787	14.695	8.94	38.852	15.064	9.17	38.852	15.064

### **3.8 Comparison of the MPEWMA and MEWMA Control Chart**

To gain more insight into the performance of the MEWMA chart under the multivariate Poisson distribution, a comparison is made between the MEWMA and MPEWMA scheme's performance. The control limits of the steady-state MEWMA chart based on the work of Prabhu and Runger (1997) are established assuming the multivariate normal distribution. The ARL performance of the MEWMA chart is reported in Table 14 in terms of a quantity of the shift size. For the proposed MEWMA monitoring scheme, the multivariate Poisson data are generated using the simulation method and conditions similar to that discussed in Section 3.4. The normal-theory limits are placed on the MPEWMA chart to obtain the true performance of the MEWMA based on the multivariate Poisson. The ARL performance comparisons are shown in Tables 15 – 16 for  $\theta = 0.5$  and 1, respectively. The in-control and out-of-control ARLs are both investigated to evaluate the robustness of the MEWMA chart

#### **3.8.1 Out of-Control ARL Comparison**

Comparing two control charts that have shifted by some amount, the chart with a smaller out-of-control ARL is preferred. For a fair comparison, the in-control ARLs for the two methods must be approximately equal. The traditional MEWMA chart and the proposed MPEWMA chart perform similarly in detecting the same shift in the process means as reported in Tables 15 and 16. It can be noticed that if the shift size,  $\delta$ , is less than 0.6, the out-of-control ARLs obtained from the MPEWMA chart are slightly but not much worse than the out-of-control ARLs for the MEWMA chart.

**Table 14** The Steady State ARL for the MEWMA chart proposed by Prabhu and Runger (1997)

p	$\delta$ (Shift size)	$\lambda$	
		0.05	0.1
4	H	11.22	12.73
	0	199.98	200.05
	0.5	29.52	33.12
	1	12.27	11.38
	1.5	7.75	6.7
	2	5.71	4.8
	3	3.82	3.14
6	H	14.6	16.27
	0	199.88	200
	0.5	31.91	37.08
	1	13.31	12.41
	1.5	8.43	7.25
	2	6.23	5.18
	3	4.17	3.38
10	H	20.72	22.67
	0	200.06	200.06
	0.5	36.87	44.19
	1	15.23	14.32
	1.5	9.64	8.23
	2	7.11	5.83
	3	4.76	3.79
15	H	27.82	30.03
	0	200.05	199.95
	0.5	41.78	51.23
	1	17.13	16.3
	1.5	10.8	9.21
	2	7.97	6.48
	3	5.32	4.18

### 3.8.2 In-Control ARL Comparison

The most important result from this study concerns the in-control ARLs. As alluded to previously, out-of-control ARLs of two or more monitoring schemes can only be compared fairly if the corresponding in-control ARLs are approximately the same value. Notice the in-control ARLs reported in Tables 15 and 16. The in-control ARLs for the MPEWMA for data that comes from a

multivariate Poisson distribution are close to 200. However, when the MEWMA using the normal-theory limits from Prahbu and Runger (1997) is applied to multivariate Poisson distributed data, the in-control ARLs are not the advertised value of 200. In fact, when the control limit for the MEWMA based on the normality assumption is applied to the multivariate Poisson-distributed data, a substantial reduction in the in-control ARL occurs. For example, instead of an in-control ARL near 200 as expected, the true in-control ARL ranges from 170 to 190 (see Tables 15 - 18). That is, using the MEWMA chart assuming multivariate normality when the underlying distribution is truly multivariate Poisson, results in a 5-15% reduction the in-control ARL and thus, an increase in false alarms. This reduction is quite obvious for small process means (5 or less) and a large number of variables (10 or more). A large in-control ARL for the MPEWMA indicates that it will result in fewer false alarms than the MEWMA scheme for normally distributed data.

The results have significant implications in practice. Specifically, we have shown that if one simply assumes the normality assumption applies (and uses published normal-theory limits) when in fact the underlying distribution is something such as the multivariate Poisson, expect an increase in out-of-control signals when the process is truly in control. The practitioner may be stopping the process when a signal occurs, when in fact the process is still in control.

### **3.8.3 SRDL Comparison**

We also examined the standard deviation of the run length (SDRL). Tables 19, 20, 21 and 22 give the SDRLs for the MEWMA and MPEWMA control

charts for two values of  $\theta$  ( $\theta = 0.5$  and  $\theta = 1$ , respectively). The SDRL results are quite similar to those ARL results for both in-control and out-of-control processes. The MEWMA relied on the normal theory approximation provides considerably lower SDRL values than the MPEWMA for the in-control case. On the other hand, there is no difference in the out-of-control SDRL performance, particularly when the size of shift becomes large.

**Table 15** Comparison of the ARL performance between the MPEWMA and MEWMA charts when  $\theta = 0.5$  and  $\lambda = 0.05$

p	Mean														
	3			5			8			10			15		
	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$
	$\lambda = 0.05$														
4	11.49	11.22	0.00	11.48	11.22	0.00	11.47	11.22	0.00	11.46	11.22	0.00	11.46	11.22	0.00
	200.124	183.885	0.56	200.114	184.081	0.46	199.806	184.378	0.57	199.200	184.579	0.49	199.549	183.509	0.49
	28.843	27.944	1.05	25.287	24.657	0.88	33.08067	32.244	1.09	24.971	24.460	0.93	30.68125	29.962	0.93
	13.115	12.849	1.37	10.964	10.814	0.88	13.801	13.530	1.58	10.505	10.309	1.36	12.826	12.573	1.36
	6.858	6.715	1.95	7.951	7.854	1.70	6.062	5.978	2.03	6.618	6.539	1.77	7.912	7.778	1.77
	4.569	4.489	2.95	5.196	5.107	2.18	4.486	4.421	2.46	4.847	4.774	2.16	5.713	5.635	2.16
	3.478	3.427	2.27	3.143	3.089	2.63	3.573	3.527	2.41	3.845	3.769	2.11	4.488	4.408	2.11
6	14.93	14.60	0.00	14.90	14.6	0.00	14.89	14.60	0.00	14.89	14.6	0.00	14.9	14.6	0.00
	200.023	180.555	0.41	199.306	182.533	0.46	199.670	181.292	0.42	199.214	180.262	0.49	200.150	181.355	0.49
	31.746	30.773	0.77	43.168	41.592	0.88	36.643	35.3168	0.81	42.204	40.455	0.68	34.287	33.070	0.68
	14.341	14.016	1.05	18.188	17.796	1.39	15.045	14.709	1.29	16.973	16.562	1.11	21.478	20.766	1.11
	9.588	9.398	1.59	11.943	11.745	2.00	8.590	8.428	1.87	9.366	9.217	1.62	11.274	10.998	1.62
	6.509	6.390	2.27	7.330	7.233	2.57	5.515	5.402	2.41	5.951	5.850	2.11	7.006	6.886	2.11
	4.328	4.248	2.15	4.802	4.726	2.57	4.058	3.991	2.41	4.372	4.290	2.11	5.078	4.983	2.11
10	21.17	20.72	0.00	21.15	20.72	0.00	21.14	20.72	0.00	21.13	20.72	0.00	21.12	20.72	0.00
	200.104	176.191	0.42	199.475	177.746	0.47	199.927	179.165	0.42	199.332	179.396	0.49	199.441	180.616	0.49
	36.169	34.635	0.98	49.796	47.262	0.89	42.214	40.368	0.81	48.818	46.410	0.70	39.676	38.183	0.70
	13.747	13.478	1.86	15.491	15.066	1.66	17.002	16.597	1.56	19.333	18.851	1.36	23.809	23.041	1.36
	10.628	10.338	2.68	6.966	6.835	2.41	7.837	7.712	2.27	8.433	8.268	2.00	9.845	9.655	2.00
	6.374	6.262	3.44	4.534	4.458	3.11	5.031	4.927	2.94	5.355	5.272	2.61	6.174	6.057	2.61
	4.226	4.157	2.83	3.407	3.343	3.11	3.735	3.663	2.94	3.947	3.889	2.61	4.476	4.407	2.61
15	28.39	27.82	0.00	28.34	27.82	0.00	28.31	27.82	0.00	28.30	27.82	0.00	28.30	27.82	0.00
	199.862	174.170	0.42	200.025	177.180	0.47	199.65	178.284	0.42	199.677	178.350	0.49	200.098	179.302	0.49
	40.647	38.745	0.77	56.139	52.923	0.97	47.175	44.857	0.91	54.607	51.791	0.81	44.790	42.781	0.81
	17.875	17.333	1.07	23.031	22.292	1.88	17.252	16.860	1.78	18.531	18.076	1.58	21.820	21.242	1.58
	11.514	11.243	2.07	15.233	14.869	2.74	7.549	7.386	2.60	8.003	7.832	2.32	9.105	8.953	2.32
	6.515	6.385	3.00	4.866	4.762	3.55	4.854	4.766	3.38	5.090	5.012	3.04	5.724	5.622	3.04
	4.307	4.237	3.00	4.486	4.417	3.55	3.599	3.532	3.38	3.763	3.687	3.04	4.167	4.094	3.04

**Table 16** Comparison of the ARL performance between the MPEWMA and MEWMA charts when  $\theta = 0.5$  and  $\lambda = 0.1$

p	Mean														
	3			5			8			10			15		
	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA
4	0.00	13.01	12.73	0.00	12.95	12.73	0.00	12.91	12.73	0.00	12.90	12.73	0.00	12.89	12.73
	0.51	200.012	182.348	0.56	199.771	184.738	0.46	200.234	186.29	0.00	198.817	187.280	0.48	199.811	189.834
	0.91	32.322	30.968	1.05	27.168	26.320	0.88	37.142	36.123	0.57	25.576	25.301	0.93	34.584	33.689
	1.57	12.491	12.168	1.37	10.033	9.867	1.70	13.017	12.806	1.09	9.378	9.276	1.58	11.886	11.740
	2.19	5.708	5.585	1.95	6.775	6.692	2.18	4.995	4.953	1.58	5.518	5.434	1.36	6.753	6.698
	2.74	3.607	3.537	2.95	4.172	4.110	2.63	3.532	3.501	2.03	3.877	3.837	1.77	4.656	4.627
6	0.00	16.65	16.27	0.00	16.54	16.27	0.00	16.50	16.27	0.00	16.48	16.27	0.00	16.49	16.27
	0.52	199.591	179.161	0.41	200.009	182.997	0.46	199.801	186.126	0.00	199.801	185.212	0.00	200.066	187.169
	0.92	36.831	34.849	0.77	51.347	49.196	0.88	42.5856	41.1436	0.42	49.655	47.697	0.49	39.700	38.219
	1.26	13.789	13.467	1.05	18.535	18.0427	1.39	14.597	14.278	0.81	16.805	16.473	0.68	22.381	21.747
	1.79	8.559	8.304	1.59	11.002	10.758	2.00	7.388	7.301	1.29	8.191	8.033	1.11	10.152	10.042
	2.52	5.326	5.205	2.27	6.147	6.044	2.57	4.43	4.36	1.87	4.830	4.773	1.62	5.829	5.744
10	0.00	3.350	2.410	0.00	3.775	3.711	0.00	3.142	3.099	0.00	3.411	3.365	0.00	4.051	3.993
	0.52	23.17	22.67	0.42	23.04	22.67	0.47	22.98	22.67	0.00	22.95	22.67	0.00	22.91	22.67
	0.92	199.268	175.325	0.42	200.122	182.320	0.47	199.828	183.217	0.00	200.06	184.810	0.00	199.469	184.569
	1.08	43.709	40.707	0.98	61.486	57.736	0.89	50.665	48.499	0.42	59.331	56.619	0.49	47.551	45.914
	1.28	12.783	12.353	1.86	14.796	14.379	1.66	16.873	16.535	0.81	19.708	19.280	0.70	25.45	24.436
	2.05	9.517	9.29	2.68	5.667	5.568	2.41	3.933	3.901	2.27	4.253	4.196	2.00	4.98	4.943
15	0.00	3.201	3.129	0.00	3.44	3.44	0.00	3.11	3.099	0.00	3.44	3.44	0.00	3.477	3.436
	0.52	30.62	30.03	0.42	30.49	30.03	0.47	30.40	30.03	0.00	30.36	30.03	0.00	30.33	30.03
	0.92	199.034	173.298	0.42	200.182	178.251	0.47	199.478	184.199	0.00	199.244	184.422	0.00	200.112	184.677
	1.08	50.393	46.438	0.77	70.966	65.627	0.97	58.461	55.399	0.42	68.097	64.615	0.49	55.192	52.887
	1.28	18.304	17.521	1.07	25.069	24.029	1.88	16.940	16.443	0.91	18.507	18.093	0.81	22.693	22.21
	2.24	10.561	10.295	2.07	14.138	14.059	2.74	6.192	6.139	1.78	6.655	6.577	1.58	7.757	7.668
15	0.00	5.138	5.02	3.00	5.542	5.468	3.00	3.745	3.683	0.00	3.961	3.916	0.00	4.541	4.492
	0.52	3.217	3.144	0.42	3.403	3.403	0.47	3.55	3.55	0.00	3.38	3.38	0.00	3.171	3.142
	0.92	199.034	173.298	0.42	200.182	178.251	0.47	199.478	184.199	0.00	199.244	184.422	0.00	200.112	184.677
	1.08	50.393	46.438	0.77	70.966	65.627	0.97	58.461	55.399	0.42	68.097	64.615	0.49	55.192	52.887
	1.28	18.304	17.521	1.07	25.069	24.029	1.88	16.940	16.443	0.91	18.507	18.093	0.81	22.693	22.21
	2.24	10.561	10.295	2.07	14.138	14.059	2.74	6.192	6.139	1.78	6.655	6.577	1.58	7.757	7.668

**Table 17** Comparison of the ARL performance between the MPEWMA and MEWMA charts when  $\theta = 1.0$  and  $\lambda = 0.05$

p	Mean														
	3			5			8			10			15		
	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$
4	$\delta/H$	11.49	11.22	11.48	11.22	11.47	11.22	11.46	11.22	11.46	11.22	11.46	11.22	11.46	11.22
	0.00	199.031	182.379	0.00	199.142	183.332	0.00	199.309	183.735	0.00	200.141	183.361	0.00	198.954	184.046
	0.54	26.558	25.863	0.56	25.254	24.599	0.46	33.638	32.645	0.53	27.063	26.531	0.49	30.577	29.815
	0.95	12.349	8.536	1.04	11.029	10.853	1.11	10.352	10.127	1.03	11.288	11.031	0.89	13.512	13.233
	1.41	7.833	7.722	1.26	8.857	8.702	1.60	6.529	6.413	1.50	7.048	6.942	1.31	8.289	8.186
6	2.00	5.141	5.075	1.81	5.691	5.618	2.07	4.789	4.723	1.94	5.165	5.084	1.71	5.99	5.886
	2.53	3.885	3.808	2.31	4.252	4.174	2.50	3.800	3.752	2.36	4.059	3.991	2.09	4.672	4.610
	$\delta/H$	14.95	14.6	14.92	14.6	14.91	14.6	14.91	14.60	14.91	14.60	14.91	14.60	14.90	14.6
	0.00	199.747	179.675	0.00	199.905	182.015	0.00	199.439	182.435	0.00	200.111	182.727	0.00	199.983	181.930
	0.55	29.068	28.056	0.43	41.300	39.8285	0.46	36.7216	35.318	0.42	42.481	40.609	0.49	34.002	32.829
10	0.97	13.404	13.120	1.07	11.740	11.524	0.88	15.061	14.759	0.80	17.153	16.615	0.68	21.573	20.990
	1.55	7.836	7.679	1.41	8.579	8.391	1.26	9.67	9.458	1.18	10.418	10.191	1.04	12.188	11.893
	2.22	5.111	5.020	2.04	5.508	5.427	1.84	6.143	6.034	1.73	6.545	6.417	1.53	7.545	7.401
	2.83	3.836	3.771	2.62	4.093	4.036	2.38	4.513	4.425	2.25	4.79	4.700	2.00	5.438	5.358
	$\delta/H$	21.19	20.72	21.14	20.72	21.13	20.72	21.13	20.72	21.13	20.72	21.13	20.72	21.12	20.72
0.00	199.484	176.648	0.00	199.739	178.941	0.00	200.081	180.012	0.00	200.194	180.788	0.00	199.188	180.138	
0.56	32.922	31.503	0.43	47.399	44.908	0.47	41.389	39.589	0.43	48.300	46.012	0.49	39.267	37.7468	
0.98	14.984	14.615	1.10	12.889	12.593	0.89	16.741	16.308	0.81	19.058	18.599	0.68	24.465	23.703	
1.69	8.168	7.988	1.58	8.581	8.408	1.45	9.322	9.173	1.38	9.852	9.666	1.24	11.153	10.937	
15	2.45	5.317	5.214	2.30	5.513	5.42	2.12	5.914	5.809	2.02	6.196	6.077	1.83	6.913	6.807
	3.16	3.965	3.883	2.98	4.095	4.012	2.76	4.352	4.264	2.64	4.525	4.455	2.39	4.998	4.916
	$\delta/H$	28.41	27.82	28.34	27.82	28.32	27.82	28.32	27.82	28.31	27.82	28.31	27.82	28.30	27.82
	0.00	200.047	174.974	0.00	199.949	176.419	0.00	199.995	178.083	0.00	199.587	178.363	0.00	199.23	178.563
	0.57	36.455	34.602	0.44	52.785	49.834	0.48	46.022	43.848	0.43	53.747	50.911	0.49	44.10313	42.174
0.98	16.549	16.062	0.87	20.435	19.861	0.91	18.326	17.912	0.82	21.075	20.454	0.71	26.549	25.470	
1.37	10.796	10.512	1.11	14.017	13.679	1.58	9.357	9.156	1.52	9.756	9.553	1.39	10.715	10.518	
1.78	8.703	8.523	2.48	5.714	5.613	2.32	5.946	5.848	2.24	6.142	6.030	2.05	6.682	6.557	
2.60	5.641	5.548	3.23	4.227	4.163	3.04	4.383	4.308	2.93	4.502	4.411	2.70	4.826	4.749	



**Table 18** Comparison of the ARL performance between the MPEWMA and MEWMA charts when  $\theta = 1.0$  and  $\lambda = 0.1$

p	Mean														
	3			5			8			10			15		
	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$
4	13.02	12.73	0.00	12.95	12.73	0.00	12.92	12.73	0.00	12.90	12.73	0.00	12.89	12.73	0.00
	199.730	179.263	0.00	200.252	185.260	0.00	200.236	187.762	0.00	200.059	186.609	0.00	199.299	187.992	0.00
	29.416	28.3795	0.56	27.102	26.413	0.46	37.845	36.714	0.53	29.124	28.472	0.49	34.326	33.352	0.49
	11.641	11.341	1.04	10.024	9.821	1.11	9.155	9.113	1.03	10.205	10.096	0.89	12.652	12.460	0.89
	6.653	6.523	1.26	7.672	7.553	1.60	5.431	5.342	1.50	5.921	5.84	1.31	7.138	7.055	1.31
	4.133	4.035	1.81	4.646	4.567	2.07	3.812	3.772	1.94	4.138	4.096	1.71	4.913	4.849	1.71
	2.988	2.925	2.31	3.319	3.274	2.50	2.948	2.898	2.36	3.166	3.125	2.09	3.716	3.670	2.09
6	16.68	16.27	0.00	16.56	16.27	0.00	16.50	16.27	0.00	16.50	16.27	0.00	16.48	16.27	0.00
	200.020	176.851	0.00	199.622	183.283	0.00	199.093	184.287	0.00	198.872	186.141	0.00	200.237	187.447	0.00
	33.037	31.254	0.43	49.4705	47.0775	0.46	42.5778	40.982	0.42	50.155	48.0322	0.49	29.296	37.9475	0.49
	12.852	12.4578	1.07	10.76	10.574	0.88	14.517	14.143	0.80	16.935	16.543	0.68	22.593	21.997	0.68
	6.538	6.407	1.41	7.291	7.16	1.26	8.459	8.331	1.18	9.216	9.109	1.04	11.157	10.953	1.04
	4.014	3.94	2.04	4.403	4.321	1.84	4.973	4.907	1.73	5.402	5.316	1.53	6.339	6.24	1.53
	2.916	2.851	2.62	3.146	3.085	2.38	3.513	3.461	2.25	3.765	3.712	2.00	4.366	4.31	2.00
10	23.20	22.67	0.00	23.03	22.67	0.00	22.98	22.67	0.00	22.94	22.67	0.00	22.94	22.67	0.00
	199.341	172.773	0.00	199.64	181.505	0.00	199.334	184.767	0.00	198.783	183.536	0.00	198.847	185.910	0.00
	38.808	36.2755	0.43	58.248	54.906	0.47	49.981	47.704	0.43	58.690	56.2496	0.49	47.1071	45.463	0.49
	14.7194	14.1605	1.10	12.056	11.763	0.89	16.680	16.145	0.81	19.381	18.949	0.68	25.556	26.001	0.68
	6.754	6.604	1.58	7.224	7.080	1.45	8.010	7.892	1.38	8.514	8.426	1.24	9.933	9.786	1.24
	4.101	4.016	2.30	4.318	4.251	2.12	4.710	4.654	2.02	4.995	4.912	1.83	5.692	5.620	1.83
	2.945	2.883	2.98	3.074	3.026	2.76	3.327	3.283	2.64	3.502	3.45	2.39	3.94	3.881	2.39
15	30.65	30.03	0.00	30.49	30.03	0.00	30.41	30.03	0.00	30.38	30.03	0.00	30.35	30.03	0.00
	199.953	171.475	0.00	199.448	179.022	0.00	200.083	182.487	0.00	199.686	182.693	0.00	199.436	184.636	0.00
	44.795	41.439	0.44	67.044	62.124	0.48	57.209	54.1469	0.43	67.435	63.7484	0.49	54.575	52.145	0.49
	16.602	15.9079	0.87	20.823	20.098	0.91	18.567	18.149	0.82	22.098	21.455	0.71	28.853	28.004	0.71
	9.721	9.399	1.11	13.400	12.940	1.58	7.971	7.84	1.52	8.400	8.256	1.39	9.393	9.285	1.39
	7.138	6.953	2.48	4.431	4.375	2.32	4.701	4.633	2.24	4.893	4.827	2.05	5.415	5.346	2.05
	4.321	4.237	3.23	3.158	3.158	3.04	3.304	3.265	2.93	3.439	3.382	2.70	3.744	3.708	2.70

