The Performance Assessment for the dMEWMA in Capturing Changes in Simple Linear Profiles

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Abstract

In traditional quality control, the quality of product is typically modeled as the univariate or multivariate distribution of the quality parameters. In more recent applications, the quality is modeled using the relationship between a response and independent variable. This paper investigates the performance of multivariate version of the double dMEWMA statistics in detecting changes in step shift in the intercept, slope, and error-variance of simple linear quality profiles. The statistical performance of the dMEWMA chart is estimated and compared versus three different charting techniques includeing the Hotelling T^2 , EWMA/R and dEWMA3. For all the compared charts, the average run length (ARL) under wide range of shift levels are estimated in order to draw beneficial conclusions.

Keywords: Profile Monitoring, dMEWMA Chart, Run Length

1. Introduction

The statistical process control (SPC) has been extensively applied in different sectors of production and service industries for the purpose of monitoring the process stability over time. Several methods have developed for improving the speed of detecting abnormal changes in the nominal values of the quality parameters. There are two different research trends under the SPC applications. These are the classical multivariate and variable selection process monitoring. Examples of these methods are Wang and Jiang (2009), Zou and Qiu (2009), Dai *et al.* (2011), Zou *et al.* (2011), Abdella *et al.* (2017), and Adeoti (2018).

Now days, the SPC research area is witnessing a new orientation in the way of characterizing the quality of the process. Rather than using the statistical distribution, the quality is described by the relationship relates the response variable with one or more process settings. Some examples of types of relationships considered in literature are a simple, multiple, and nonlinear functions.

In 2000, which is the real start of the profile monitoring research trend, Kang and Albin (2000) suggested two different methods, multivariate T^2 and EWMA/R, for detecting changes in slope and intercept of a simple linear quality profiles. In 2003, Kim *et al.* suggested the transformation of the explanatory variables to have a zero average and make the regression estimates independent on each other. After that, they used three individual EWMA control charts to monitor the three parameters of the simple linear quality profiles. This method is referred to as EWMA3. Mahmoud and Woodall (2004) developed a novel technique using the Global F-test to observe the changes in the regression estimates of the simple linear profiles and a single control chart to monitor the fluctuations around the linear regression line. In 2007, Zou *et al.* examined a novel multivariate method (MEWMA) for observing general linear models. Mahmoud *et al.* (2006) proposed another method based on the change point. Saghaei *et al.*(2009) proposed a profiling technique using an accumulative sum statistics for detecting changes in the linear quality profiles. Mahmoud (2008) proposed a new method for Phase I multiple. The Simulation results revealed the powerful performance of the suggested method comapring with several of its existing counterparts. Saghaei *et al.* (2009) considered the case of drift shift and investigated the performance of three of well-known phase II methods for monitoring simple linear profiles. Zhang *et al.*(2009) introduced an EWMA control chart based on the likelihood ratio for detecting changes the linear quality functions. Abdella *et al.* (2010) studied the effect of the spacing between the indpendent varaibles in the performance of the Hotelling T^2 chart for detecting changes in polynomial quality functions. Ameri *et al.* (2012) developed a mthod based on integrating MEWMA with dimension reduction approach for the purpose of detecting changes in multiple linear quality functions. Solemani *et.al* (2013) investigated the impact of the violation of the independence assumption of observations within a profile. Abdella *et al.* (2014) developed an adaptive T^2 chart for detecting deviations in regression coifficents of simple linear profiles.

This paper provides a comparative study of the performance of three phase II methods using the dEWMA statistics in monitoring and capturing undesirable deviations in the slope and the intercept of the linear quality profiles. The first method follows the transformation procedure suggested by Kim *et al.* (2003) and uses three individual dEWMA control charts, named as dEWMA3; see Abbas *et al.* (2017). The second method is a direct extension for the dMEWMA method, proposed by Alkahtani and Schaffer (2012), to profile monitoring research area. Similar method was used by Abdella *et al.* (2016) for observing deviations in the second-order polynomial profiles. Like the EWMA/R, the third method uses two dEWMA charts with a single R-Chart for monitoring the variability.

The rest of this paper is structured as follows: Section two is devoted for describing the dEWMA3 and dMEWMA methods and stating the control statistics. The results of the simulation studies are reported in section 3. Conclusions and remarks can be found in section 4.