**Table 19** Comparison of the SDRL performance between the MPEWMA and MEWMA charts when  $\theta = 0.5$  and  $\lambda = 0.05$

p	Mean														
	3			5			8			10			15		
	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$
$\lambda = 0.05$															
4	0.00	11.22	185.840	0.00	11.22	183.939	0.00	11.22	184.764	0.00	11.22	185.678	0.00	11.22	183.501
	0.51	19.132	18.479	0.56	16.089	15.611	0.46	23.128	22.446	0.57	15.324	15.346	0.49	20.918	21.096
	0.91	6.608	6.487	1.05	5.267	5.241	0.88	7.231	6.990	1.09	5.056	4.955	0.93	6.524	6.410
	1.57	2.762	2.752	1.37	3.465	3.453	1.70	2.554	2.520	1.58	2.841	2.812	1.36	3.569	3.523
	2.19	1.693	1.669	1.95	2.059	2.032	2.18	1.793	1.777	2.03	1.981	1.956	1.77	2.443	2.414
	2.74	1.220	1.225	2.95	1.140	1.143	2.63	1.375	1.376	2.46	1.516	1.511	2.16	1.858	1.832
6	0.00	14.93	14.60	0.00	14.60	14.90	0.00	14.89	14.60	0.00	14.89	14.60	0.00	14.90	14.60
	0.52	21.313	20.611	0.41	32.147	30.828	0.46	25.956	25.025	0.42	31.258	30.007	0.49	23.723	22.976
	0.92	6.750	7.016	0.77	10.049	9.798	0.88	7.764	7.706	0.81	9.148	9.067	0.68	12.583	12.306
	1.26	4.221	4.155	1.05	5.744	5.596	1.39	3.734	3.699	1.29	4.181	4.159	1.11	5.348	5.296
	1.79	2.454	2.443	1.59	2.980	2.946	2.00	2.153	2.153	1.87	2.407	2.384	1.62	2.963	2.943
	2.52	1.487	1.473	2.27	1.768	1.767	2.57	1.520	1.514	2.41	1.683	1.678	2.11	2.039	2.026
10	0.00	21.17	20.72	0.00	21.15	20.72	0.00	21.14	20.72	0.00	21.13	20.72	0.00	21.12	20.72
	0.52	24.965	23.623	0.42	38.094	47.262	0.47	30.552	29.142	0.42	37.096	35.125	0.49	28.210	27.117
	1.08	6.135	6.060	0.98	7.502	15.066	0.89	8.817	8.656	0.81	10.555	10.278	0.70	13.996	13.517
	1.28	4.623	4.538	1.86	2.581	6.835	1.66	3.126	3.104	1.56	3.485	3.435	1.36	4.278	4.241
	2.05	2.197	2.176	2.68	1.527	4.458	2.41	1.822	1.788	2.27	1.990	1.977	2.00	2.422	2.385
	2.93	1.309	1.308	3.44	1.095	3.343	3.11	1.282	1.275	2.94	1.403	1.391	2.61	1.672	1.667
15	0.00	28.39	27.82	0.00	28.34	27.82	0.00	28.31	27.82	0.00	28.30	27.82	0.00	28.30	27.82
	0.52	28.583	26.987	0.42	44.097	41.010	0.47	35.018	33.097	0.42	42.622	40.060	0.49	32.725	31.051
	0.93	9.120	8.848	0.77	13.029	12.595	0.97	8.561	8.375	0.91	9.527	9.329	0.81	12.032	11.701
	1.29	5.044	4.906	1.07	6.971	6.874	1.88	2.813	2.797	1.78	3.089	3.034	1.58	3.765	3.672
	2.24	2.071	2.053	2.07	2.384	2.366	2.74	1.638	1.632	2.60	1.774	1.768	2.32	2.107	2.093
	3.22	1.230	1.224	3.00	1.395	1.396	3.55	1.150	1.149	3.38	1.244	1.244	3.04	1.470	1.449

**Table 20** Comparison of the SDRL performance between the MPEWMA and MEWMA charts when  $\theta = 0.5$  and  $\lambda = 0.1$

p	Mean														
	3			5			8			10			15		
	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$
4	$\delta/H$	13.01	12.73	0.00	12.95	12.73	0.00	12.91	12.73	0.00	12.90	12.73	0.00	12.89	12.73
	0.00	202.314	183.725	0.00	200.438	187.493	0.00	201.147	189.018	0.00	200.082	188.435	0.00	201.745	190.196
	0.51	25.675	24.481	0.56	20.775	20.118	0.46	30.656	29.775	0.57	20.253	19.163	0.48	28.135	27.300
	0.91	7.444	7.231	1.05	5.568	5.512	0.88	7.971	7.841	1.09	5.147	5.140	0.93	7.079	6.941
	1.57	2.583	2.568	1.37	3.328	3.278	1.70	2.287	2.286	1.58	2.618	2.585	1.36	3.401	3.342
6	$\delta/H$	1.477	1.459	1.95	1.811	1.787	2.18	1.518	1.522	2.03	1.707	1.707	1.77	2.158	2.159
	2.74	1.038	1.025	2.95	0.950	0.965	2.63	1.149	1.146	2.46	1.281	1.264	2.16	1.576	1.574
	$\delta/H$	16.65	16.27	0.00	16.54	16.27	0.00	16.50	16.27	0.00	16.48	16.27	0.00	16.49	16.27
	0.00	200.140	180.710	0.00	200.923	183.194	0.00	201.853	185.680	0.00	200.417	187.714	0.00	201.493	190.234
	0.52	29.153	28.209	0.41	44.941	42.839	0.46	35.852	34.384	0.42	43.152	41.402	0.49	32.888	31.624
10	$\delta/H$	8.234	8.059	0.77	12.450	11.981	0.88	9.101	8.738	0.81	10.969	10.706	0.68	15.975	15.597
	1.26	4.308	4.190	1.05	6.164	5.951	1.39	3.589	3.554	1.29	4.153	4.100	1.11	5.573	5.531
	1.79	2.252	2.211	1.59	2.801	2.752	2.00	1.868	1.875	1.87	2.138	2.132	1.62	2.729	2.696
	2.52	1.274	1.257	2.27	1.528	1.515	2.57	1.273	1.263	2.41	1.413	1.413	2.11	1.761	1.737
	$\delta/H$	23.17	22.67	0.00	23.04	22.67	0.00	22.98	22.67	0.00	22.95	22.67	0.00	22.91	22.67
0.00	200.787	174.891	0.00	202.111	182.105	0.00	201.510	184.177	0.00	201.003	185.787	0.00	202.550	185.687	
0.52	36.515	33.516	0.42	54.956	51.041	0.47	43.745	41.437	0.42	52.683	49.893	0.49	40.633	38.871	
1.08	6.998	6.780	0.98	8.722	8.470	0.89	10.639	10.370	0.81	13.171	12.740	0.70	18.423	17.486	
1.28	4.802	4.694	1.86	2.366	2.321	1.66	2.918	2.895	1.56	3.274	3.281	1.36	4.278	4.183	
2.05	1.972	1.946	2.68	1.287	1.283	2.41	1.554	1.535	2.27	1.739	1.703	2.00	2.113	2.102	
15	$\delta/H$	1.104	1.096	3.44	0.900	0.896	3.11	1.056	1.052	2.94	1.152	1.152	2.61	1.404	1.382
	0.00	30.62	30.03	0.00	30.49	30.03	0.00	30.40	30.03	0.00	30.36	30.03	0.00	30.33	30.03
	0.00	202.938	175.244	0.00	201.443	178.855	0.00	200.623	184.936	0.00	201.435	186.337	0.00	203.247	185.506
	0.52	43.190	39.496	0.42	64.634	59.346	0.47	51.605	48.502	0.42	61.689	58.197	0.49	48.306	45.765
	0.93	11.565	10.961	0.77	17.766	16.890	0.97	10.305	9.989	0.91	11.835	11.393	0.81	15.595	15.126
1.29	5.398	5.213	1.07	8.121	7.945	1.88	2.594	2.568	1.78	2.871	2.854	1.58	3.606	3.525	
2.24	1.849	1.820	2.07	2.156	2.142	2.74	1.368	1.367	2.60	1.498	1.495	2.32	1.821	1.807	
3.22	1.031	1.025	3.00	1.174	1.165	3.55	0.935	0.934	3.38	1.016	1.011	3.04	1.206	1.195	

**Table 21** Comparison of the SDRL performance between the MPEWMA and MEWMA charts when  $\theta = 1.0$  and  $\lambda = 0.05$

p	Mean														
	3			5			8			10			15		
	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$
4	$\delta/H$	11.49	11.22	11.48	11.22	11.47	11.22	11.46	11.22	11.46	11.22	11.46	11.46	11.22	11.46
	0.00	200.534	183.040	0.00	200.347	183.983	0.00	200.577	183.385	0.00	201.088	185.203	0.00	199.868	184.600
	0.54	17.088	16.729	0.56	25.254	15.536	0.46	23.548	22.832	0.53	17.600	17.232	0.49	20.877	20.261
	0.95	6.068	5.953	1.04	11.029	5.220	1.11	4.900	4.790	1.03	5.501	5.361	0.89	6.989	6.872
	1.41	3.249	3.230	1.26	8.857	3.867	1.60	2.759	2.731	1.50	3.067	3.019	1.31	3.796	3.743
6	$\delta/H$	1.932	1.912	1.81	5.691	2.267	2.07	1.929	1.910	1.94	2.120	2.093	1.71	2.569	2.533
	2.53	1.381	1.361	2.31	4.252	1.599	2.50	1.486	1.475	2.36	1.621	1.599	2.09	1.942	1.919
	$\delta/H$	14.95	14.6	14.92	14.6	14.91	14.6	14.91	14.60	14.91	14.60	14.91	14.60	14.91	14.6
	0.00	200.636	180.352	0.00	201.829	183.272	0.00	202.657	181.310	0.00	201.069	185.575	0.00	201.725	182.679
	0.55	18.914	18.133	0.43	30.244	29.034	0.46	26.022	25.037	0.42	31.563	30.182	0.49	23.524	22.735
10	$\delta/H$	6.552	6.418	1.07	5.565	5.479	0.88	7.815	7.589	0.80	9.285	9.128	0.68	12.789	12.479
	1.55	3.016	3.003	1.41	3.574	3.524	1.26	4.297	4.257	1.18	4.731	4.704	1.04	5.878	5.793
	2.22	1.786	1.772	2.04	2.061	2.047	1.84	2.465	2.426	1.73	2.672	2.660	1.53	3.246	3.211
	2.83	1.270	1.265	2.62	1.446	1.434	2.38	1.693	1.689	2.25	1.850	1.844	2.00	2.207	2.190
	$\delta/H$	21.19	20.72	21.14	20.72	21.13	20.72	21.13	20.72	21.13	20.72	21.13	20.72	21.13	20.72
15	0.00	200.799	179.518	0.00	201.164	180.636	0.00	201.381	181.373	0.00	202.238	180.771	0.00	200.625	179.907
	0.56	21.760	20.724	0.43	35.670	33.455	0.47	29.843	28.323	0.43	36.632	34.644	0.49	27.814	26.556
	0.98	7.334	7.134	1.10	6.053	5.941	0.89	8.698	8.455	0.81	10.376	10.121	0.68	14.588	14.059
	1.69	2.894	2.851	1.58	3.290	3.245	1.45	3.854	3.793	1.38	4.181	4.113	1.24	5.014	4.938
	2.45	1.671	1.670	2.30	1.876	1.870	2.12	2.165	2.141	2.02	2.343	2.324	1.83	2.754	2.725
15	$\delta/H$	1.181	1.182	2.98	1.314	1.308	2.76	1.500	1.488	2.64	1.602	1.600	2.39	1.870	1.861
	2.83	1.270	1.265	2.62	1.446	1.434	2.38	1.693	1.689	2.25	1.850	1.844	2.00	2.207	2.190
	$\delta/H$	28.41	27.82	28.34	27.82	28.32	27.82	28.32	27.82	28.32	27.82	28.32	27.82	28.32	27.82
	0.00	200.324	175.553	0.00	200.396	175.814	0.00	201.743	178.416	0.00	199.869	179.730	0.00	199.234	178.772
	0.57	24.491	23.118	0.44	40.432	38.147	0.48	33.894	32.106	0.43	41.730	39.225	0.49	32.055	30.478
15	$\delta/H$	8.175	7.921	0.87	10.324	10.112	0.91	9.548	9.326	0.82	11.517	11.174	0.71	15.648	15.103
	1.37	4.546	4.488	1.11	6.586	6.435	1.58	3.653	3.616	1.52	3.916	3.884	1.39	4.557	4.528
	1.78	2.880	2.850	2.48	1.805	1.794	2.32	2.023	2.026	2.24	2.183	2.164	2.05	2.504	2.483
	2.60	1.635	1.614	3.23	1.253	1.252	3.04	1.398	1.394	2.93	1.489	1.493	2.70	1.706	1.698
	$\delta/H$	28.41	27.82	28.34	27.82	28.32	27.82	28.32	27.82	28.32	27.82	28.32	27.82	28.32	27.82

**Table 22** Comparison of the SDRL performance between the MPEWMA and MEWMA charts when  $\theta = 1.0$  and  $\lambda = 0.1$

$\rho$	Mean														
	3			5			8			10			15		
	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA	$\delta/H$	MPEWMA	MEWMA
4	0.00	13.02	12.73	0.00	12.95	12.73	0.00	12.92	12.73	0.00	12.90	12.73	0.00	12.89	12.73
	0.54	202.437	178.674	0.56	202.086	184.831	0.46	201.463	189.096	0.53	202.059	187.053	0.49	201.212	187.930
	0.95	6.752	6.567	1.04	5.572	5.487	1.11	4.941	4.921	1.03	5.685	5.697	0.89	7.138	7.520
	1.41	3.128	3.085	1.26	3.846	3.809	1.60	2.521	2.514	1.50	2.842	2.814	1.31	3.622	3.589
	2.00	1.706	1.686	1.81	2.039	2.031	2.07	1.658	1.652	1.94	1.847	1.827	1.71	2.285	2.286
	2.53	1.170	1.168	2.31	1.375	1.374	2.50	1.246	1.231	2.36	1.358	1.354	2.09	1.657	1.652
6	0.00	16.68	16.27	0.00	16.56	16.27	0.00	16.5	16.27	0.00	16.50	16.27	0.00	16.48	16.27
	0.55	200.901	176.880	0.43	202.104	183.693	0.46	200.512	184.501	0.42	199.387	188.195	0.49	204.029	190.544
	0.97	7.483	7.210	1.07	5.913	5.835	0.88	8.956	8.724	0.80	11.035	10.832	0.68	16.110	15.790
	1.55	2.884	2.847	1.41	3.449	3.401	1.26	4.291	4.220	1.18	4.850	4.827	1.04	6.296	6.171
	2.22	1.546	1.538	2.04	1.814	1.789	1.84	2.169	2.147	1.73	2.410	2.397	1.53	3.000	2.986
	2.83	1.070	1.063	2.62	1.217	1.206	2.38	1.426	1.425	2.25	1.577	1.565	2.00	1.900	1.895
10	0.00	23.2	22.67	0.00	23.03	22.67	0.00	22.98	22.67	0.00	22.94	22.67	0.00	22.94	22.67
	0.56	201.3614	173.263	0.43	200.237	182.603	0.47	200.540	185.776	0.43	200.292	182.879	0.49	200.826	185.468
	0.98	4.328523	8.332	1.10	6.683	6.469	0.89	10.500	10.009	0.81	12.891	12.426	0.68	19.435	19.025
	1.69	2.778131	2.717	1.58	3.168	3.152	1.45	3.771	3.728	1.38	4.154	4.100	1.24	5.138	5.074
	2.45	1.450696	1.435	2.30	1.635	1.628	2.12	1.897	1.887	2.02	2.060	2.048	1.83	2.478	2.451
	3.16	0.982212	0.976	2.98	1.089	1.086	2.76	1.248	1.252	2.64	1.352	1.337	2.39	1.578	1.575
15	0.00	30.65	30.03	0.00	30.49	30.03	0.00	30.41	30.03	0.00	30.38	30.03	0.00	30.35	30.03
	0.57	37.468	34.277	0.44	60.442	55.375	0.48	50.238	47.159	0.43	60.927	56.984	0.49	47.477	45.037
	0.98	10.076	9.571	0.87	13.399	12.922	0.91	11.839	11.490	0.82	15.070	14.541	0.71	21.470	20.590
	1.37	4.734	4.620	1.11	7.578	7.225	1.58	3.545	3.533	1.52	3.853	3.829	1.39	4.615	4.548
	1.78	2.772	2.723	2.48	1.563	1.560	2.32	1.763	1.768	2.24	1.897	1.899	2.05	2.222	2.200
	2.60	1.416	1.401	3.23	1.035	1.033	3.04	1.165	1.161	2.93	1.245	1.236	2.70	1.431	1.428

### 3.9 Examples

We illustrate how to apply the proposed MPEWMA control chart to a situation where we monitor four different types of GaN-epitaxial layer defects (particles, micropits, microcracks, crescents) that may occur after polishing the sapphire substrates in the light emitting diode (LED) manufacturing process. The count for each defect type follows a Poisson distribution with a mean of 3. A total of three-hundred observations are collected at inspection points over two months. It is appropriate to apply the MPEWMA scheme since the numbers of defects tends to follow a multivariate Poisson rather than the normality assumption. The values of all theta parameters ( $\theta_1, \theta_2, \theta_3, \theta_4$ , and  $\theta$ ) are needed to be determined before using the MPEWMA control chart. Two ways of obtaining these parameter values are: using the true mean value (if they are known) and the estimated value of the means (if they are unknown).

#### 3.9.1 True Parameter Value

Suppose we know that the true value of  $\theta$  is 1. The sample mean and the variance-covariance matrix of the four-variate Poisson data are given by

$$\bar{\mathbf{X}}^* = \begin{bmatrix} \theta_1 + \theta \\ \theta_2 + \theta \\ \theta_3 + \theta \\ \theta_4 + \theta \end{bmatrix} = \begin{bmatrix} 3 \\ 3 \\ 3 \\ 3 \end{bmatrix}, \quad \text{and} \quad \mathbf{S}^* = \begin{bmatrix} \theta_1 + \theta & \theta & \theta & \theta \\ \theta & \theta_2 + \theta & \theta & \theta \\ \theta & \theta & \theta_3 + \theta & \theta \\ \theta & \theta & \theta & \theta_4 + \theta \end{bmatrix} = \begin{bmatrix} 3 & 1.0 & 1.0 & 1.0 \\ 1.0 & 3 & 1.0 & 1.0 \\ 1.0 & 1.0 & 3 & 1.0 \\ 1.0 & 1.0 & 1.0 & 3 \end{bmatrix}$$

Thus, all  $\theta_1, \theta_2, \theta_3, \theta_4$  are equal to 2. The MPEWMA chart is constructed using a smoothing weight of 0.05 ( $\lambda = 0.05$ ). To demonstrate the  $T_i^2$  computations,

consider the first period,  $\mathbf{X}_1 = \begin{bmatrix} 6 \\ 1 \\ 3 \\ 5 \end{bmatrix}$ ,  $\lambda = 0.05$ , and  $\mathbf{Z}_0 = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$ .