2. Phase II Profiling Methods

2.1 The dEWMA3 Method

The dEWMA3 method is a direct extension of the dEWMA statistic used by Brown (1962) for predicting future-time series observations. Shamma and Shamma (1992) recommended and used this dEWMA statistic to improve the detection accuracy of the EWMA chart in capturing abnormal changes in the mean vector. Recently, Abbas *et al.* (2017) proposed three phase II univariate Bayesian dEWMA charting techniques for capturing the changes in the intercepts, slopes, and variances of linear profiles. The statistical performance of the Bayesian dEWMA charts was evaluated versus the classical dEWMA. The comparative study has revealed the advantage of the Bayesian dEWMA over the classical dEWMA. In this paper, the effectiveness of the dEWMA3 is examined versus some of existing method other than the Bayesian dEWMA. The following section is dedicated for introducing the dEWMA3 method.

Assume that the response of a process is described as a random variable Y, which has a linear relation with explanatory variable X; that is

$$Y_{ij} = A_0 + A_1 X_i + \varepsilon_{ij} \quad i = 1,2,\dots,n \quad ,j = 1,2,\dots, \tag{1}$$

where A_0 and A_1 are the in-control parameters of intercept and slope. This paper uses the term ε to refer to the random error, which is an independent a random variable with a normal distribution having a mean 0 and variance σ^2. The vector $\boldsymbol{\mu} = (A_0, A_1)^T$is the mean vector of the bivariate distribution of the vector of the estimators a_{0j} and a_{1j}, the variance–covariance matrix ($\boldsymbol{\Sigma_0}$) is as below:

$$\boldsymbol{\Sigma_0} = \begin{pmatrix} \sigma_0^2 & \sigma_{01}^2 \\ \sigma_{01}^2 & \sigma_1^2 \end{pmatrix} \tag{2}$$

At each sampling point the process parameters will be calculated using the least square estimators such that $a_{0j} = \bar{Y} - a_{1j}\bar{x}$ and $a_{1j} = S_{xy(j)}S_{xx}^{-1}$. Their variances can be estimated by using $\sigma_0^2 = (\sigma^2 n^{-1} + \bar{x}^2\sigma^2 S_{xx}^{-1})$ and $\sigma_1^2 = \sigma^2 S_{xx}^{-1}$.

However, the covariance of a_{0j} and a_{1j} is calculated by using $\sigma_{01}^2 = -\sigma^2\bar{x}S_{xx}^{-1}$. The transformation approach proposed and followed by Kim *et al.* (2003) is applied in order to have the coefficients of the linear function independent of each other. Their method is usually referred to as KMW method. The transformed model is as follows:

$$Y_i = B_0 + B_1 X_i^* + \varepsilon_{ij} i = 1,2,\dots,n \tag{3}$$

where $B_0 = A_0 + A_1 * \bar{X}$ and $B_1 = A_0$. The explanatory variable is coded by subtracting each value from the mean ($\bar{X}$); hence $X_i^* = (X_i - \bar{X})$. Kim *et al.* (2003) reported that the mean and variance of the coefficients of the coded model are $\mu_{b_0} = B_0 = A_0 + A_1 * \bar{X}$, $\sigma_{b_0}^2 = \sigma^2/n$, $\mu_{b_1} = B_1 = A_1$ and $\sigma_{b_1}^2 = \sigma^2/S_{xx}$, respectively.

Without loss of generality, this work assumes that the three model parameters positively change and once the shift occurs, its value stays constant until it is detected. The dEWMA statistic for the intercept, slope, and error are as follows:

Intercept:

$$W_j^{(b_0)} = \lambda_2^{(b_0)} Z_j^{(b_0)} + (1 - \lambda_2^{(b_0)}) W_{j-1}^{(b_0)}$$

$$Z_j^{(b_0)} = \lambda_1^{(b_0)} b_{0j} + (1 - \lambda_1^{(b_0)}) Z_{j-1}^{(b_0)}, \qquad \text{j=1,2,………,} \tag{4}$$

Slope:

$$W_j^{(b_1)} = \lambda_2^{(b_1)} Z_j^{(b_1)} + (1 - \lambda_2^{(b_1)}) W_{j-1}^{(b_1)}$$

$$Z_j^{(b_1)} = \lambda_1^{(b_1)} a_{1j} + (1-\lambda_1^{(b_1)}) Z_{j-1}^{(b_1)}, \qquad j=1,2,\ldots\ldots\ldots, \tag{5}$$

where $Z_0^{(b_0)}$, $W_0^{(b_0)}$,$Z_0^{(b_1)}$, and $W_0^{(b_1)}$ are set to equal zero and $\lambda_1^{(b_0)}$,$\lambda_2^{(b_0)}$,$\lambda_1^{(b_1)}$ and $\lambda_2^{(b_1)}$are smoothing parameters and $\lambda_1^{(.)} > 0, \lambda_2^{(.)} \leq 1$.