The calculation of  $\mathbf{Z}_1$  is  $\mathbf{Z}_1 = \lambda(\mathbf{X}_1 - \bar{\mathbf{X}}^*) + (1-\lambda)\mathbf{Z}_0 = \begin{bmatrix} 0.15 \\ -0.10 \\ 0 \\ 0.10 \end{bmatrix}$ . Since

$\mathbf{Z}_1 = \begin{bmatrix} 0.15 \\ -0.10 \\ 0 \\ 0.10 \end{bmatrix}$ , and  $\Sigma_{\mathbf{Z}_1} = \left\{ \frac{\lambda}{2-\lambda} \right\} \Sigma = \left\{ \frac{0.05}{2-0.05} \right\} \mathbf{S}^*$ , we obtain

$$T_1^2 = \mathbf{Z}_1' \Sigma_{\mathbf{Z}_1}^{-1} \mathbf{Z}_1 = 0.7556$$

Table 23 presents the sample calculations of  $Z_t$  and  $T_t^2$  for the first ten observations. The control limit of the MPEWMA chart can be read directly from Table 4 ( $H = 11.49$ ). If the MEWMA scheme is employed instead of the MPEWMA, the normal-theory limit is obtained from Table 11 ( $H = 11.22$ ). It is noticed that the T-square statistics of the MPEWMA and MEWMA control charts are identical, but the control limit of the proposed MPEWMA chart ( $H = 11.49$  for Poisson limit) is slightly wider than the traditional MEWMA chart ( $H = 11.22$  for Normal limit).

**Table 23** Example of calculations the T-square statistics of the MPEWMA chart for the first 10 observations.

Obs	x1	x2	x3	x4	MPEWMA ( $\lambda = 0.05$ )				$T^2_t$
					$Z_t$				
1	6	1	3	5	0.1500	-0.1000	0.0000	0.1000	0.7556
2	7	7	6	4	0.3425	0.1050	0.1500	0.1450	1.5595
3	1	3	1	3	0.2254	0.0998	0.0425	0.1378	0.7597
4	3	3	4	5	0.2141	0.0948	0.0904	0.2309	0.9772
5	4	1	1	2	0.2534	-0.0100	-0.0141	0.1693	1.3007
6	4	5	5	7	0.2907	0.0905	0.0866	0.3609	2.2616
7	2	2	1	0	0.2262	0.0360	-0.0178	0.1928	1.1327
8	3	3	2	4	0.2149	0.0342	-0.0669	0.2332	1.5099
9	4	2	1	4	0.2149	0.0342	-0.0669	0.2332	2.8385
10	2	1	1	2	0.1914	-0.1166	-0.2554	0.2079	3.0921

**Figure 2** Comparison of the MPEWMA and MEWMA charts on monitoring the number of defects

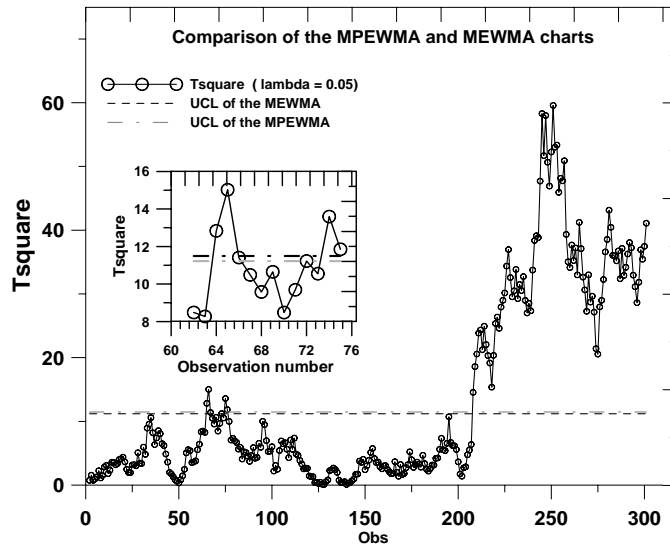
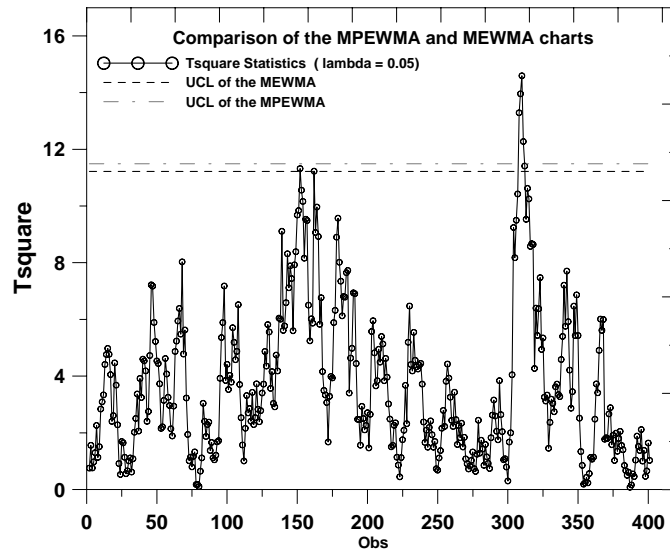


Figure 2 displays the comparison of applying the normal and Poisson control limits to the T-square statistics when the data truly comes from the multivariate Poisson distribution. These two limits perform similarly when the



process shifts to an out of control state as the first out-of-control signal occurs at the same period 207. This may result from the similar out-of-control ARL performance. However, it can be seen that the normal-theory limit gives 5 false alarms whereas only 3 false alarms occur under the Poisson limit. These false alarms arise between period 62 and period 74 as shown in Figure 2 inset. The MPEWMA scheme reduces the number of false alarms that indicate the chance of misinterpreting the in-control process to be out-of-control status due to the better in-control ARL performance.

**Figure 3** Comparison of the MPEWMA and MEWMA charts based on the in-control condition



We provide another example to amplify the importance of a larger in-control ARL value. Let's continue with the previous example by considering the new scenario of an in-control process over a long period (a total of 400

observations). Figure 3 shows a comparison between the MPEWMA and MEWMA charts on monitoring an in-control process. The plot shows that no alarm is given in the first two hundred periods by using the Poisson limit on the MPEWMA scheme whereas the MEWMA relied on the normal limit signals 2 false alarms at period 151 and 161, respectively. After that both schemes simultaneously detect the out-of-control signals at period 307 to 310. The result demonstrates a difference in false alarm rate as the wider control limit produces fewer false alarms. Thus, the MEWMA chart tends to have more false alarms than the MPEWMA, resulting in more stops in production pace to investigate and fix a problem when one does not occur.

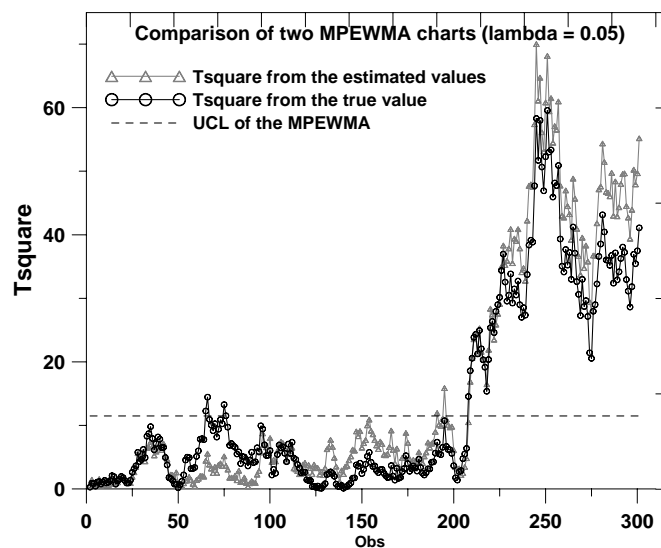
### 3.9.2 Parameter Estimation

We also look at the scenario where the estimated values of  $\theta_1, \theta_2, \theta_3, \theta_4,$  and  $\theta$  are used in place of the true values. If the values of all parameters are unknown, we would estimate these values from historical data if available. (See Section 3.2.1 for details on various methods of estimating these parameters.). The purpose of using estimates is that in practice, the mean values will not necessarily be known, but historical data from an in-control process may be available. Going back to the previous example, all the theta parameter values ( $\theta_1, \theta_2, \theta_3, \theta_4,$  and  $\theta$ ) are obtained by applying the composite likelihood concept (Jost *et al.* (2006)) to the historical data set with 100 observations. The estimation of the theta parameters are  $\theta_1 = 2.3791, \theta_2 = 2.0652, \theta_3 = 2.1085, \theta_4 = 2.4543,$  and  $\theta = 0.7607.$  Therefore, the sample means and variance-covariance matrix based on the estimated theta parameters are

$$\bar{\mathbf{X}}^* = \begin{bmatrix} 2.3791+0.7607 \\ 2.0652+0.7607 \\ 2.1085+0.7607 \\ 2.4543+0.7607 \end{bmatrix} = \begin{bmatrix} 3.1398 \\ 2.8259 \\ 2.8692 \\ 3.2150 \end{bmatrix} \quad \text{and} \quad \mathbf{S}^* = \begin{bmatrix} 3.1398 & 0.7607 & 0.7607 & 0.7607 \\ 0.7607 & 2.8259 & 0.7607 & 0.7607 \\ 0.7607 & 0.7607 & 2.8692 & 0.7607 \\ 0.7607 & 0.7607 & 0.7607 & 3.2150 \end{bmatrix}$$

It can be seen that the mean values of all four variables are roughly three and the thetafix parameter is about 1. Thus, the same control limit ( $H = 11.49$ ) is chosen for the smoothing weights of 0.05. Again, we calculate the T-square statistics by following the steps described above. Two T-square statistics based on the true and estimated value of all theta parameters are plotted in Figure 4. These two MPEWMA schemes show the same pattern, but they have the magnitude differences of the T-square statistics. The effect of the estimation of the theta parameters ( $\theta_1, \theta_2, \theta_3, \theta_4,$  and  $\theta$ ) could make substantial differences in magnitude for both directions toward increasing or decreasing the T-square statistics.

**Figure 4** Comparison of the two MPEWMA charts using the true and estimated mean and variance-covariance matrix.



## Chapter 4

### ONE-SIDED MEWMA CONTROL CHART

#### 4.1 Introduction

The multivariate exponentially weighted moving average (MEWMA) control chart is frequently used to monitor both decreasing and increasing mean shifts in several processes concurrently. The MEWMA scheme is commonly employed in industry and manufacturing, but is finding increased popularity in monitoring public health and bioterrorism surveillance data. Regardless of application, the MEWMA control chart is most often constructed assuming that the underlying distribution of the data is multivariate normal. In other words, the common assumption of the central limit theorem or the normal approximation will apply when the true underlying distribution of the data is not normal (or multivariate normal) and in some cases not even continuous. Examples would include monitoring the increase in the rate of occurrences such as the number of cracks in road pavement surfaces, number of misprints and errors found on manuscript pages, or number of failures observed during testing processes. In each of these situations, the data collected most commonly follows a Poisson or multivariate Poisson distribution. However, the control charts applied are based on normal theory assuming the central limit theorem will apply.

There is an interest in detecting a positive shift in count since the upward trend is evidence for abnormal conditions in the manufacturing process or public health surveillance. For instance, a large number of defects observed during the inspection periods or an increasing number of daily visit to clinic and health care

counts. These can be considered as a signal to stop and fix an existing problem whereas the downward direction shows a good performance (i.e. less number of defects found or the process has improved product quality). Hence, applying the one-sided MEWMA scheme is more appropriate than the two-sided because it will not signal if the mean counts decrease.

We propose a one-sided multivariate Poisson EWMA (MPEWMA) control chart to detect small and medium upward shifts in the process when the process consists of count data. For our method, we do not assume the normal approximation is appropriate and instead construct the control charts using the multivariate Poisson distribution. The average run length (ARL) and standard deviation of the run length (SDRL) are examined for both steady-state in-control and out-of-control processes. We then compare the MPEWMA with the MEWMA control schemes. In addition, we examine the performance of the MPEWMA chart when a signal is defined as two or more points in a row beyond the control limits. There are several applications where a single point beyond the control limits is not of concern, but rather a run of say 2, 3, 4, or 5 points is of concern. This is often the case in monitoring public health data.

#### 4.2 One-sided MPEWMA chart

The one-sided MPEWMA chart has been established by the works of Joner *et al.* (2005) and Joner *et al.* (2008). The one-sided MEWMA statistic is

$$\mathbf{Z}_t = \max\{\lambda(\mathbf{X}_t - \boldsymbol{\mu}_0) + (\mathbf{I} - \lambda)\mathbf{Z}_{t-1}, \mathbf{0}\} \quad (13)$$

where  $\mathbf{Z}_0 = \mathbf{0}$ , and  $\lambda$  is the smoothing weight. The maximum operator is defined as a comparison of the two element-wise vectors. Thus,  $\mathbf{Z}_t$  will be equal to or greater

than 0, and the one-sided MPEWMA chart shows only a signal for an increase in the means. Suppose we are monitoring  $p$  random variables simultaneously. Assuming all  $p$  variables are given equal weight ( $\lambda > 0$ ), the covariance matrix of  $\mathbf{Z}_t$  is given by

$$\Sigma_{Z_t} = \left\{ \frac{\lambda [1 - (1 - \lambda)^{2t}]}{2 - \lambda} \right\} \Sigma \quad (14)$$

where  $\Sigma$  is assumed to be the known covariance matrix of the  $p$  random variables.

The asymptotic covariance matrix ( $t \rightarrow \infty$ ) can be shown to be

$$\Sigma_{Z_{t \rightarrow \infty}} = \left\{ \frac{\lambda}{2 - \lambda} \right\} \Sigma \quad (15)$$

An out-of-control signal is generated if

$$MEW_t = \mathbf{Z}'_t \Sigma_{Z_t}^{-1} \mathbf{Z}_t > H \quad (16)$$

where  $H$  is the control limit chosen to achieve a specific in-control ARL. The asymptotic covariance matrix is again used to calculate the statistics  $MEW_t$  given in Equation (16). To monitor the multivariate Poisson data, the one-sided MPEWMA statistics are computed using the above Equations (13) – (16). The covariance matrix of the one-sided MPEWMA chart is obtained from the asymptotic covariance matrix given in Equation (15). The performance of the MEWMA control chart depends on several parameters including the number of variables ( $p$ ), the variable mean values, and the smoothing weight ( $\lambda$ ). Similar to the two-sided MPEWMA chart, the mean and the thetfix values are additionally considered in establishing the control limits of the one-sided MPEWMA when the multivariate Poisson data are simulated following the method of the two-sided

case. We obtain appropriate control limits that will result in the desired in-control ARL for various practical combinations of these parameters.

### 4.3 Simulation Conditions

Monte-Carlo simulation is used to generate the multivariate Poisson distribution as the sum of two independent Poisson random variables. The Poisson data is produced under the same conditions applied to the two-sided version. The threshold or control limit ( $H$ ) was selected to achieve a desired in-control average run length (ARL) of 200. To evaluate the statistical performance of the proposed one-sided scheme, we consider both average run length (ARL) and standard deviation of run length (SDRL) when testing various combinations of parameters discussed previously for various shift sizes. Several shift sizes are added to the mean of one or more variables simultaneously by one, two, and three units. Joner *et al.* (2008) noted that the shift size should be calculated in terms of percentage change, not the units of the standard deviation as previously proposed by Lowry *et al.* (1992). Since a Poisson distribution has the property that the variance is equal to its mean, it may not be easy to interpret the shift size in situations where the out-of-control condition is due to a standard deviation increase. The percentage of change developed based on Lucas (1985) is given by

$$\% \text{ of shift} = \frac{u}{\mu_a} \times 100 \quad (17)$$

where  $u$  is the unit of the shift size, and  $\mu_a$  is the mean of the data before the shift has occurred. To illustrate, suppose we simultaneously monitor four Poisson process means when all means are equal to 3. In addition, we are interested in a

two unit shift in the second process variable, and there are no shifts in the other variables (variables 1, 3, and 4). The shift size percentage in the second process using Equation (17) is  $\frac{2}{3} \times 100 = 67\%$  whereas the percentages of shift size in the other processes (variable 1, 3, or 4) are zero. Thus, it can be seen that a two unit shift in any of these four variables (variable 1-4) would result in the same shift size (67%). Consider a unit of two shifts of one unit in the first and second variables that also represents a two-unit shift in the process means. The percentages of shift size in the first and second process means using equation (17) are  $\frac{1}{3} \times 100 = 33\%$ . It shows that the percentage of two-unit shift size calculated from a two-unit shift in one variable is not equivalent to one-unit shift in each of two variables. Therefore, the same unit shift in the mean will not always have the same values for the percentage of the shift.

#### **4.4 Results**

We investigate the one-sided MPEWMA control chart under the “steady-state” condition. That is, we assume that the control chart operates under normal conditions for two-hundred time periods before a shift occurs at period 201. The out-of-control average run length (ARL) is calculated as the average number of samples taken before detecting an upward shift when the process actually goes out of control. It helps to determine how quickly the proposed chart detects this upward shift. Summaries of the ARL performances for the control limits chosen to achieve the steady-state ARL of 200 are shown in Table 24 (for  $\theta = 0.5$ ) and



Table 25 (for  $\theta = 1$ ). Examining these tables, it can be seen that the out-of-control ARL drops significantly when a large shift is added to any single mean. We illustrate this reduction using the previous example of monitoring four process means. From Table 20 with  $\lambda = 0.05$ , and  $\theta = 0.5$ , the ARL value decreases from 28.574 (33% shift in one variable) to 12.277 (67% shift in one variable). In addition, the out-of-control ARL value in Table 20 is reduced from 28.574 (33% shift in any one variable shifted) to 16.907 (33% shift in any two variables shifted), and to 10.263 (33% shift in all four variables shifted).

Since the means of all variables are equal, we found that a number of units shifted in the mean and not the variable shifted is directly related to the chart's ability in detecting the upward shift. Again, we use the previous example of monitoring four variables to demonstrate this relationship. Suppose now we are interested in a two-unit shift in the process mean. A shift of two units can be denoted by either two units in a single mean (variable 1 [2, 0, 0, 0], variable 2 [0, 2, 0, 0], variable 3 [0, 0, 2, 0], and variable 4 [0, 0, 0, 2]) or one unit in any two means (variable 1 and 2 [1, 1, 0, 0], variable 1 and 3 [1, 0, 1, 0], and variable 1 and 4 [1, 0, 0, 1]). The out-of-control ARL of 12.277 for two units in a single mean shift are approximately the same among these four variables ([2, 0, 0, 0], [0, 2, 0, 0], [0, 0, 2, 0], and [0, 0, 0, 2]). However, the out-of-control ARL of 16.907 for a unit shift in two means [1, 1, 0, 0] is similar to those of [1, 0, 1, 0] or [1, 0, 0, 1].

In addition to the ARL performance of the one-sided MPEWMA chart, we examine the standard deviation of the run length (SDRL) for all scenarios. The

SDRL is calculated by pooling the standard deviations among the same shift size. Table 26 and 27 display the summarized SDRL values of the one-sided MPEWMA scheme for  $\theta = 0.5$  and  $\theta = 1$ , respectively. The SDRLs have the same behavior as the ARLs, but are substantially lower than the ARL.

#### 4.5 The one-sided MPEWMA and MEWMA Chart Comparisons

We next compare the proposed one-sided MPEWMA with the one-sided MEWMA chart introduced by Joner *et al.* (2008). The one-sided MEWMA scheme has been developed by using normal approximations to Poisson distributions. The means of each count data are large enough (let's say 10 or larger) to appropriately assume the normal approximation. Thus, the data are simulated from a multivariate normal distribution and the in-control ARL values are calculated based upon 10,000 replicates. The control limits are chosen to provide a specific in-control ARL of 100 with certain correlation value ( $\rho = 0.2, 0.5, \text{ and } 0.7$ ). The summary of the one-sided MEWMA chart's performance is presented in Table 28.