The exact and asymptotic variance of the three dEWMA statistics is calculated the same way proposed and used by Zhang and Chen (2005). Only the symbols were adjusted to fit the context of this paper, for more details refer to Zhang and Chen (2005), Mahmoud and Woodall (2010), Alkahtani (2013), and Abbas *et al.* (2017). This paper only considers the case where the smoothing constant of the three dEWMA chart are similar; i.e., $\lambda_1^{(.)} = \lambda_2^{(.)} = \lambda^{(.)}$. The exact variances of the three-model parameters are as follows:

$$\sigma^2_{Z_j^{(b_0)}} = \left(\lambda^{(a_0)}\right)^4 \frac{\left[1+\left(\Lambda^{(a_0)}\right)^2-(j^2+2j+1)\left(\Lambda^{(a_0)}\right)^{2j}+(2j^2+2j-1)\left(\Lambda^{(a_0)}\right)^{2j+2}-j^2\left(\Lambda^{(a_0)}\right)^{2j+4}\right]}{(1-(\Lambda^{(a_0)})^2)^3}\sigma^2_{b_0} \tag{6}$$

$$\sigma^2_{Z_j^{(b_1)}} = \left(\lambda^{(a_1)}\right)^4 \frac{\left[1+\left(\Lambda^{(a_1)}\right)^2-(j^2+2j+1)\left(\Lambda^{(a_1)}\right)^{2j}+(2j^2+2j-1)\left(\Lambda^{(a_1)}\right)^{2j+2}-j^2\left(\Lambda^{(a_1)}\right)^{2j+4}\right]}{(1-(\Lambda^{(a_1)})^2)^3}\sigma^2_{b_1} \tag{7}$$

where $\Lambda^{(b_0)}$=(1-$\lambda^{(b_0)}$) and$\Lambda^{(b_1)}$=(1-$\lambda^{(b_1)}$). The EWMA/R method (Kang and Albin 2000) uses the average residuals statistic, the difference between the observed and estimated value, as an estimator for the error-variance. Here, the residual is calculated by using $e_{ij} = y_{ij} - B_0 - B_1 X_i^*$ and its average is $\bar{e}_j = \sum_{i=1}^{n} e_{ij}/n$; where *n* is the number of independent variables used to develop the *j*th profile. The dEWMA statistic for such estimator is denoted by $W_j^{(e)}$and calculated as follows; see Alkahtani and Schaeffer 2012:

$$W_j^{(e)} = \lambda_2^{(e)} Z_j^{(e)} + (1-\lambda_2^{(e)}) W_{j-1}^{(e)}$$

$$Z_j^{(e)} = \lambda_{j1}^{(e)} \bar{e}_j + (1-\lambda_1^{(e)}) Z_{j-1}^{(e)}, \qquad \text{j=1,2,………,} \tag{8}$$

And; the exact variance

$$\sigma^2_{Z_j^{(e)}} = \left(\lambda^{(e)}\right)^4 \frac{\left[1+\left(\Lambda^{(e)}\right)^2 - (j^2+2j+1)\left(\Lambda^{(e)}\right)^{2j} + (2j^2+2j-1)\left(\Lambda^{(e)}\right)^{2j+2} - j^2\left(\Lambda^{(e)}\right)^{2j+4}\right]}{(1-(\Lambda^{(e)})^2)^3} \sigma_e^2 \tag{9}$$

where $\Lambda^{(e)}$=(1-$\lambda^{(e)}$)and $\sigma_e^2 = \sigma^2/n$. The threshold values of the three dEWMA control charts are found using $h_{ij} = \pm L_i \sigma^2_{exact}$, where $i = 1{,}2{,}3$ is the dEWMA chart number and j is the profile number. The value of L_i is found to satisfy a certain false alarm rate.