In this study, we investigate three different scenarios of a 20% shift in 10 variables with all means  $\mu = 10$ : 1) a shift in variable 1 only; 2) a shift in variables 1, 2, and 4; and, 3) a shift in variables 1, 6, and 10. The control limits of each shift case (1)  $H = 12.325$ ; 2)  $H = 14.695$ ; and 3)  $H = 14.430$  for different selected values of  $\lambda$ ) are presented on the left side of Table 28. For the purpose of comparison, the control limits of the proposed one-sided MPEWMA chart are developed based on the same correlation value ( $\rho = 0.5$ ). The multivariate Poisson correlation structure is given by

**Table 24** Summary of the ARL for the one-sided MPEWMA control chart when the  $\theta$  = 0.5

p	Actual Region Shifted	Mean												
		3			5			8			10			15
		$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	
4	None	%shift/H	10.29	12.11	%shift/H	10.44	12.09	%shift/H	10.56	12.07	%shift/H	10.59	12.07	
	1 or 2	0	200.132	199.393	0	199.979	200.044	0	199.210	199.244	0	198.993	199.965	
	1 and 2	33	28.574	35.739	20	37.294	47.189	12.5	48.236	59.875	10	54.341	67.115	
	All	33	16.907	19.263	20	21.500	25.153	12.5	27.462	32.873	10	30.992	37.347	
	1 or 2	33	10.263	10.713	20	12.327	13.204	12.5	15.169	16.563	10	16.968	18.950	
	All	67	12.277	12.799	40	15.152	16.447	25	19.140	21.569	20	21.614	24.935	
	1 and 2	67	7.551	7.246	40	8.978	8.903	25	11.103	11.366	20	12.340	12.969	
	All	67	4.748	4.299	40	5.427	5.004	25	6.436	6.053	20	7.045	6.797	
	All	100	3.162	2.685	60	3.512	3.052	37.5	4.058	3.547	30	4.410	3.901	
	All	133	2.422	1.981	80	2.620	2.171	50	2.960	2.488	40	3.177	2.721	
	6	None	%shift/H	12.64	14.70	%shift/H	12.95	14.76	%shift/H	13.21	14.87	%shift/H	13.31	14.93
		1 or 2	0	199.654	199.052	0	199.631	199.630	0	199.883	199.726	0	199.889	199.750
1 and 2		33	32.891	42.462	20	43.440	55.798	12.5	55.911	70.976	10	62.441	78.533	
All		33	19.471	23.056	20	25.154	30.357	12.5	32.325	39.652	10	36.451	45.102	
1 or 2		33	9.159	9.273	20	10.553	10.951	12.5	12.701	13.499	10	13.954	15.099	
All		67	13.843	14.788	40	17.234	19.148	25	21.879	25.369	20	24.697	29.445	
1 and 2		67	8.547	8.288	40	10.314	10.363	25	12.741	13.332	20	14.165	15.259	
All		67	4.250	3.746	40	4.717	4.254	25	5.434	4.958	20	5.875	5.494	
All		100	2.825	2.342	60	3.060	2.571	37.5	3.434	2.936	30	3.668	3.195	
10		None	%shift/H	16.54	19.04	%shift/H	17.04	19.22	%shift/H	17.59	19.51	%shift/H	17.84	19.66
		1 or 2	0	200.061	199.575	0	199.373	199.910	0	199.826	199.163	0	199.004	199.536
		1 and 2	33	39.484	53.100	20	52.459	70.076	12.5	67.814	86.424	10	75.015	94.463
	All	33	23.383	29.029	20	30.646	39.289	12.5	39.780	51.051	10	45.049	57.308	
	1 or 2	33	8.255	8.132	20	9.031	9.112	12.5	10.365	10.717	10	11.260	11.780	
	All	67	16.110	17.866	40	20.273	23.696	25	25.987	31.713	20	29.565	36.633	
	1 and 2	67	9.927	9.868	40	12.227	12.723	25	15.135	16.543	20	17.077	19.018	
	All	67	3.587	3.332	40	4.058	3.559	25	4.517	4.008	20	4.819	4.337	
	All	100	2.556	2.069	60	2.648	2.165	37.5	2.867	2.373	30	3.027	2.546	
	15	None	%shift/H	20.77	23.74	%shift/H	21.39	23.94	%shift/H	22.17	24.38	%shift/H	22.58	24.67
		1 or 2	0	200.176	199.289	0	199.987	199.835	0	199.189	199.020	0	199.574	199.640
		1 and 2	33	45.706	63.655	20	61.135	82.896	12.5	78.218	100.325	10	86.847	108.851
All		33	27.073	35.126	20	36.240	48.275	12.5	47.378	62.236	10	53.446	69.523	
1 or 2		33	7.841	7.520	20	8.274	8.046	12.5	9.143	9.143	10	9.717	9.864	
All		67	18.236	21.037	40	23.271	28.372	25	30.095	38.220	20	34.245	44.364	
1 and 2		67	11.211	11.443	40	13.906	14.973	25	17.580	19.881	20	19.807	23.008	
All		67	3.728	3.141	40	3.770	3.233	25	4.019	3.496	20	4.222	3.711	
All		100	2.454	1.957	60	2.459	1.964	37.5	2.565	2.080	30	2.688	2.181	

**Table 25** Summary of the ARL for the one-sided MPEWMA control chart when the  $\theta$ tafix = 1

p	Mean																	
	3			5			8			10			15					
Actual Region	Shifted	%	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$		
4	None	%shift/H	9.80	11.68	9.98	11.68	10.18	11.73	10.27	11.76	10.40	11.76	10.40	11.83	10.40	11.83		
		%shift/H	200.163	199.483	200.196	199.975	199.399	199.056	199.436	199.644	200.147	199.948	200.147	199.948	200.147	199.948	200.147	
	1 or 2		28.114	35.087	37.854	47.618	49.152	61.373	55.515	68.614	66.7	68.032	66.7	68.032	66.7	68.032	66.7	
	1 and 2		17.476	20.014	22.618	26.707	28.783	34.510	32.353	39.033	39.033	40.130	39.033	40.130	39.033	40.130	39.033	
	All		11.993	12.765	13.827	15.082	16.494	18.382	18.256	20.450	20.450	22.155	20.450	22.155	20.450	22.155	20.450	
	1 or 2		12.017	12.500	15.175	16.531	19.361	21.916	21.886	25.339	25.339	27.692	25.339	27.692	25.339	27.692	25.339	
	1 and 2		7.733	7.426	9.349	9.351	11.501	11.915	12.769	13.408	13.33	15.756	13.33	15.756	13.33	15.756	13.33	
	All		5.434	5.014	5.985	5.624	6.908	6.629	7.561	7.304	7.304	8.973	7.304	8.973	7.304	8.973	7.304	
	All		3.554	3.068	3.846	3.362	4.329	3.855	4.649	4.189	4.189	5.458	4.189	5.458	4.189	5.458	4.189	
	All		2.664	2.218	2.843	2.393	3.163	2.677	3.362	2.892	2.892	3.895	2.892	3.895	2.892	3.895	2.892	
	6	None	%shift/H	12.02	14.17	12.23	14.16	12.56	14.30	12.71	14.39	13.00	14.56	13.00	14.56	13.00	14.56	
			%shift/H	199.222	199.563	199.904	199.405	199.747	200.181	199.941	199.756	199.941	199.363	199.314	199.941	199.363	199.314	199.941
1 or 2			32.074	41.381	43.698	56.772	57.354	73.158	64.214	80.675	66.7	78.204	66.7	78.204	66.7	78.204	66.7	
1 and 2			19.724	23.288	26.182	32.160	33.882	42.148	38.134	47.493	47.493	47.470	47.493	47.470	47.493	47.470	47.493	
All			11.388	11.910	12.436	13.363	14.278	15.592	15.565	17.138	17.138	18.416	17.138	18.416	17.138	18.416	17.138	
1 or 2			13.462	14.288	17.175	19.174	22.066	25.945	25.047	30.005	30.005	32.041	30.005	32.041	30.005	32.041	30.005	
1 and 2			8.581	8.306	10.619	10.738	13.183	13.949	14.746	15.947	15.947	18.310	15.947	18.310	15.947	18.310	15.947	
All			5.160	4.667	5.491	5.000	6.088	5.701	6.522	6.128	6.128	7.561	6.128	7.561	6.128	7.561	6.128	
All			3.371	2.858	3.495	2.998	3.819	3.308	4.052	3.548	3.548	4.607	3.548	4.607	3.548	4.607	3.548	
10		None	%shift/H	15.87	18.48	16.03	18.34	16.47	18.53	16.73	18.69	17.25	19.04	17.25	19.04	17.25	19.04	
			%shift/H	199.992	199.530	199.679	199.917	200.280	199.965	199.363	199.363	199.363	199.772	199.363	199.772	199.363	199.772	199.363
		1 or 2		38.145	50.879	52.721	70.580	68.982	88.991	77.147	97.368	66.7	93.048	66.7	93.048	66.7	93.048	66.7
	1 and 2		11.017	11.271	11.397	11.804	12.428	13.183	13.273	14.128	14.128	15.192	14.128	15.192	14.128	15.192	14.128	
	All		23.098	28.319	20.139	23.543	26.225	32.322	29.944	37.740	37.740	38.509	37.740	38.509	37.740	38.509	37.740	
	1 or 2		15.551	17.103	20.377	23.885	25.677	32.322	29.944	37.740	37.740	40.457	37.740	40.457	37.740	40.457	37.740	
	1 and 2		9.833	9.673	12.377	12.885	15.677	17.162	17.162	19.943	19.943	22.180	19.943	22.180	19.943	22.180	19.943	
	All		5.098	4.470	5.101	4.528	5.362	4.869	5.629	5.147	5.147	6.271	5.147	6.271	5.147	6.271	5.147	
	All		3.321	2.745	3.279	2.735	3.399	2.875	3.524	3.000	3.000	3.863	3.000	3.863	3.000	3.863	3.000	
	15	None	%shift/H	20.30	23.41	20.22	22.96	20.69	23.10	21.00	23.29	21.74	23.74	21.74	23.74	21.74	23.74	
			%shift/H	199.107	199.935	199.582	199.955	200.203	199.338	199.629	199.450	199.629	199.009	199.874	199.629	199.009	199.874	199.629
		1 or 2		44.384	60.342	61.529	82.747	80.577	103.312	89.354	112.559	66.7	105.641	66.7	105.641	66.7	105.641	66.7
1 and 2			26.676	33.861	37.187	49.306	49.646	65.901	56.204	73.554	66.7	69.393	66.7	69.393	66.7	69.393	66.7	
All			10.996	10.944	10.881	11.012	11.572	11.916	11.994	12.526	12.526	13.344	12.526	13.344	12.526	13.344	12.526	
1 or 2			17.725	20.155	23.026	28.041	30.386	39.051	34.805	45.518	45.518	44.944	45.518	44.944	45.518	44.944	45.518	
1 and 2			11.107	4.000	14.091	15.128	18.092	20.574	20.466	24.113	24.113	26.073	24.113	26.073	24.113	26.073	24.113	
All			5.226	11.227	4.997	4.366	5.087	4.496	5.197	4.642	4.642	5.655	4.642	5.655	4.642	5.655	4.642	
All			3.441	2.774	3.240	2.647	3.217	2.669	3.279	2.726	2.726	3.486	2.726	3.486	2.726	3.486	2.726	

**Table 26** Summary of the SDRL for the one-sided MPEWMA control chart when  $\theta = 0.5$

p	Actual Region Shifted	Mean														
		3			5			8			10			15		
		$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	
4	None	0	201.017	199.308	0	199.984	199.010	0	199.952	199.333	0	198.858	200.251	0	201.911	
	1 or 2	33	20.642	30.527	20	29.552	42.781	12.5	40.952	56.111	10	47.670	63.695	6.67	60.784	
	1 and 2	33	10.789	14.802	20	15.203	20.925	12.5	27.462	28.889	10	24.703	33.243	6.67	32.813	
	All	33	5.944	7.301	20	7.803	9.760	12.5	15.169	13.161	10	12.108	15.559	6.67	16.171	
	1 or 2	67	6.561	8.185	40	8.909	11.634	25	19.140	16.771	20	14.685	19.987	13.33	20.308	
	1 and 2	67	3.621	4.000	40	4.733	5.450	25	11.103	7.707	20	7.358	9.128	13.33	9.941	
	All	67	2.189	2.195	40	2.672	2.784	25	6.436	3.668	20	3.902	4.276	13.33	5.044	
	All	100	1.329	1.242	60	1.591	1.510	37.5	4.058	1.880	30	2.188	2.132	20	2.731	
	All	133	0.966	0.875	80	1.130	1.026	50	2.960	1.251	40	1.509	1.404	26.67	1.847	
	All	100	1.146	1.042	60	1.333	1.228	37.5	1.606	1.497	30	1.762	1.675	20	2.171	
6	None	0	199.059	200.657	0	199.991	199.044	0	200.956	200.998	0	200.115	198.565	0	201.259	
	1 or 2	33	24.177	36.947	20	34.999	51.207	12.5	48.248	66.971	10	55.448	75.086	6.67	71.160	
	1 and 2	33	12.433	18.035	20	17.858	25.568	12.5	25.135	35.434	10	29.301	41.056	6.67	39.025	
	All	33	5.040	6.010	20	6.293	7.668	12.5	8.177	10.140	10	9.357	11.784	6.67	12.233	
	1 or 2	67	7.351	9.591	40	10.158	13.781	25	14.284	19.971	20	16.863	24.115	13.33	23.494	
	1 and 2	67	4.023	4.579	40	5.348	6.368	25	7.421	9.071	20	8.472	10.833	13.33	11.531	
	All	67	1.866	1.830	40	2.247	2.238	25	2.758	2.809	20	3.098	3.242	13.33	3.915	
	All	100	1.146	1.042	60	1.333	1.228	37.5	1.606	1.497	30	1.762	1.675	20	2.171	
	All	100	1.146	1.042	60	1.333	1.228	37.5	1.606	1.497	30	1.762	1.675	20	2.171	
	All	100	1.146	1.042	60	1.333	1.228	37.5	1.606	1.497	30	1.762	1.675	20	2.171	
10	None	0	200.588	198.185	0	198.970	201.254	0	200.225	201.240	0	196.589	199.881	0	201.142	
	1 or 2	33	29.815	47.553	20	43.250	65.526	12.5	59.798	83.118	10	67.795	90.760	6.67	84.038	
	1 and 2	33	15.168	23.324	20	22.207	34.149	12.5	31.677	46.479	10	37.231	53.106	6.67	49.047	
	All	33	4.261	4.887	20	5.043	5.980	12.5	6.195	7.506	10	7.039	8.549	6.67	8.870	
	1 or 2	67	8.585	11.942	40	12.006	17.605	25	17.196	25.707	20	20.569	30.813	13.33	28.649	
	1 and 2	67	4.632	5.502	40	6.275	7.995	25	8.576	11.579	20	10.213	13.938	13.33	13.938	
	All	67	1.602	1.514	40	1.840	1.762	25	2.189	2.133	20	2.405	2.376	13.33	2.951	
	All	100	0.988	0.876	60	1.215	1.000	37.5	1.295	1.168	30	1.416	1.278	20	1.678	
	All	100	0.988	0.876	60	1.215	1.000	37.5	1.295	1.168	30	1.416	1.278	20	1.678	
	All	100	0.988	0.876	60	1.215	1.000	37.5	1.295	1.168	30	1.416	1.278	20	1.678	
15	None	0	200.206	201.687	0	200.613	201.856	0	198.282	199.909	0	200.066	199.655	0	199.341	
	1 or 2	33	35.338	57.871	20	51.625	78.815	12.5	70.168	97.199	10	79.426	105.943	6.67	97.200	
	1 and 2	33	17.875	29.028	20	26.937	42.868	12.5	38.612	57.857	10	45.228	65.548	6.67	58.759	
	All	33	3.846	4.305	20	4.386	4.990	12.5	5.197	6.100	10	5.704	6.751	6.67	7.023	
	1 or 2	67	9.855	14.532	40	14.061	21.708	25	20.344	31.895	20	24.331	38.286	13.33	34.267	
	1 and 2	67	5.190	6.471	40	7.140	9.545	25	10.081	14.173	20	11.996	17.275	13.33	16.709	
	All	67	1.479	1.354	40	1.639	1.528	25	1.876	1.784	20	2.028	1.950	13.33	2.404	
	All	100	0.914	0.793	60	1.007	0.878	37.5	1.136	0.993	30	1.219	1.071	20	1.412	
	All	100	0.914	0.793	60	1.007	0.878	37.5	1.136	0.993	30	1.219	1.071	20	1.412	
	All	100	0.914	0.793	60	1.007	0.878	37.5	1.136	0.993	30	1.219	1.071	20	1.412	

**Table 27 Summary of the SDRL for the one-sided MPEWMA control chart when thetatafix = 1**

p	Actual Region Shifted	Mean													
		3			5			8			10			15	
		$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.05$	$\lambda = 0.1$		
4	None	%shift/H	9.80	11.68	%shift/H	9.98	11.68	%shift/H	10.18	11.73	%shift/H	10.27	11.76		
		0	200.167	199.051	0	199.131	201.920	0	198.409	199.168	0	200.182	200.321	0	
	1 or 2	%shift/H	20.176	30.022	20	30.209	43.317	12.5	41.905	57.499	10	48.417	65.484	6.67	
		33	11.232	15.367	20	16.144	22.324	12.5	22.282	30.283	10	25.948	35.238	6.67	
	1 and 2	%shift/H	7.239	9.142	20	8.971	11.428	10	13.279	16.884	10	13.279	16.884	6.67	
		33	6.344	7.931	40	8.863	11.705	25	12.545	17.051	20	14.901	20.413	13.33	
	1 or 2	%shift/H	3.675	4.159	40	4.970	5.729	25	6.652	8.089	20	7.685	9.526	13.33	
		67	2.544	2.637	40	3.025	3.191	25	3.745	4.063	20	4.227	4.663	13.33	
	1 and 2	%shift/H	1.500	1.429	60	1.760	1.679	37.5	2.115	2.063	30	2.342	2.306	20	
		100	1.078	0.975	80	1.240	1.134	50	1.462	1.353	40	1.596	1.500	26.67	
		133	12.02	14.17	%shift/H	12.23	14.16	%shift/H	12.56	14.30	%shift/H	12.71	14.39	%shift/H	13.00
	6	None	0	200.393	199.906	0	199.915	199.723	0	200.391	202.496	0	198.936	200.606	0
1 or 2		%shift/H	23.282	35.771	20	35.276	52.146	12.5	49.634	69.444	10	57.356	77.038	6.67	
		33	12.626	18.136	20	18.772	27.326	12.5	26.517	37.702	10	31.080	43.446	6.67	
1 and 2		%shift/H	6.518	8.166	20	7.722	9.789	12.5	9.423	12.052	10	10.689	13.591	6.67	
		33	7.033	9.157	40	10.069	13.785	25	14.361	20.488	20	17.142	24.621	13.33	
1 or 2		%shift/H	3.994	4.562	40	5.495	6.632	25	7.520	9.579	20	8.824	11.494	13.33	
		67	2.308	2.332	40	2.653	2.691	25	3.140	3.318	20	3.479	3.696	13.33	
1 and 2		%shift/H	1.365	1.261	60	1.542	1.442	37.5	1.792	1.691	30	1.959	1.872	20	
		100	15.87	18.48	%shift/H	16.03	18.34	%shift/H	16.47	18.53	%shift/H	16.73	18.69	%shift/H	17.25
10		None	0	201.214	199.656	0	201.007	199.539	0	201.433	198.822	0	198.083	200.703	0
		1 or 2	%shift/H	28.468	45.478	20	43.603	65.939	12.5	61.046	85.496	10	69.332	93.708	6.67
			33	6.013	7.336	20	23.212	36.524	12.5	33.544	49.574	10	39.421	56.651	6.67
	1 and 2	%shift/H	14.950	21.197	20	6.700	8.131	12.5	7.751	9.682	10	8.518	10.711	6.67	
		33	8.193	11.271	40	11.900	17.442	25	17.317	26.336	20	20.913	31.866	13.33	
	1 or 2	%shift/H	4.548	5.390	40	6.346	8.080	25	8.911	11.993	20	10.605	14.773	13.33	
		67	2.119	2.078	40	2.332	2.315	25	2.638	2.673	20	2.839	2.911	13.33	
	1 and 2	%shift/H	1.256	1.138	60	1.376	1.235	37.5	1.538	1.406	30	1.645	1.507	20	
		100	20.30	23.41	%shift/H	20.22	22.96	%shift/H	20.69	23.10	%shift/H	21.00	23.29	%shift/H	21.74
	15	None	0	198.975	199.843	0	201.491	201.107	0	201.665	199.258	0	199.413	201.215	0
		1 or 2	%shift/H	33.893	54.671	20	52.006	78.552	12.5	72.659	100.328	10	81.790	109.949	6.67
			33	17.692	27.876	20	27.805	43.989	12.5	40.781	61.365	10	47.782	69.572	6.67
1 and 2		%shift/H	5.857	6.853	20	6.082	7.336	12.5	6.913	8.380	10	7.349	9.110	6.67	
		33	9.520	13.782	40	13.876	21.407	25	20.470	32.696	20	24.798	39.441	13.33	
1 or 2		%shift/H	5.124	2.052	40	7.232	9.656	25	10.325	14.943	20	12.393	18.547	13.33	
		67	2.046	6.389	40	2.184	2.116	25	2.403	2.345	20	2.532	2.505	13.33	
1 and 2		%shift/H	1.212	1.084	60	1.285	1.149	37.5	1.395	1.250	30	1.486	1.331	20	
		100	198.975	199.843	0	201.491	201.107	0	201.665	199.258	0	199.413	201.215	0	
		33	33.893	54.671	20	52.006	78.552	12.5	72.659	100.328	10	81.790	109.949	6.67	
		33	17.692	27.876	20	27.805	43.989	12.5	40.781	61.365	10	47.782	69.572	6.67	
		33	5.857	6.853	20	6.082	7.336	12.5	6.913	8.380	10	7.349	9.110	6.67	
	67	9.520	13.782	40	13.876	21.407	25	20.470	32.696	20	24.798	39.441	13.33		
	67	5.124	2.052	40	7.232	9.656	25	10.325	14.943	20	12.393	18.547	13.33		
	67	2.046	6.389	40	2.184	2.116	25	2.403	2.345	20	2.532	2.505	13.33		
	100	1.212	1.084	60	1.285	1.149	37.5	1.395	1.250	30	1.486	1.331	20		

$$\rho_{ij} = \frac{\theta}{\sqrt{(\theta + \theta_i)(\theta + \theta_j)}}, \quad i \neq j \quad (18)$$

where  $\theta$ ,  $\theta_i$ , and  $\theta_j$  are the Poisson means of  $Y$ ,  $Y_i$ , and  $Y_j$ , respectively. Since we know that the process means of the first two variables ( $Y_1$  and  $Y_2$ ) are 10 ( $\theta + \theta_1$  and  $\theta + \theta_2$ ), then the value of  $\theta$  is determined to be 5 (obtained using Equation (18)) and, consequently, both  $\theta_1$  and  $\theta_2$  are equal to 5.

**Table 28** Summary of the one-sided MEWMA chart's performance proposed by Joner *et al.* (2008) for 10 variables with  $\rho = 0.5$ .

Variable Shifted	% shift	$\mu_0$	$\lambda$	One-sided MEWMA chart		
				Control limit (H)	out-of-control ARL	$SE_{ARL}$
1	20	10	0.05	12.325	15.01	0.031
1	20	50	0.19	15.960	5.10	0.009
1	10	100	0.11	14.695	8.34	0.015
1, 2, and 4	20	10	0.11	14.695	9.09	0.019
1, 2, and 4	20	50	0.37	16.970	3.00	0.005
1, 2, and 4	10	100	0.22	16.255	4.97	0.009
1, 6, and 10	20	10	0.10	14.430	7.08	0.013
1, 6, and 10	20	50	0.44	17.120	2.28	0.004
1, 6, and 10	10	100	0.26	16.510	3.80	0.007
All	10	100	0.34	16.890	3.15	0.006

**Table 29** Comparison of the performance between the one-sided MEWMA and MPEWMA charts for in-control ARL of 100 when  $\theta = 5$ .

p	Variable Shifted	% shift	$\lambda$	Normal theory limits with u = 10			Poisson limits with u = 10		
				Control limit (H)	out-of-control ARL	$SE_{ARL}$	Control limit (H)	out-of-control ARL	$SE_{ARL}$
10	1	20	0.05	12.325	15.010	0.031	12.68	20.144	0.063
	1, 2, and 4	20	0.11	14.695	9.090	0.019	15.420	10.903	0.035
	1, 6, and 10	20	0.10	14.430	7.080	0.013	15.140	10.737	0.034

Table 29 shows a comparison of two one-sided schemes for an in-control ARL of 100. The Poisson-limits obtained for the chosen three cases are 12.68, 15.420, and 15.14 respectively. The out-of-control ARLs are 20.144, 10.903, and 10.737. The results indicate that the control limits calculated from the normal approximation are narrower than the Poisson distribution themselves. The differences in detecting the same shift in the mean vectors of both one-sided control charts are quite small.

We investigate another issue of applying the normal-theory limits to the multivariate Poisson distribution. Let us use the above conditions as an example. Suppose we ignore the Poisson assumption and use the normal approximation for the Poisson distribution. In the other word, the control limits from the normal-theory ( $H = 12.325, 14.695, \text{ and } 14.430$ ) are applied to the data generated from the multivariate Poisson distribution. The important result here is that the one-sided MEWMA charts of all three scenarios have in-control ARLs much lower than the stated level of 100 as shown in Table 30. The in-control ARLs are sufficiently dropped to 91.392, 81.773, and 83.565, respectively. In order to achieve the in-control ARL of 100, the Poisson limits ( $H = 12.68, 15.42, \text{ and } 15.14$ ) should be applied instead of those normal-theory limits. Moreover, the out-of-control ARLs are 19.428, 10.208, and 10.114 and they are quite similar to the expected values (20.144, 10.903, and 10.737) on the right hand side of Table 29. In practice, one can also expect an earlier false alarm when the normal approximation is applied to multivariate Poisson data.



**Table 30** The performance of the one-sided MEWMA applied to the multivariate Poisson distribution with  $\theta = 5$  (The advertised in-control ARL of 100).

Normal theory limits with $u = 10$							
$p$	Variable Shifted	% shift	$\lambda$	Control limit (H)	In-control ARL	out-of-control ARL	$SE_{ARL}$
10	1	20	0.05	12.325	91.392	19.428	0.061
	1, 2, and 4	20	0.11	14.695	81.773	10.208	0.033
	1, 6, and 10	20	0.10	14.430	83.565	10.114	0.045

#### 4.6 Individual and a Row of Out-of-Control Signal

Commonly, an out-of-control signal in the one-sided MPEWMA control chart occurs if a single point is out of control. However, there are some situations where we are interested in consecutive points plotting beyond the control limit for a signal. For example, suppose we are monitoring the incidence rates of asthma from several locations over 120 weeks. Suppose one out-of-control signal is given at period 100 and no other signals are detected. It is quite difficult to conclude that the asthma rate has increased and that there is evidence for spread of asthma disease in those areas since only one signal has occurred. Thus, it would be better to wait for several out-of-control signals in a row rather than an individual out-of-control signal. In this section, we study the detection performance on four test cases in which data are generated by the multivariate Poisson model. The details of each case are described below.

Case 1: Four variables each with  $\mu = 3$  and  $\theta = 1$ .

Case 2: Four variables each with  $\mu = 3$  and  $\theta = 0.5$ .

Case 3: Six variables each with  $\mu = 5$  and  $\theta = 1$ .

Case 4: Six variables each with  $\mu = 5$  and  $\theta = 0.5$ .

To assure the steady-state condition, the process runs in control for the first 200 time periods. After that, the process shifts to an out-of-control state by one of three different shift sizes randomly applied to demonstrate the proposed chart performance – one unit shift in the first variable, one unit shift in the first two variables, and one unit shift in all variables. The shifts  $[1, 0, 0, 0]$ ,  $[1, 1, 0, 0]$ , and  $[1, 1, 1, 1]$  are used for the case of four variables. Two smoothing weights used are  $\lambda = 0.05$  and  $\lambda = 0.1$ . The control limits are obtained from Tables 24-25. For instance, the control limits of case 1 are 9.8 ( $\lambda = 0.05$ ) and 11.68 ( $\lambda = 0.1$ ) as shown in Table 25.

We examine two different approaches for signaling an out-of-control state using the same control limits - an individual signal and a run of signals. A run of signals is defined by any two or more consecutive out-of-control signals. Four scenarios of the runs of out-of-control signals are tested, including two, three, four, and five points in a row, respectively. To demonstrate how to declare an out-of-control signal in these scenarios, let's assume that we are interested in a run of three out-of-control signals. If an individual signal or two consecutive out-of-control points signal are found, the process is not considered out-of-control. When we detect three out-of-control points in a row, it means that we also detect an individual and two out-of-control points in a row in the earlier period. Suppose three consecutive out-of-control points are found at period 205, 206 and 207. We treat these three out-of-control signals as one of an individual out-of-control point at the time period 205, one of the two out-of-control points in a row at the time

period 206, and one of the three out-of-control points in a row at the time period 207.

We evaluate the performance of the one-sided MPEWMA chart for monitoring the 500 simulated data based on two criteria – the percentage of cases where an out-of-control signal is detected and the time period of the first out-of-control signal detection after the shift has occurred at period 201. Table 31 presents the percentage of cases where an out-of-control signal has been detected using the one-sided MPEWMA chart. The one-sided MPEWMA scheme is able to detect the mean shift when at least one out-of-control signal has occurred. The results indicate that the percentage of cases decreases as the number of consecutive out-of-control points increases, particularly for mean shifts of one or two variables. The reason for the reduction in the percentage of cases corresponds to the lower chance of having consecutive out-of-control points, particularly for a small shift size. A significant decrease in the percentages of detected cases occurred for larger smoothing weights. For example, consider a unit shift in one out of six variables from Case 4 (i.e. the shift matrix  $[1, 0, 0, 0, 0, 0]$ ). When  $\lambda = 0.05$ , there is no obvious difference between using either an individual signal (99.98%) or two to five out-of-control points in a row (98.63% - 99.94%). However, for  $\lambda = 0.1$ , the differences between two the approaches are large - 99.67% for detecting an individual signal and as low as 71.64% for detecting a run of two to five out-of-control signals.

**Table 31** The percentage of cases that detected an out-of-control signal for all four scenarios

Case	$\lambda$	shift matrix	The percentage of detecting an out-of-control				
			1 point	2 points	3 points	4 points	5 points
1	0.05	[1,0,0,0]	100.00	100.00	100.00	100.00	99.99
		[1,1,0,0]	100.00	100.00	100.00	100.00	100.00
		[1,1,1,1]	100.00	100.00	100.00	100.00	100.00
	0.1	[1,0,0,0]	100.00	99.95	99.56	98.47	96.30
		[1,1,0,0]	100.00	100.00	100.00	100.00	100.00
		[1,1,1,1]	100.00	100.00	100.00	100.00	99.99
2	0.05	[1,0,0,0]	100.00	100.00	99.99	99.99	99.99
		[1,1,0,0]	100.00	100.00	100.00	100.00	100.00
		[1,1,1,1]	100.00	100.00	100.00	100.00	100.00
	0.1	[1,0,0,0]	100.00	99.86	99.22	97.66	94.55
		[1,1,0,0]	100.00	100.00	100.00	100.00	99.99
		[1,1,1,1]	100.00	100.00	100.00	100.00	100.00
3	0.05	[1,0,0,0,0,0]	99.98	99.87	99.69	99.27	98.63
		[1,1,0,0,0,0]	100.00	100.00	100.00	100.00	100.00
		[1,1,1,1,1,1]	100.00	100.00	100.00	100.00	100.00
	0.1	[1,0,0,0,0,0]	99.68	96.99	90.88	82.07	71.52
		[1,1,0,0,0,0]	100.00	99.99	99.66	98.71	96.60
		[1,1,1,1,1,1]	100.00	100.00	100.00	100.00	100.00
4	0.05	[1,0,0,0,0,0]	99.98	99.94	99.62	99.2	98.63
		[1,1,0,0,0,0]	100.00	99.99	99.99	99.99	99.99
		[1,1,1,1,1,1]	100.00	100.00	100.00	100.00	100.00
	0.1	[1,0,0,0,0,0]	99.67	97.38	91.71	82.41	71.64
		[1,1,0,0,0,0]	100.00	100.00	99.86	99.04	97.42
		[1,1,1,1,1,1]	100.00	100.00	100.00	100.00	100.00

Table 32 reports the average period of time to detect the first out-of-control signal for all four scenarios. The average of the times is calculated from the first out-of-control signal detected by the one-sided MPEWMA scheme within each replication. For example, the first case study with  $\lambda = 0.05$  shows that the first individual out-of-control signal is detected with average time of 29.0907

(period = 230) after the shift  $[1, 0, 0, 0]$  has occurred at period 200. The results demonstrate that the shift in one and two variables can be quickly detected by a single out-of-control point as compared to a run of consecutive out-of-control points for all four cases. A run of 5 consecutive out-of-control points is the slowest out of control condition to be detected since we have to wait until all five consecutive points exceed the control limit. For example, consider Case 4 with  $\lambda = 0.1$ . The time until the first out-of-control signal occurs increases from 58.284 (an individual) to 82.7172, 101.8237, 117.0436, and 127.6594 for two, three, four, and five points in a row, respectively. Thus, it will take an average of 69 additional periods to detect an out-of-control situation when applying a run of five out-of-control points instead of an individual.

The time-delay for detection tends to become shorter with larger numbers of variables shifted. Consider the previous example with individual out-of-control signal. The time to detect the first out-of-control signal reduces from 58.284 to 31.711, and 11.9623 when the number of variables shifted increases to two and six variables, respectively. The use of an individual approach is recommended over a run of 2 or more occurs for detecting a shift in one or two variables. The consecutive out-of-control points method improves if shifts occur in two or more variables. There is no considerable increase in detection time. For instance, if all six variables shifted (the shift  $[1, 1, 1, 1, 1, 1]$ ) such as in Case 4, the detection time increases from 12.7318 to 14.2853, 15.6401, 16.914, and 18.1616.

**Table 32** Summary of the first out-of-control signal period detected by the one-sided MPEWMA chart for all four scenarios

Case	$\lambda$	shift matrix	The first period to detect an out-of-control signal				
			1 point	2 points	3 points	4 points	5 points
1	0.05	[1,0,0,0]	29.0907	34.2840	38.9742	43.0704	46.9790
		[1,1,0,0]	18.5769	21.3951	23.8374	26.0050	28.2012
		[1,1,1,1]	13.9113	15.7539	17.3141	18.7701	20.1483
	0.1	[1,0,0,0]	36.6166	51.0260	65.4608	78.1542	90.3734
		[1,1,0,0]	20.8885	27.3465	33.4023	39.5808	45.7962
		[1,1,1,1]	13.9071	17.1756	21.0479	24.4276	27.6739
2	0.05	[1,0,0,0]	29.5135	35.0677	39.9803	44.3125	48.7262
		[1,1,0,0]	18.1188	20.9985	23.4479	25.6407	27.7250
		[1,1,1,1]	12.6268	13.9811	15.2246	16.4003	17.5337
	0.1	[1,0,0,0]	37.3561	52.6916	67.6304	82.7736	95.1820
		[1,1,0,0]	20.1862	26.5004	32.5465	38.7679	45.035
		[1,1,1,1]	11.7540	14.7180	17.3741	19.8542	22.3003
3	0.05	[1,0,0,0,0,0]	45.1418	55.6943	64.5467	72.4852	79.9108
		[1,1,0,0,0,0]	27.3583	32.4666	37.0147	40.9685	44.9837
		[1,1,1,1,1,1]	13.9702	16.1032	17.8595	19.4734	20.9719
	0.1	[1,0,0,0,0,0]	58.31	82.0819	101.2547	115.6195	126.9829
		[1,1,0,0,0,0]	33.9501	47.3816	61.2324	74.6788	87.5655
		[1,1,1,1,1,1]	14.1226	18.3333	22.1978	26.0304	29.8291
4	0.05	[1,0,0,0,0,0]	45.2154	55.7593	64.6804	73.2164	80.8801
		[1,1,0,0,0,0]	26.4281	31.411	35.5505	39.4522	43.3637
		[1,1,1,1,1,1]	12.7318	14.2853	15.6401	16.914	18.1616
	0.1	[1,0,0,0,0,0]	58.284	82.7172	101.8237	117.0436	127.6594
		[1,1,0,0,0,0]	31.711	44.8519	57.8931	70.8977	84.1669
		[1,1,1,1,1,1]	11.9623	15.2091	18.1433	20.9336	23.6991

#### 4.7 Examples

We illustrate an example of using the one-sided MPEWMA chart to monitor public-health data. Let's consider the monitoring of one of six common air pollutants, Carbon Monoxide (or CO). The hourly CO concentration (in parts per million (ppm)) at 4 different stations being monitored are denoted by  $X_i$  where

$i = 1, 2, 3,$  and  $4$ . The hourly average CO concentration measured from each station,  $X_i$ , is the combination of the overall and the area effects. The effect on overall CO in the atmosphere can be represented by  $Y$  and the effect of CO emissions at each area is represented by  $Y_i$  for  $i = 1, 2, 3,$  and  $4$ . Thus, it is reasonable to assume the data can be sufficiently modeled by a multivariate Poisson distribution assuming a correlation exists between variables. Suppose the mean hourly CO concentration for each of the 4 stations is 3 ppm and the common effect is 0.5 ( $\theta = 0.5$ ). Given this information, the sample mean and the covariance matrix are given by

$$\boldsymbol{\mu}_0 = [3, 3, 3, 3] \quad \text{and} \quad \boldsymbol{\Sigma} = \begin{bmatrix} 3 & 0.5 & 0.5 & 0.5 \\ 0.5 & 3 & 0.5 & 0.5 \\ 0.5 & 0.5 & 3 & 0.5 \\ 0.5 & 0.5 & 0.5 & 3 \end{bmatrix}$$

Data are collected on day  $t$  for  $t = 1, 2, \dots, 200$  over a 6 month period. In this example, we use the known means and covariance matrix to compute the one-sided MPEWMA (or  $MEW_t$ ) statistics. A smoothing weight of 0.05 is selected, and the control limit obtained from Table 24 is 10.29. For From Equation (13),

$$\mathbf{Z}_1 = \max \left\{ \lambda(\mathbf{X}_1 - \boldsymbol{\mu}_0) + (1 - \lambda)\mathbf{Z}_0, \mathbf{0} \right\}$$

To illustrate the calculations of the  $MEW_t$  statistics considered

$$\mathbf{Z}_1 = \max \left\{ 0.05 \left( \begin{bmatrix} 3 \\ 3 \\ 3 \\ 7 \end{bmatrix} - \begin{bmatrix} 3 \\ 3 \\ 3 \\ 3 \end{bmatrix} \right) + (1 - 0.05) \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \right\} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0.2 \end{bmatrix}$$

Using Equation (15) we obtain:

$$\Sigma_{Z_1} = \frac{\lambda}{2 - \lambda} \Sigma = \frac{0.05}{2 - 0.05} \Sigma.$$

Day 1: the  $MEW_t$  statistics using Equation (16) is

$$MEW_1 = Z_1' \Sigma_{Z_1}^{-1} Z_1 = 0.5547$$

The calculations of the  $MEW_t$  statistics for the first 10 samples are presented in Table 33. If the values of  $\theta_1$ ,  $\theta_2$ ,  $\theta_3$ ,  $\theta_4$ , and  $\theta$  are unknown, we can estimate all these parameters from historical data by using several methods (for more details, see Section 2.4.2).

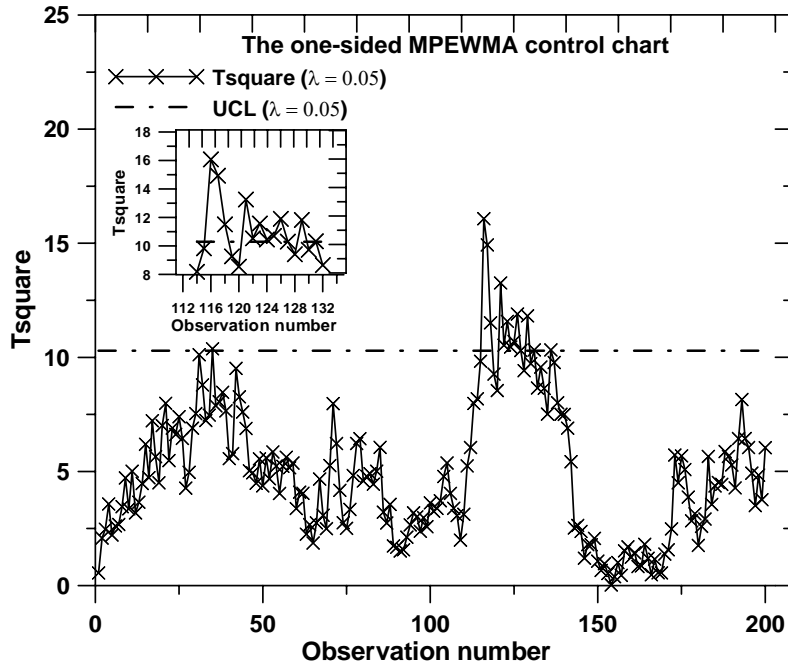
Figure 5 displays the plot of the one-sided MPEWMA chart for the hourly CO concentration. The first out-of-control signal is given at period 116 since the  $MEW_t$  statistics of 16.0734 exceeds the control limits ( $H = 10.29$ ). If we consider a run of out-of-control signals instead of an individual, the first out-of-control signal is still found at the same period 116 for the cases of two and three signals in a row. However, the first out-of-control signal is detected at period 121 while waiting for four and five out-of-control signals to occur. The time-delay of detection with 5 periods could be problematic, particularly if the mean hourly CO concentration exceeds the air quality standard. Hence, the individual signal method can be implemented if the mean hourly CO concentration lies near the level of the air quality standard. Implementation of the long-run ( $n = 4$ , and  $5$ ) method can be applied when the mean hourly CO concentration is far beyond the standard level of the air quality.



**Table 33** Example of the calculation of the first 10 samples of the one-sided MPEWMA statistics.

Obs	x1	x2	x3	x4	$\lambda = 0.05$				MEW <sub>t</sub>
					$Z_t$				
					0	0	0	0	
1	3	3	3	7	0.0000	0.0000	0.0000	0.2000	0.5547
2	6	8	8	5	0.1500	0.2500	0.2500	0.2900	2.0814
3	3	5	4	2	0.1425	0.3375	0.2875	0.2255	2.4673
4	1	3	3	7	0.0354	0.3206	0.2731	0.4142	3.5767
5	2	0	4	1	0.0000	0.1546	0.3095	0.2935	2.2160
6	5	3	3	5	0.1000	0.1469	0.2940	0.3788	2.6136
7	3	5	1	4	0.0950	0.2395	0.1793	0.4099	2.6793
8	3	2	4	5	0.0902	0.1775	0.2203	0.4894	3.4562
9	2	0	4	5	0.0357	0.0187	0.2593	0.5649	4.7149
10	6	3	4	1	0.1840	0.0177	0.2963	0.4367	3.3632

**Figure 5** The one-sided MPEWMA chart of the hourly CO concentration



## Chapter 5

### COMPARISON OF THE MULTIVARIATE CHARTS FOR MULTIVARIATE POISSON DATA

#### **5.1 Introduction**

There have been many studies on the quality control methods for monitoring multivariate data. In general, the control charts are applied to the raw or unprocessed data. The adequacy of the normality and independence assumptions must be assessed before applying any control scheme. It is not always appropriate to assume normality in the situation where the variables follow the Poisson distribution, particularly for small mean counts. If the data depart from the normality assumption, then methods based on other distributions should be employed. The process knowledge has been utilized to improve the sensitivity of the control chart by fitting a regression model to the data. The coefficients of the model are estimated by the regression technique. The residuals from the model are plotted on the conventional control chart. Thus, this method is referred to as the model-based or the residual-based control charting. The model-based control method has relied on the normally distributed data because the control statistics are based on residuals.

There are a few studies of the model-based control approach on monitoring multivariate Poisson data. It is interesting to investigate the model-based control chart's performance in detecting a shift in the mean count. Two regression analyses are chosen to demonstrate the ability for modeling the Poisson counts. The Poisson counts are generated through Monte Carlo simulation. The

residuals are plotted on the multiple Exponentially Weighted Moving Average (EWMA) charts because of the good performance for detecting a small mean shift. The Average Run Length (ARL) performances are reported and evaluated by several combinations of the parameters including mean values, number of variables, and various sizes of shift. In addition, we make a comparison between those model-based schemes and the multivariate Poisson EWMA chart, for which the control limits are directly obtained from the Poisson distribution. The results can help clarify a better method for the early detection of a mean shift.

## 5.2 Methodology

Typically, the Ordinary Least Squares (OLS) regression is performed to estimate the coefficients of the model. The model computed from the OLS is limited to normal data. In this study, two regression techniques are selected to model the Poisson distributed data - the regression adjustment and generalized linear regression. The details of each regression method are discussed below.

### 5.2.1 Regression Adjustment

Hawkins (1993) introduced the regression-adjustment based on Y and Z scales. The standardization of the original scale is recommended before transformation into the Y and Z scales. All X, Y, and Z scales correspond to the Hotelling  $T^2$  statistics. The Hotelling  $T^2$  statistic is

$$T_i^2 = (\mathbf{X}_i - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{X}_i - \boldsymbol{\mu}) \quad (19)$$

The  $T^2$  can be expressed as

$$T_i^2 = \mathbf{Y}' \mathbf{Y} = \sum_{j=1}^p Y_j^2 \quad (20)$$

where  $Y_j$  is the decomposition of  $T^2$ .  $Y$  can be rewrite in terms of the linear transformation of  $\mathbf{X}$  as

$$Y = C(\mathbf{X} - \mu) \quad (21)$$

where  $C$  is the Cholesky decomposition over the lower triangular root of the inverse of the covariance matrix ( $CC' = \Sigma^{-1}$ ). Another decomposition of  $T^2$  is

$$T_i^2 = (\mathbf{X}_i - \mu)' \mathbf{Z} \quad (22)$$

where  $\mathbf{Z} = \Sigma^{-1}(\mathbf{X}_i - \mu)$  and  $\mathbf{Z}$  is a  $p \times 1$  vector.

The residuals obtained from both regression techniques above are plotted on the multiple Exponentially Weighted Moving Average (EWMA) charts to monitor the shift in means separately since the residuals are considered as independent and approximately normally distributed. The discussion of the EWMA chart is provided below.

### 5.2.2 Exponentially Weighted Moving Average Chart

Roberts (1959) proposed the EWMA chart by defining the control statistics as previously shown in Equation (6) where  $\mathbf{Z}_0 = \mu_0$ . The value of the smoothing weight ( $\lambda$ ) ranges from 0 to 1. The control limits of the steady-state EWMA are given by

$$UCL = \mu_0 + L\sigma\sqrt{\frac{\lambda}{2-\lambda}} \quad (27)$$

$$CL = \mu_0 \quad (28)$$

$$LCL = \mu_0 - L\sigma\sqrt{\frac{\lambda}{2-\lambda}} \quad (29)$$

where  $L$  is the multiple of standard deviation used in the control limits.

### 5.3 Simulation Results

The multivariate Poisson data is simulated by the Monte Carlo simulation as the sum of two independent Poisson random variables. The Poisson counts are generated under the same conditions as previously discussed in Sections 3.4 and 4.3. Two different regression methods are applied to the simulated multivariate Poisson data. The residuals are computed and plotted on multiple EWMA charts. In this study, we consider using the EWMA chart with the smoothing weight ( $\lambda$ ) of 0.05 due to its good performance in detection of a small shift. For each regression technique, the control limits ( $L$ ) of the EWMA chart are independently chosen to achieve an in-control ARL of 200 (performed with 10000 repetitions).

The out-of-control ARL performances of these two residual-based control charts are tested against a wide variety of conditions. We shift the mean of one or more variables, at the same time, by adding one, two, three and four unit sizes. The shift has occurred at the period of 200 to ensure the steady-state condition. The results appear in the relation between the region shifted and percentage of change. The percentage of change is calculated using Equation (17). For example, the shift of one unit in the mean of 3 is  $\frac{1}{3} \times 100 = 33\%$ . The performance of all two residual-based control methods on monitoring the multivariate Poisson-distributed data are reported in terms of the ARL values below.

The appropriate multiple of sigma employed in the control limits for the regression adjustment are  $L = 2.15, 2.2, 2.25,$  and  $2.3$  (for  $\theta = 0.5$ ) and  $L = 2.35, 2.4, 2.45,$  and  $2.55$  (for  $\theta = 1$ ) to obtain the desired in-control ARL of 200 for the case of four, six, ten, and fifteen variables, respectively. Table 30 presents the ARL performance of four EWMA charts (four-variable case) obtained from both Y and Z scales. The ARL values reported in all the tables below are chosen from the lowest ARL among all multiple EWMA charts. The regression adjustment on the Y scale performs as well as the Z scale for both thetafix values ( $\theta = 0.5,$  and  $1$ ) due to the similar in-control and out-of-control ARLs. It is noticed that the in-control ARLs of the Z scale are slightly less than the Y scale, but the difference tends to be larger for a mean of 5 or smaller. However, it is unclear whether the Y scale has actually outperformed the Z scale or not.

#### **5.4 Comparison of model-based control charts**

We compare the proposed two-sided multivariate Poisson EWMA schemes to the other two model-based control methods for monitoring the multiple counts. As we stated earlier, there is no difference in applying the regression adjustment on the Y and Z scales. For the purpose of comparison, the regression adjustment on the Y scale is selected based on the larger in-of-control ARL performance. The comparisons of all control charts are summarized in Table 33 – 40. The performances of the two model-based control methods are quite comparable due to the similar out-of-control ARLs. It is clearly shown that the two-sided MPEWMA chart provides the smallest out-of-control ARL values

among all three methods. Hence, the two-sided MPEWMA method has superior performance than those two residual-based control charts for all scenarios.

### 5.5 Examples

Reconsider the problem of monitoring four types of defects in the LED manufacturing process as we early mentioned in Section 3.9. We simulate the number of defects by setting the mean of each defect type to 3 with a common mean of 0.5. A shift in the first defect type to the new mean of 4 is generated to determine the out-of-control performance. Three different control methods are used to monitor the defects: the regression adjustment with the EWMA chart, the generalized linear model with the EWMA chart, and the multivariate Poisson EWMA chart. Both the EWMA and MPEWMA charts are constructed using the smoothing weight of 0.05 ( $\lambda = 0.05$ ).

A comparison of the EWMA charts for the regression adjustment on both Y and Z scales is shown in Figure 6. The EWMA statistics and the control limits for the Y scale are little different from the Z scale. The out-of-control signals are given by the EWMA chart of Y1 and Z1 at the same time during period 276 to period 293. In addition, the EWMA scheme of Y2 also detects one additional out-of-control signal during period 270 to 272. In other words, there is an indication that the process has changed. The MPEWMA chart is plotted in Figure 7. It signals an out-of-control condition at period 266 because the T-square statistics exceed the control limit. Thus, it will require 10 samples less than the regression adjustment technique to detect an increase in the mean number of defects.

**Table 34** The Average Run Lengths performance of the regression adjustment with the multiple EWMA charts for 4 variables case.

Mean	Actual Region Shifted	Region % shift	I. Regression adjustment Y scale + EWMA		I. Regression adjustment Z scale + EWMA		
			Thetafix = 0.5, L = 2.15		Thetafix = 0.5, L = 2.15		
			and $\lambda = 0.05$	ARL*	and $\lambda = 0.05$	ARL*	
3	None	0	199.779	201.066	204.186	205.795	
	1	33	30.486	29.748	31.753	28.791	
	2	33	31.362	29.460	34.370	28.786	
	(1,2)	33	30.067	29.805	31.497	28.170	
	All	33	29.335	29.047	30.771	27.684	
	1	67	14.943	14.584	16.459	14.689	
	2	67	15.317	14.413	17.484	14.837	
	(1,2)	67	14.094	14.042	14.506	14.500	
	All	67	12.579	12.940	13.240	13.492	
	All	100	5.041	5.255	5.472	5.744	
	All	133	2.057	2.124	2.185	2.682	
	5	None	0	209.706	207.846	228.679	227.277
		1	20	39.606	39.378	44.504	42.768
2		20	40.446	39.349	46.206	42.553	
(1,2)		20	39.245	39.155	43.553	41.850	
All		20	38.630	38.528	43.105	41.368	
1		40	20.155	20.027	23.356	22.335	
2		40	20.595	20.158	23.861	22.210	
(1,2)		40	19.432	19.959	21.982	21.609	
All		40	18.389	18.870	20.753	20.584	
All		60	9.647	9.998	11.013	11.062	
All		80	4.418	4.593	5.340	5.816	
8		None	0	211.364	212.532	239.254	237.014
		1	12.5	48.887	48.899	55.520	54.901
	2	12.5	48.697	47.983	57.197	55.284	
	(1,2)	12.5	48.269	48.389	55.433	54.388	
	All	12.5	47.461	47.558	55.005	54.360	
	1	25	26.103	26.016	29.807	29.458	
	2	25	25.994	25.731	30.647	29.604	
	(1,2)	25	26.243	26.510	29.135	28.948	
	All	25	24.777	25.330	28.328	28.320	
	All	37.5	14.489	14.864	17.231	17.556	
	All	50	8.406	8.692	10.466	10.482	
	10	None	0	213.104	211.939	240.106	237.920
		1	10	52.220	52.308	60.219	59.850
2		10	52.406	51.910	61.246	59.852	
(1,2)		10	51.620	52.794	59.943	58.780	
All		10	51.291	51.414	59.139	58.520	
1		20	28.679	28.873	33.925	33.557	
2		20	29.157	28.858	34.482	33.709	
(1,2)		20	28.514	28.185	33.738	33.178	
All		20	28.170	28.809	32.537	32.458	
All		30	17.274	17.724	20.165	20.023	
All		40	10.644	10.987	12.941	12.741	
15		None	0	210.976	210.613	241.091	240.296
		1	6.67	58.348	58.322	67.401	67.355
	2	6.67	59.274	58.726	68.229	67.650	
	(1,2)	6.67	58.701	58.278	67.194	67.202	
	All	6.67	58.554	58.155	67.178	67.197	
	1	13.33	35.133	35.190	41.751	41.693	
	2	13.33	35.237	34.922	42.177	41.573	
	(1,2)	13.33	35.397	35.181	41.640	41.226	
	All	13.33	34.586	34.386	40.691	40.410	
	All	20	22.213	22.716	26.309	26.558	
	All	26.67	15.465	15.877	18.262	18.557	

Note: ARL\* represents the lowest ARL obtained from those EWMA control charts



**Table 35** Comparison of the Average Run Lengths between four multiple EWMA charts for  $\theta_{\text{fix}} = 0.5$  and 4 variables case.

Mean	Actual Region Shifted	% shift	I. Regression Adjustment of Y scale + EWMA		II MPEWMA
			L = 2.15 and $\lambda = 0.05$		$\lambda = 0.05$
3			ARL*		H = 11.49
	None	0	199.779		210.573
	1	33	30.486		23.033
	2	33	31.362		23.139
	(1,2)	33	30.067		15.693
	All	33	29.335		12.170
	1	67	14.943		10.053
	2	67	15.317		10.014
	(1,2)	67	14.094		7.202
	All	67	12.579		5.724
	All	100	5.041		3.839
	All	133	2.057		2.945
	5			ARL*	
None		0	209.706		211.002
1		20	39.606		31.196
2		20	40.446		31.417
(1,2)		20	39.245		21.916
All		20	38.630		15.469
1		40	20.155		13.682
2		40	20.595		13.725
(1,2)		40	19.432		9.496
All		40	18.389		7.087
All		60	9.647		4.661
All		80	4.418		3.541
8				ARL*	
	None	0	211.364		209.804
	1	12.5	48.887		38.307
	2	12.5	48.697		38.359
	(1,2)	12.5	48.269		28.732
	All	12.5	47.461		20.030
	1	25	26.103		18.503
	2	25	25.994		18.484
	(1,2)	25	26.243		12.445
	All	25	24.777		8.833
	All	37.5	14.489		5.650
	All	50	8.406		4.268
	10			ARL*	
None		0	213.104		210.250
1		10	52.220		40.090
2		10	52.406		40.379
(1,2)		10	51.620		32.180
All		10	51.291		22.557
1		20	28.679		21.395
2		20	29.157		21.345
(1,2)		20	28.514		14.056
All		20	28.170		9.755
All		30	17.274		6.298
All		40	10.644		4.719
15				ARL*	
	None	0	210.976		211.350
	1	6.67	58.348		43.318
	2	6.67	59.274		43.390
	(1,2)	6.67	58.701		37.281
	All	6.67	58.554		28.040
	1	13.33	35.133		27.658
	2	13.33	35.237		27.209
	(1,2)	13.33	35.397		18.160
	All	13.33	34.586		12.045
	All	20	22.213		7.677
	All	26.67	15.465		5.700

Note: ARL\* represents the lowest ARL obtained from those individual EWMA control charts

**Table 36** Comparison of the Average Run Lengths between six multiple EWMA charts for  $\theta = 0.5$  and 6 variables case.

Mean	Actual Region Shifted	% shift	I. Regression Adjustment of Y scale + EWMA		II MPEWMA
			L = 2.2 and $\lambda = 0.05$		$\lambda = 0.05$
3			ARL*		H = 14.93
	None	0	203.872		210.021
	1	33	30.944		24.692
	2	33	32.276		25.041
	(1,2)	33	30.344		16.836
	All	33	29.855		11.546
	1	67	15.350		10.708
	2	67	15.676		10.775
	(1,2)	67	14.402		7.565
	All	67	12.488		5.429
	All	100	4.795		3.613
	All	133	1.871		2.806
	5			ARL*	
None		0	212.519		210.145
1		20	40.244		33.167
2		20	41.369		33.810
(1,2)		20	40.128		23.745
All		20	39.677		14.179
1		40	20.844		14.994
2		40	21.380		14.956
(1,2)		40	19.997		10.191
All		40	18.651		6.526
All		60	9.409		4.340
All		80	4.405		3.302
8				ARL*	
	None	0	216.016		209.733
	1	12.5	49.459		39.937
	2	12.5	50.370		40.162
	(1,2)	12.5	49.531		30.922
	All	12.5	49.134		17.841
	1	25	26.927		20.249
	2	25	26.815		20.105
	(1,2)	25	26.197		13.422
	All	25	25.408		7.926
	All	37.5	14.814		5.193
	All	50	8.384		3.913
	10			ARL*	
None		0	216.923		209.776
1		10	53.915		42.413
2		10	54.153		42.072
(1,2)		10	53.222		34.616
All		10	53.477		20.322
1		20	29.879		23.477
2		20	30.146		23.382
(1,2)		20	29.411		15.354
All		20	28.775		8.804
All		30	17.345		5.687
All		40	10.932		4.226
15				ARL*	
	None	0	220.222		211.031
	1	6.67	60.392		44.087
	2	6.67	60.793		44.251
	(1,2)	6.67	60.3692		39.832
	All	6.67	59.676		25.218
	1	13.33	36.041		30.108
	2	13.33	36.487		29.906
	(1,2)	13.33	36.558		19.734
	All	13.33	35.546		10.772
	All	20	22.579		6.844
	All	26.67	15.369		5.077

Note: ARL\* represents the lowest ARL obtained from those individual EWMA control charts

**Table 37** Comparison of the Average Run Lengths between ten multiple EWMA charts for  $\theta = 0.5$  and 10 variables case.

Mean	Actual Region Shifted	% shift	I. Regression Adjustment of Y scale + EWMA (parshift)	
			L = 2.25 and $\lambda = 0.05$	IV MPEWMA $\lambda = 0.05$
3			ARL*	H = 21.17
	None	0	205.650	211.413
	1	33	31.829	27.844
	2	33	31.874	27.484
	(1,2)	33	31.273	18.429
	All	33	29.756	10.817
	1	67	15.555	11.864
	2	67	15.804	11.947
	(1,2)	67	14.370	8.194
	All	67	12.269	5.138
	All	100	4.917	3.490
	All	133	1.813	2.683
	5			ARL*
None		0	216.317	211.050
1		20	41.380	36.894
2		20	41.635	36.646
(1,2)		20	41.451	26.348
All		20	40.070	13.183
1		40	21.224	16.634
2		40	21.592	16.645
(1,2)		40	20.671	11.122
All		40	18.588	6.134
All		60	9.400	4.055
All		80	4.183	3.129
8				ARL*
	None	0	222.257	211.074
	1	12.5	50.793	42.561
	2	12.5	50.869	41.737
	(1,2)	12.5	50.351	34.729
	All	12.5	49.767	16.073
	1	25	27.551	22.901
	2	25	27.271	22.945
	(1,2)	25	26.903	15.084
	All	25	25.235	7.221
	All	37.5	14.683	4.768
	All	50	8.421	3.593
	10			ARL*
None		0	222.673	210.791
1		10	54.563	44.087
2		10	55.142	43.807
(1,2)		10	54.506	37.626
All		10	54.382	17.910
1		20	30.709	26.519
2		20	31.236	26.900
(1,2)		20	30.345	17.321
All		20	29.378	7.910
All		30	17.628	5.184
All		40	10.567	3.874
15				ARL*
	None	0	223.709	210.355
	1	6.67	62.139	45.261
	2	6.67	61.988	44.668
	(1,2)	6.67	62.373	42.046
	All	6.67	61.821	21.944
	1	13.33	37.378	33.580
	2	13.33	38.140	33.371
	(1,2)	13.33	37.641	22.388
	All	13.33	37.154	9.415
	All	20	22.978	6.048
	All	26.67	15.284	4.525

Note: ARL\* represents the lowest ARL obtained from those individual EWMA control charts

**Table 38** Comparison of the Average Run Lengths between fifteen multiple EWMA charts for  $\theta = 0.5$  and 15 variables case.

Mean	Actual Region Shifted	% shift	I. Regression Adjustment of Y scale + EWMA		II MPEWMA
			L = 2.3 and $\lambda = 0.05$		$\lambda = 0.05$
3			ARL*		H = 28.39
	None	0	205.740		212.430
	1	33	31.672		30.162
	2	33	32.463		30.304
	(1,2)	33	31.251		20.124
	All	33	30.273		10.565
	1	67	16.030		12.937
	2	67	16.176		12.811
	(1,2)	67	14.781		8.785
	All	67	12.330		5.019
	All	100	4.798		3.405
	All	133	1.858		2.620
5			ARL*		H = 28.34
	None	0	219.482		210.961
	1	20	42.388		39.355
	2	20	42.255		38.929
	(1,2)	20	41.857		28.677
	All	20	40.785		12.826
	1	40	21.743		18.390
	2	40	22.007		18.343
	(1,2)	40	20.841		12.093
	All	40	18.679		5.891
	All	60	9.459		3.952
	All	80	4.272		3.032
8			ARL*		H = 28.31
	None	0	224.872		211.828
	1	12.5	52.618		44.036
	2	12.5	52.194		43.131
	(1,2)	12.5	51.708		37.589
	All	12.5	51.556		15.397
	1	25	28.099		25.128
	2	25	28.215		25.454
	(1,2)	25	27.550		16.411
	All	25	25.760		6.839
	All	37.5	14.868		4.520
	All	50	8.234		3.445
10			ARL*		H = 28.30
	None	0	227.023		210.381
	1	10	56.338		44.687
	2	10	56.652		44.460
	(1,2)	10	56.398		39.743
	All	10	55.517		16.573
	1	20	31.323		29.444
	2	20	31.613		29.497
	(1,2)	20	31.127		18.847
	All	20	29.791		7.423
	All	30	17.806		4.856
	All	40	10.566		3.674
15			ARL*		H = 28.30
	None	0	228.241		211.097
	1	6.67	62.679		45.247
	2	6.67	63.514		45.592
	(1,2)	6.67	63.251		43.665
	All	6.67	62.422		19.954
	1	13.33	38.284		36.140
	2	13.33	38.806		36.230
	(1,2)	13.33	38.494		24.969
	All	13.33	37.236		8.740
	All	20	23.182		5.645
	All	26.67	15.644		4.220

Note: ARL\* represents the lowest ARL obtained from those individual EWMA control charts

**Table 39** Comparison of the Average Run Lengths between four multiple EWMA charts for  $\theta = 1$  and 4 variables case.

Mean	Actual Region Shifted	% shift	I. Regression Adjustment of Y scale + EWMA		II MPEWMA
			L = 2.35 and $\lambda = 0.05$		$\lambda = 0.05$
3			ARL*		H = 11.49
	None	0	204.186		209.945
	1	33	31.753		20.736
	2	33	34.370		20.817
	(1,2)	33	31.497		14.953
	All	33	30.771		13.964
	1	67	16.459		9.149
	2	67	17.484		9.207
	(1,2)	67	14.506		6.882
	All	67	13.240		6.408
	All	100	5.472		4.268
	All	133	2.185		3.270
	5			ARL*	
None		0	228.679		211.177
1		20	44.504		30.391
2		20	46.206		30.196
(1,2)		20	43.553		21.806
All		20	43.105		17.223
1		40	23.356		13.242
2		40	23.861		13.126
(1,2)		40	21.982		9.591
All		40	20.753		7.746
All		60	11.013		5.099
All		80	5.340		3.875
8				ARL*	
	None	0	239.254		210.074
	1	12.5	55.520		37.854
	2	12.5	57.197		37.638
	(1,2)	12.5	55.433		28.970
	All	12.5	55.005		21.736
	1	25	29.807		18.116
	2	25	30.647		18.225
	(1,2)	25	29.135		12.614
	All	25	28.328		9.508
	All	37.5	17.231		6.068
	All	50	10.466		4.570
	10			ARL*	
None		0	240.106		209.354
1		10	60.219		39.709
2		10	61.246		40.308
(1,2)		10	59.943		32.740
All		10	60.139		24.204
1		20	33.925		21.140
2		20	34.482		21.131
(1,2)		20	41.227		14.247
All		20	32.537		10.489
All		30	20.165		6.681
All		40	12.941		4.974
15				ARL*	
	None	0	241.091		209.510
	1	6.67	67.401		42.515
	2	6.67	68.229		42.743
	(1,2)	6.67	67.194		37.760
	All	6.67	67.178		29.715
	1	13.33	41.751		27.403
	2	13.33	42.177		27.163
	(1,2)	13.33	41.640		18.112
	All	13.33	40.691		12.778
	All	20	26.309		8.038
	All	26.67	18.262		5.918

Note: ARL\* represents the lowest ARL obtained from those individual EWMA control charts

**Table 40** Comparison of the Average Run Lengths between four multiple EWMA charts for  $\theta_{\text{fix}} = 1$  and 6 variables case.

Mean	Actual Region Shifted	% shift	I. Regression Adjustment of Y scale + EWMA		II MPEWMA
			L = 2.4 and $\lambda = 0.05$		$\lambda = 0.05$
3			ARL*		H = 14.95
	None	0	200.876		208.494
	1	33	31.785		22.197
	2	33	33.611		22.134
	(1,2)	33	30.815		15.431
	All	33	30.243		13.465
	1	67	16.433		9.808
	2	67	17.326		9.734
	(1,2)	67	14.716		7.068
	All	67	12.736		6.255
	All	100	5.226		4.141
	All	133	1.993		3.178
5			ARL*		H = 14.92
	None	0	227.943		209.71
	1	20	44.665		32.773
	2	20	46.177		32.322
	(1,2)	20	44.064		23.033
	All	20	43.544		16.392
	1	40	23.334		14.274
	2	40	24.001		14.368
	(1,2)	40	22.108		10.003
	All	40	20.676		7.453
	All	60	10.632		4.883
	All	80	5.036		3.706
8			ARL*		H = 14.91
	None	0	240.600		210.096
	1	12.5	56.772		39.621
	2	12.5	57.988		39.804
	(1,2)	12.5	56.733		31.109
	All	12.5	55.291		20.175
	1	25	30.547		19.880
	2	25	30.956		19.747
	(1,2)	25	30.068		13.406
	All	25	28.798		8.900
	All	37.5	16.806		5.757
	All	50	9.930		4.284
10			ARL*		H = 14.91
	None	0	240.673		210.320
	1	10	62.300		41.720
	2	10	62.523		42.455
	(1,2)	10	61.038		35.049
	All	10	60.527		22.494
	1	20	34.627		23.239
	2	20	34.970		22.995
	(1,2)	20	34.269		15.485
	All	20	33.082		9.718
	All	30	20.394		6.218
	All	40	13.038		4.648
15			ARL*		H = 14.90
	None	0	244.579		209.452
	1	6.67	69.809		43.628
	2	6.67	69.694		43.870
	(1,2)	6.67	68.722		39.950
	All	6.67	68.576		27.270
	1	13.33	43.161		30.238
	2	13.33	43.677		29.860
	(1,2)	13.33	43.185		19.963
	All	13.33	42.221		11.535
	All	20	26.667		7.308
	All	26.67	18.113		5.398

Note: ARL\* represents the lowest ARL obtained from those individual EWMA control charts

**Table 41** Comparison of the Average Run Lengths between four multiple EWMA charts for  $\theta_{\text{fix}} = 1$  and 10 variables case.

Mean	Actual Region Shifted	% shift	I. Regression Adjustment of Y scale + EWMA		II MPEWMA
			L = 2.45 and $\lambda = 0.05$		$\lambda = 0.05$
3			ARL*		H = 21.19
	None	0	197.275		212.060
	1	33	32.077		24.349
	2	33	32.365		24.588
	(1,2)	33	31.020		16.435
	All	33	29.859		13.139
	1	67	16.505		10.540
	2	67	17.134		10.564
	(1,2)	67	14.974		7.416
	All	67	12.428		6.050
	All	100	4.932		4.054
	All	133	1.935		3.084
	5			ARL*	
None		0	228.754		211.92
1		20	44.765		35.644
2		20	46.138		35.442
(1,2)		20	44.175		25.038
All		20	43.858		16.014
1		40	23.215		15.755
2		40	23.726		15.704
(1,2)		40	22.255		10.711
All		40	20.034		7.254
All		60	10.483		4.773
All		80	4.796		3.606
8				ARL*	
	None	0	242.032		212.212
	1	12.5	57.075		41.982
	2	12.5	58.389		42.035
	(1,2)	12.5	57.266		34.383
	All	12.5	56.624		19.318
	1	25	30.948		22.011
	2	25	31.413		22.269
	(1,2)	25	30.376		14.767
	All	25	28.893		8.502
	All	37.5	16.691		5.466
	All	50	9.634		4.102
	10			ARL*	
None		0	243.229		209.904
1		10	61.899		43.342
2		10	63.042		43.475
(1,2)		10	62.262		37.833
All		10	62.045		21.214
1		20	35.300		26.039
2		20	35.549		25.893
(1,2)		20	35.086		17.165
All		20	33.288		9.069
All		30	20.053		5.859
All		40	12.468		4.387
15				ARL*	
	None	0	247.037		211.668
	1	6.67	69.722		44.877
	2	6.67	70.594		45.454
	(1,2)	6.67	70.066		42.3493
	All	6.67	69.559		24.629
	1	13.33	43.729		33.124
	2	13.33	44.513		33.064
	(1,2)	13.33	43.757		22.402
	All	13.33	42.201		10.523
	All	20	26.792		6.738
	All	26.67	17.866		4.998

Note: ARL\* represents the lowest ARL obtained from those individual EWMA control charts

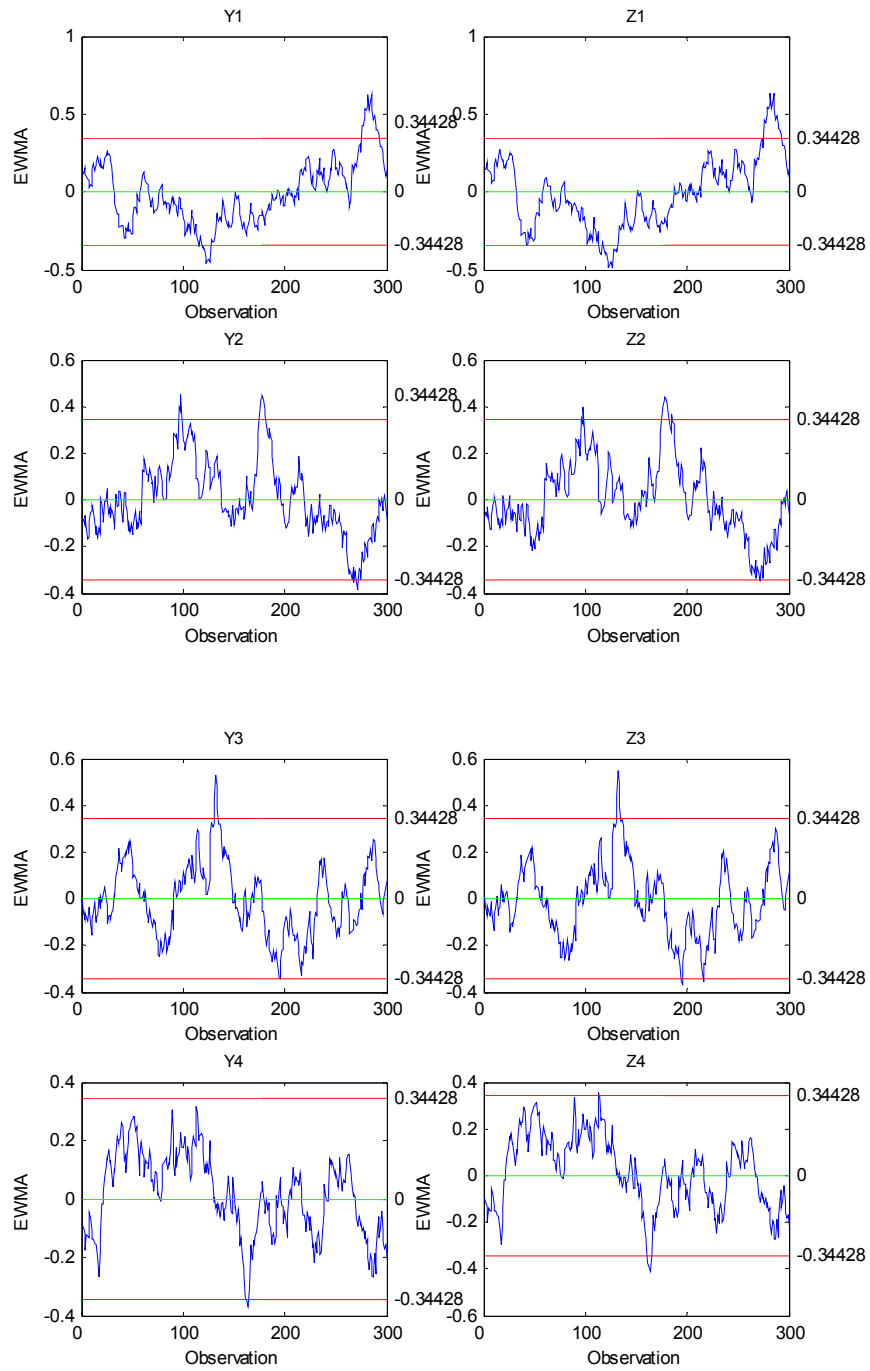
**Table 42** Comparison of the Average Run Lengths between four multiple EWMA charts for thetalfix = 1 and 15 variables case.

Mean	Actual Region Shifted	% shift	I. Regression Adjustment of Y scale + EWMA		II MPEWMA
			L = 2.55 and $\lambda = 0.05$		$\lambda = 0.05$
3			ARL*		H = 28.41
	None	0	201.580		209.948
	1	33	32.816		26.690
	2	33	33.627		26.711
	(1,2)	33	32.145		17.530
	All	33	30.419		12.831
	1	67	17.629		11.360
	2	67	17.898		11.326
	(1,2)	67	15.920		7.863
	All	67	12.801		5.956
	All	100	5.156		3.912
	All	133	2.012		3.015
5			ARL*		H = 28.34
	None	0	236.314		210.28
	1	20	46.573		37.585
	2	20	47.508		37.684
	(1,2)	20	46.552		27.600
	All	20	45.137		15.965
	1	40	24.260		17.299
	2	40	24.845		17.218
	(1,2)	40	23.929		11.493
	All	40	20.944		7.162
	All	60	11.135		4.700
	All	80	5.065		3.563
8			ARL*		H = 28.32
	None	0	247.979		212.357
	1	12.5	59.843		43.275
	2	12.5	60.348		43.340
	(1,2)	12.5	59.056		36.480
	All	12.5	58.423		18.810
	1	25	32.939		24.787
	2	25	33.154		24.597
	(1,2)	25	31.877		16.130
	All	25	30.136		8.248
	All	37.5	17.611		5.371
	All	50	10.208		4.005
10			ARL*		H = 28.31
	None	0	250.813		211.739
	1	10	64.449		44.388
	2	10	65.815		44.621
	(1,2)	10	64.435		39.922
	All	10	63.555		20.420
	1	20	36.650		28.375
	2	20	37.369		28.833
	(1,2)	20	36.436		18.800
	All	20	34.622		8.776
	All	30	21.103		5.724
	All	40	13.093		4.284
15			ARL*		H = 28.3
	None	0	255.313		211.468
	1	6.67	72.635		45.452
	2	6.67	73.671		46.359
	(1,2)	6.67	72.568		43.198
	All	6.67	71.895		23.741
	1	13.33	46.328		35.940
	2	13.33	46.750		36.070
	(1,2)	13.33	46.248		24.901
	All	13.33	44.604		10.014
	All	20	27.925		6.431
	All	26.67	18.832		4.808

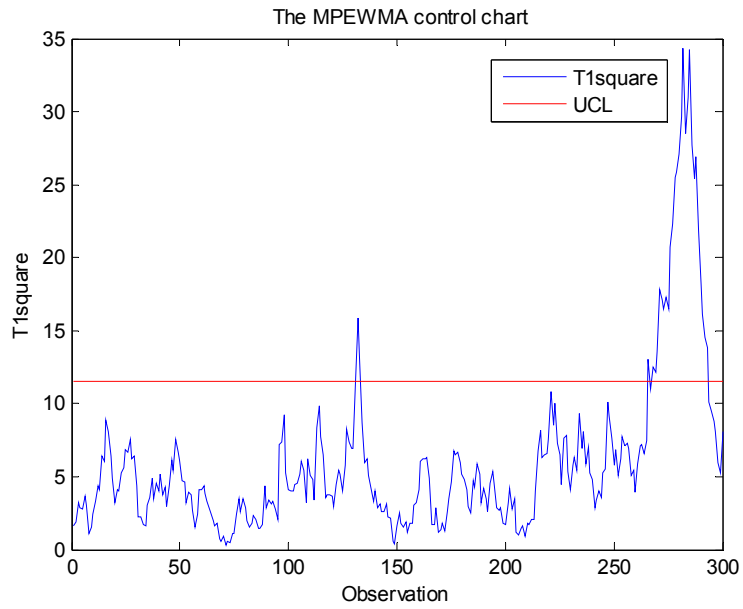
Note: ARL\* represents the lowest ARL obtained from those individual EWMA control charts



**Figure 6** Plots of EWMA charts of the regression adjustment on both Y and Z scales



**Figure 7** Plots of MPEWMA chart with  $H = 11.49$



## Chapter 6

### CONCLUSION AND RECOMMENDATIONS

#### 6.1 Conclusion

We presented a new type of the multivariate Exponentially Weighted Moving Average control chart for monitoring multiple related count data. This kind of data can usually be found when monitoring several types of defects per unit of product or defects per area of product in the manufacturing process. In fact, often the number of defects is small and tends to depart from a normal distribution. There is also some common relationship among all variables and consequently it can be assumed that the multivariate Poisson distribution holds. The multivariate Poisson EWMA (or MPEWMA) chart has been proposed to detect small and medium changes in the mean counts. The Poisson limits are directly derived from the multivariate Poisson distribution, instead of the normality.

We have demonstrated that control chart performance in monitoring multivariate Poisson-distributed data is slightly different between a scheme based on normal-theory limits and a scheme based directly on multivariate Poisson-distribution limits. ARL tables are presented to show the general performance of the MPEWMA scheme. The control limits of the proposed method are slightly wider than those that relied on the normality assumption. Based on the ARL results, we find that the proposed control chart produces out-of-control ARL values similar to the standard normal-theory MEWMA. However, the MPEWMA

control chart is superior to the traditional MEWMA in terms of the in-control ARL. The use of the normal-theory limits can lead to substantially smaller in-control ARL values than what is stated when the data follow a multivariate Poisson distribution. Thus, the result shows the potential of using the MPEWMA with Poisson-distributed data in reducing the false alarm rate. The standard deviation run length is provided, and therefore the standard error of the mean can be obtained if desired. Furthermore, we illustrate some examples of implementation the MPEWMA chart in practice.

We extended the two-sided multivariate Poisson EWMA to the one-sided control chart based on the multivariate Poisson assumption as a method for detecting only upward shifts in the mean of multiple count data. The control limits are again established using the multivariate Poisson distribution instead of the normal approximation limits. The results indicate that the multivariate Poisson-distribution limits are wider than the normal-theory limits. The statistical performances of the one-sided MPEWMA scheme are presented by both average and standard deviation of the run length. The results indicate that applying the one-sided MEWMA with the normal-theory limits to the multivariate Poisson distribution can result in a smaller in-control ARL than the advertised value. MEWMA causes a high false alarm rate when the process is actually in control.

Four case studies are illustrated to investigate the one-sided MPEWMA performance for detecting a single and a run of out-of-control signals (2 to 5 consecutive points). The time-delay in detection tends to increase with the amount of out-of-control points waiting to signal, particularly when there is a shift in a

few variables. The use of the consecutive points method is similar to the single point method when monitoring a shift in all variables because it takes a slightly longer time to detect the first out-of-control signal. The single point approach is preferred to detect a shift in one or possible two variables since it reduces detection times compared to a long run of out-of-control signals.

The proposed MPEWMA chart is also compared with other model-based control charts for monitoring count data from multiple sources. Two techniques for model building are investigated: 1) the regression adjustment and 2) the generalized linear model. We consider the regression adjustment based on two ways of decomposing the Hotelling  $T^2$  statistics, and they are called the Y and Z scales. For the generalized linear model, Poisson regression is selected for modeling the Poisson distribution. The residuals (computed from the regression adjustment) and deviance residuals (calculated from the Poisson regression) are plotted on the multiple EWMA charts as those residuals are approximately normally distributed. The comparison results show that the MPEWMA scheme outperforms two residual-based control charts for all scenarios due to the small out-of-control ARL values. Hence, the MPEWMA chart can detect changes in the mean of a Poisson count earlier than those model-based control methods. Fewer samples will be taken to indicate that the process mean has increased.

## **6.2 Future work**

Several concerns of the multivariate Poisson EWMA chart still require further exploration. Firstly, this paper uses a multivariate Poisson model that allowed only positive correlation. It is also interesting to develop the multivariate

Poisson distribution with the general correlation structure, and therefore a new control scheme can be extended to allow negative correlation among variables. A theoretical framework of the multivariate Poisson model and an effective method for generating data are desirable to examine the statistical performance of the new scheme.

Secondly, one disadvantage of using the multivariate control scheme is in interpretation of the out-of-control signal. It is not easy to determine which quality characteristic is associated with the mean shift signal, particularly for the high dimensional case. Moreover, the change in either local ( $\theta_i$ ) or common ( $\theta$ ) variables can result in an increased mean. An advanced method is needed to identify the variables that correspond to an increase in the mean. Consequently, a proper action can be taken to correct the problem.

Thirdly, it is necessary to investigate additional conditions of the parameters. For example, a study on the effect of the  $\theta$  parameter and its role in the average run length performance. In this research, we have only explored two values of  $\theta$ , 0.5 and 1, and the ARL values of  $\theta = 0.5$  appear to be slightly larger than for the  $\theta = 1$ . The parameter should vary over a wide range of values in order to investigate the MPEWMA chart's performance. The results are needed to gain more insight into the detection of the mean change in the common variable. In addition, we simplified the process monitoring problem by assuming that all quality characteristics have equal means. This is too restrictive an assumption in many real world applications. The mean of one variable can be different than the others. Thus, it is more appealing to estimate the control chart

performance under this circumstance (i.e. unequal means of the variables). One more thing, the change in the means is limited to a permanent upward shift, in other words, the count means increase and hold on to the new level after the shift has occurred. However, the shift is sometimes happen during a certain period of time (e.g. the spike of the mean shift). It is also a good idea to find some way to detect this spike shift as well as the permanent shift in the multiple count data.

Lastly, an existing method of estimation the theta parameters in the multivariate Poisson model is not guaranteed to have a good performance in the high dimensional problems. The advanced method is needed to provide more accurate the theta estimates. Thus, phase I of the proposed MPEWMA chart can be established based on this method. The statistical performance of the MPEWMA scheme in phase I will be evaluated on the basis of the run length distribution.

## REFERENCES

- Bersimis, S., Psarakis, S. and Panaretos, J. (2006) 'Multivariate Statistical Process Control Charts: An Overview', *Quality and Reliability Engineering International*, Vol. 5, No. 23, pp.517-543.
- Box, G.E.P., Luceño, A. and Paniagua-Quiñones, M.C. (2009) *Statistical Control by Monitoring and Feedback Adjustment*, New York NY: John Wiley & Sons, Inc.
- Burkom, H.S., Elbert, Y., Feldman, A. and Lin, J. (2004) 'Role of Data Aggregation in Biosurveillance Detection Strategies with Applications from Essence', *Morbidity and Mortality Weekly Report, the Epidemiology Program Office, Centers for Disease Control and Prevention (CDC)*, Vol. 53(Suppl), pp.67-73.
- Burkom, H.S., Murphy, S., Coberly, J. and Hurt-Mullen, K. (2005) 'Public Health Monitoring Tools for Multiple Data Streams', *Morbidity and Mortality Weekly Report, the Epidemiology Program Office, Centers for Disease Control and Prevention (CDC)*, Vol. 54(Suppl), pp.55-62.
- Burkom, H.S., Murphy, S.P. and Shmueli, G. (2007) 'Automated Time Series Forecasting for Biosurveillance', *Statistics in Medicine*, Vol. 26, Iss. 22, pp.4202-4218.
- Chiu, J.E. and Kuo T.I. (2008) 'Attribute Control Chart for Multivariate Poisson Distribution', *Communications in Statistics-Theory and Methods*, Vol. 37, pp.146-158.
- Cook, R.D. and Weisberg S. (1982) *Residuals and Influence in Regression*, New York: Chapman and Hall.
- Fassò, A. (1999) 'One-Sided MEWMA Control Charts', *Communications in Statistics: Simulation and Computation*, Vol. 28, No. 2, pp.381-401.



- FassÖ, A. and Locatelli S. (2007) 'Asymmetric Monitoring of Multivariate Data with nonlinear dynamics', *AStA Advances in Statistical Analysis*, Vol. 91, pp.23-37.
- Follmann, D. (1996) 'A Simple Multivariate Test for One-sided Alternatives' *Journal of the American Statistical Association*, Vol. 91, No. 434, pp.854-861.
- Fricker R.D. (2009) 'Some Methodological Issues in Biosurveillance', (draft dated September 30, 2009).
- Fricker, Jr., R.D., Knitt, M.C. and Hu, C.X. (2008) 'Comparing Directionally Sensitive MCUSUM and MEWMA Procedures with Application to Biosurveillance', *Quality Engineering*, Vol. 20, Iss. 4, pp.478-494.
- Hawkins, D.M. (1991) 'Multivariate Quality Control Based on Regression-Adjusted Variables', *Technometrics*, Vol. 33, No. 1, pp.61-75.
- Hawkins, D.M. (1993) 'Regression Adjustment for Variables in Multivariate Quality Control', *Journal of Quality Technology*, Vol. 25, Iss. 3, pp.170-182.
- Hawkins, D.M. and Maboudou-Tchao, E.M. (2008) 'Multivariate Exponentially Weighted Moving Covariance Matrix', *Technometrics*, Vol. 50, No. 2, pp.155-166.
- Healy, JD. (1987) 'A Note on Multivariate CUSUM Procedure', *Technometrics*, Vol. 29, No. 4, pp.409-412.
- Holgate, P. (1964) 'Miscellanea: Estimation for the Bivariate Poisson Distribution', *Biometrika*, Vol. 51, pp.241-245.
- Johnson, N.L., Kotz, S. and Balakrishnan, N. (1997) *Discrete Multivariate Distributions*, New York: John Wiley & Sons, Inc.

- Joner, Jr., M.D., Woodall, W.H. and Reynolds, Jr., M.R. (2005) 'The Use of Multivariate Control Charts to Detect Changes in the Spatial Patterns of Disease'. *Paper Presented at the 2005 Joint Statistical Meetings. August 7-11, 2005. Minneapolis, Minnesota. (Submitted for publication)*
- Joner, Jr., M.D., Woodall, W.H., Reynolds, Jr., M.R. and Fricker, Jr., R.D. (2008) 'A One-sided MEWMA Chart for Health Surveillance', *Quality and Reliability Engineering International*, Vol. 24, pp.503-518.
- Jost, T.A., Brcich, R.F. and Zoubir, A.M. (2006) 'Estimating The Parameters of The Multivariate Poisson Distribution Using The Composite Likelihood Concept', *The Proceedings of the 31<sup>st</sup> IEEE International Conference On Acoustics, Speech and Signal Processing*. May 14-19, 2006. Toulouse, France.
- Karlis, D. (2003) 'An EM Algorithm for Multivariate Poisson Distribution and Related Models', *Journal of Applied Statistics*, Vol. 30, Iss. 1, pp.63-77.
- Kawamura, K. (1979) 'The Structure of Multivariate Poisson Distribution', *Kodai Mathematical Journal*, Vol. 2, No. 3, pp.337-345.
- Kuo T.I. and Chiu, J.E. (2008) 'Regression-Based Limits for Multivariate Poisson Control Chart', *Proceedings of the Industrial Engineering and Engineering Management 2008 International Conference*. December 8-10, 2008. Singapore.
- Lewis, S.L., Montgomery, D.C. and Myers, R.H. (2001) 'Confidence Interval Coverage for Designed Experiments Analyzed with Generalized Linear Models' *Journal of Quality Technology*, Vol. 33. Iss. 3, pp.279-292.
- Lindsay, B.G. (1988) 'Composite Likelihood Methods', *Contemporary Mathematics*, Vol. 80, pp.221-239.
- Lotze T. and Shmueli G. (2008) 'On the Relationship between Forecase Accuracy and Detection Performance: An Application to Biosurveillance', *2008 IEEE Conference on Technologies for Homeland Security*. May 12-13, 2008 Boston, MA, pp.100-105.

- Lotze T., Murphy, S. and Shmueli G. (2008) 'Implementation and Comparison of Preprocessing Methods for Biosurveillance Data', *Advances in Disease Surveillance*, Vol. 6, No. 1, pp.1-20.
- Lowry, C.A., Woodall, W.H., Champ, C.W. and Rigdon, S.E. (1992) 'A Multivariate Exponential Weighted Moving Average Control Chart', *Technometrics*, Vol. 34, No. 1, pp.46-53.
- Lucas, J.M. (1985) 'Counted data CUSUM's', *Technometrics*, Vol 27, No. 2, pp.129-144.
- Mandel B.J. (1969) 'The Regression Control Chart', *Journal of Quality Technology*, Vol. 1, Iss. 1, pp.1-9.
- Montgomery, D.C. (2009) *Introduction to Statistical Quality Control*, Hoboken NJ: John Wiley & Sons, Inc.
- Myers, R.H., Montgomery, D.C. and Vining, G.G. (2001) *Generalized Linear Models: With Applications in Engineering and the Science*, New York NY: John Wiley & Sons, Inc.
- Niaki, S.T.A. and Abbasi, B. (2005) 'Fault Diagnosis in Multivariate Control Charts Using Artificial Neural Networks', *Quality and Reliability Engineering International*, Vol. 21, Iss. 8, pp.825-840.
- Patel, H.I. (1973) 'Quality Control Methods for Multivariate Binomial and Poisson Distributions', *Technometrics*, Vol. 15, No. 1, pp.103-112.
- Prabhu, S.S. and Runger, G.C. (1997) 'Designing a Multivariate EWMA Control Chart', *Journal of Quality Technology*, Vol. 29, Iss. 1, pp.8-15
- Rigdon, S.E. (1995a) 'An Integral Equation for the In-Control Average Run Length of a Multivariate Exponentially Weighted Moving Average Control Chart', *Journal of Statistical Computation and Simulation*, Vol. 52, Iss. 4, pp.351-365.

- Rigdon, S.E. (1995b) 'A Double-Integral Equation for the Average Run Length of a Multivariate Exponentially Weighted Moving Average Control Chart', *Statistics & Probability Letters*, Vol. 24, Iss. 4, pp.365-373.
- Roberts, S. W. (1959). 'Control Chart Tests Based on Geometric Moving Averages', *Technometrics*, Vol. 1, No. 3, pp.239-250.
- Rolka, H., Burkom, H., Cooper, G.F., Kulldorff, M., Madigan, D. and Wong, W.K. (2007) 'Issues in Applied Statistics for Public Health Bioterrorism Surveillance Using Multiple Data Streams: Research needs', *Statistics in Medicine*, Vol. 26, pp.1834-1856.
- Runger, G.C. and Prabhu, S.S. (1996) 'A Markov chain model for the multivariate exponentially weighted moving averages control chart', *Journal of the American Statistical Association*, Vol. 91, No. 436, pp.1701-1706.
- Shmueli G. (2009) 'Statistical Challenges in Modern Biosurveillance', *Technometrics*, to be published.
- Shmueli G. and Fienberg S.E. (2006) 'Current and Potential Statistical methods for Monitoring Multiple Data Streams for Bio-surveillance', *In: Wilson, A.G., Wilson, G.D., and Olwell D.H. (ed.), Statistical Methods in Counter-Terrorism: Game Theory, Modeling, Syndromic Surveillance, and Biometric Authentication*, (109-140), Springer: New York.
- Skinner, K.R., Montgomery, D.C. and Runger, G.C. (2003). 'Process Monitoring for Multiple Count Data Using Generalized Linear model-based control charts', *International Journal of Production Research*, Vol. 41, No. 6, pp.1167-1180.
- Skinner, K.R., Montgomery, D.C. and Runger, G.C. (2004). 'Generalized Linear model-based Control Charts for Discrete Semiconductor Process Data', *Quality and Reliability Engineering International*, Vol. 20, Iss. 8, pp.777-786.
- Skinner, K.R., Runger, G.C. and Montgomery, D.C. (2006). 'Process Monitoring for Multiple Count Data Using a Deleted-Y Statistic', *Quality Technology and Quantitative Management*, Vol. 3, pp.247-262.

- Sonesson, C. and Frisén, M. (2005) 'Multivariate Surveillance', *In: Lawson, A.B., Kleinman, K. (ed.), Spatial and Syndromic Surveillance*, (pp.153-166), Wiley: West Sussex.
- Stoto, M.A., Fricker, Jr., R.D., Jain, A., Diamond, A., Davies-Cole, J.O., Glymph, C., Kidane, G., Lum, G., Jones, L., Dehan, K. and Yuan, C. (2006) 'Evaluating Statistical Methods for Syndromic Surveillance', *In: Wilson, A.G., Wilson, G.D., and Olwell D.H. (ed.), Statistical Methods in Counterterrorism*, (pp.141-172), Springer: New York.
- Stoumbos, Z.G. and Sullivan, J.H. (2002) 'Robustness to Non-normality of the Multivariate EWMA Control Chart', *Journal of Quality Technology*, Vol. 34, Iss. 3, pp.260-276.
- Sullivan, J.H. and Woodall, W.H. (1996) 'A Comparison of Multivariate Quality Control Charts for Individual Observations', *Journal of Quality Technology*, Vol. 28, Iss. 4, pp.398-408.
- Sullivan, J.H. and Woodall, W.H. (1998). "Adapting Control Charts for the Preliminary Analysis of Multivariate Observations." *Communications in Statistics-Simulation and Computation*, Vol. 27, Iss. 4, pp.953-979.
- Testik, M.C., Runger, G.C. and Borrór, C.M. (2003) 'Robustness Properties of Multivariate EWMA Control Charts', *Quality and Reliability Engineering International*, Vol. 19, Iss. 1, pp.31-38.
- Testik, M.C. and Borrór, C.M. (2004) 'Design Strategies for the Multivariate Exponentially Weighted Moving Average Control Chart', *Quality and Reliability Engineering International*, Vol. 20, Iss. 6, pp.571-577.
- Testik, M.C. and Runger, G.C. (2006) 'Multivariate One-sided Control Charts', *IIE Transactions*, Vol. 38, No. 8, pp.635-645.
- Williams, J.D., Woodall, W.H., Birch, J.B., and Sullivan, J.H. (2006) 'On the Distribution of Hotelling's  $T^2$  Statistics Based on the Successive Difference Estimator', *Journal of Quality Technology*, Vol. 38, Iss. 3, pp.217-229.

- Woodall, W.H. (2006) 'The Use of Control Charts in Health-Care and Public-Health Surveillance', *Journal of Quality Technology*, Vol. 38, Iss. 2, pp.89-134.
- Woodall, W.H. and Mahmoud, M.A. (2005) 'The Inertial Properties of Quality Control Charts', *Technometrics*, Vol. 47, No. 4, pp.425-436.
- Yan P., Chen H. and Zeng D. (2008) 'Syndromic Surveillance Systems: Public Health and Biodefense', *Annual Review of Information Science and Technology*, Vol. 42, pp.425-495.
- Yahav, I. and Shmueli, G. (2009). An Elegant Method for Generating Multivariate Poisson Data. Obtained through the Internet: [arXiv:0710.5670v2](https://arxiv.org/abs/0710.5670v2) [accessed 5/10/2009].
- Yahav, I. and Shmueli, G. (2010). Directionally- Sensitive Multivariate Control Charts in Practice: Application to Biosurveillance. Obtained through the Internet: <http://www.bmgt.umd.edu/faculty/gshmueli/web/images/mcharts-jr3+submitted.pdf>, [accessed 15/5/2010].
- Xie, M., Goh, T.N. and Kuralmani, V. (2002) *Statistical Models and Control Charts for High Quality Processes*, Boston MA: Kluwer Academic Publishers.
- Zhang GX. (1984). 'A New Type of Control Charts and a Theory of Diagnosis with Control Charts', *World Quality Congress Transactions*, pp.175-185.

## APPENDIX A

## APPENDIX A

### MATLAB CODING FOR OBTAINING THE CONTROL LIMITS

#### OF THE MPEWMA CHART

```
close all;
clear all;

% Set the variables
n = 4;           % number of variables of interest
lamda = 0.05;   % define value of lambda
M = 3;          % define value of the mean vector
thetafix = 0.5; % define value of the common mean
t = 0;          % define the trail value of the control limit
shift_position = 201; % set the occurrence of the mean shift
cycle = 50000;  % set the number of maximum cycles
lp_max = 100000; % set the number of maximum loops to prevent infinity run

% Set the location to save result file
dir = 'H:\Research\Result\';

% Normal Theory limits
nlambdaH=[4,0.05,11.22;4,0.1,12.73;6,0.05,14.60;6,0.1,16.27;10,0.05,20.72;
10,0.1,22.67;15,0.05,27.82;15,0.1,30.03];

% Assign shift matrix
shiftmatrix=[0,0,0,0;1,0,0,0;0,1,0,0;2,0,0,0;0,2,0,0;1,1,0,0;2,2,0,0;1,0,1,0;0,0,2,0;
1,0,0,1;0,0,0,2;1,1,1,1;2,2,2,2;3,3,3,3;4,4,4,4];
countshift = max(size(shiftmatrix));

% Fix variables
Me = zeros(n,1);
Cov = zeros(n,n);
Yi = zeros(n,1);
Xi0 = zeros(n+1,1);
theta_tmp = zeros(n,1);
countall = ones(1,cycle);

% Using trial and error based on the normal limits to obtain the Poisson limits
countnlH = max(size(nlambdaH(:,1)));
for i=1:countnlH
    if (nlambdaH(i,1)== n) & (nlambdaH(i,2)== lamda)
        H = nlambdaH(i,3);
    end
end
```



```

    end
end
H = H + t;

% Find mean vector assuming all means are equal
for i = 1:n
    Me(i) = M;
end
% Find covariance matrix
for i = 1:n
    for j = 1:n
        if i == j
            Cov(i,j) = Me(i);
        else
            Cov(i,j) = thetafix;
        end
    end
end
end

lamda001 = 1/(lamda/(2-lamda));
thetafix_N = thetafix*ones(n,1);

% Calculate the control limits for each shift matrix
for s = 1:countshift
    shift = shiftmatrix(s,:);
    cyc_cnt = 1;

    % To satisfy the steady-state condition, each cycle will loop for at least 200
    % periods. If fail before reaching 200 loops, we re-do simulation. If not fail
    % after 200 loops pass, the simulation continues until fail or reach lp_max
    while (cyc_cnt <= cycle)
        Me_shift = Me;
        theta_tmp = Me_shift - thetafix_N;
        z = zeros(n,1);
        lp_cnt = 1;
        while ( lp_cnt < lp_max )
            % Generate Xi and Yi
            Xi0 = poissrnd([thetafix;theta_tmp]);
            for i=1:n
                Yi(i) = Xi0(i+1) + Xi0(1);
            end

            % Calculate T-square based on asymptotic assumption
            z = (lamda*(Xi-Me)) + ((1-lamda)* z);
            invCov = inv(Cov);

```

```

Covarinv = lamda001*invCov;
T1square = z' * Covarinv * z;

% Check if the T-square is in or out of control
if(T1square > H)
    if(lp_cnt<shift_position)
        lp_cnt = 1;
        z = zeros(n,1);
        Me_shift = Me;
        theta_tmp = Me_shift - thetfix_N;
    else
        break;
    end
else
    if(lp_cnt==shift_position)
        %Change in the mean vector after the shift period
        Me_shift = Me + shift;
        theta_tmp = Me_shift - thetfix_N;
        %Change in the variance-covariance matrix after the shift period
        for i = 1:n
            for j = 1:n
                if i == j
                    Cov(i,j) = Me_shift(i);
                else
                    end
                end
            end
        end
        lp_cnt = lp_cnt + 1;
    end
end
countall(cyc_cnt) = lp_cnt - shift_position - 1;
cyc_cnt = cyc_cnt+1;
end
countall_s(s,:) = countall(:);

% Create the result file
str = strcat('Total_ARL','M=',num2str(M),'thetfix=',num2str(thetfix),'H=',
num2str(H),'VAR=',num2str(n),'S=',num2str(s),'Lamda=',num2str(lamda),
'Poi=',num2str(shift_position),'.dat');
filename = [dir,str];
fid1 = fopen(filename,'w');
% Print the average run length from all cycles and run length of each cycle
fprintf(fid1,'n%12s','ARL');

```

```
MeanARL = mean(countall_s(s,:));
fprintf(fid1, '%12.3f',MeanARL);
fprintf(fid1, '\n%12s','Loop');
fprintf(fid1, '%10s%2d','No,s=',s);
fprintf(fid1, '\n');
for cyc_cnt = 1:cycle;
    fprintf(fid1, '%12d',cyc_cnt);
    fprintf(fid1, '%12d',countall_s(s,cyc_cnt));
    fprintf(fid1, '\n');
end
fclose(fid1);
end
```