2.2 The dMEWMA Method

Alkahtani and Schaffer (2012) investigated the performance of the dMEWMA statistic in capturing changes in process location under the classical multivariate context. Abdella *et al.* (2016) extended the dMEWMA for monitoring shifts in the in-control parameters of second-order polynomial profiles. Motivated by their findings, this paper continues testing the effectiveness of the dMEWMA statistic capturing deviation the coefficients of simple linear profiles. For not losing generality, the dEWMA statistics mentioned in Equations 4 and 5 are modified as follows:

$$\boldsymbol{W}_j = \lambda_{2M} \boldsymbol{Z}_j + (1-\lambda_{2M}) \boldsymbol{Z}_{j-1}$$

$$\boldsymbol{Z}_j = \lambda_{1M} \boldsymbol{y}_j + (1-\lambda_{1M}) \boldsymbol{y}_{j-1} \quad \text{j=1,2,………,} \tag{10}$$

where $\boldsymbol{W}_j = (w_j^{(a_0)},\ w_j^{(a_1)})$, and $\boldsymbol{Z}_j = (z_j^{(a_0)},\ z_j^{(a_1)})$ are the first and second MEWMA vectors of intercept and slope of the *j*th profile, respectively. The initial vectors $\boldsymbol{W}_0$ and $\boldsymbol{Z}_0$ are set to equal $\boldsymbol{\mu}_0 = (0,0)$ and λ_{1M} and $\lambda_{2M} > 0$ are the smoothing factors.

Considering the situation that λ_{1M}=λ_{2M}=λ_M; the exact and asymptotic covariance matrices of dMEWMA are as follows (Alkhatani and Schaffer 2012):

The exact covariance matrix:

$$\Sigma_{\boldsymbol{W}_j} = (\lambda_M)^4 \frac{\left[1 + (\Lambda)^2 - (j^2 + 2j + 1)(\Lambda)^{2j} + (2j^2 + 2j - 1)(\Lambda)^{2j+2} - j^2(\Lambda)^{2j+4}\right]}{(1 - (\Lambda)^2)^3} \Sigma_{\boldsymbol{0}}$$

j=1,2,………, (11)

The asymptotic covariance matrix:

$$\Sigma_{\boldsymbol{W}_j} = \frac{\lambda_M [2 - 2\lambda_M + (\lambda_M)^2]}{(2 - \lambda_M)^3} \Sigma_{\boldsymbol{0}}$$

j=1,2,………, (12)

The dMEWMA chart alarms when $Q_j^2 > h$, where *h* is set to maintain a certain in-control ARL and

$$Q_j^2 = \boldsymbol{W}_j^T \Sigma_{\boldsymbol{w}_i}^{-1} \boldsymbol{W}_j \tag{13}$$

This paper adopts the assumption that the average run length will reach its steady state at the same point of time when the process parameter is assumed to be changed.

2. ARL Performance Comparisons

The zero-state ARL performance of the dMEWMA is estimated and compared with some of the existing profiling methods, namely the Hoteling T^2, dEWMA3 and EWMA/R. Further performance analysis of T^2 and EWMA/R can be found in Kang and Albin (2000), Kim *et al.* (2003), Saghaei *et al.* (2009). Moreover, this paper considers the Phase II analysis in which the steady state parameters of the quality model are known. The in-control situation is described by $Y_i = 3 + 2X_i + \varepsilon_{ij}$; where x={2,4,6,8} and ε_{ij} is a normally distributed with μ_e =0 and σ^2=1. The L_i values of three individual dEWMA charts are selected such that in-control ARL=385. With this, the overall in-control ARL of the dEWMA3 is 200. The transformed model used in this paper is $Y_{ij} = (3 + 2 * 5) + 2X_i^* + \varepsilon_{ij}$.

Similar to Kang and Albin (2000) and Kim *et al.* (2003), three different types of step shift are considered. These are shift in the intercept, slope, and the variability around the regression line. The simulation results conducted by using MATLAB software based on more than 22,000 replications. The average run length and the standard deviation of the run length for step shift in intercept (A_0) are shown in Table 1 below.

Table 1 Zero-state ARL and SDRL comparison study under shift in intercept (A_0)

Methods		$A_0 = A_0 + \theta\sigma$										
		0.2	0.3	0.4	0.5	0.6	0.8	1.0	1.5	2.0	2.5	3
T^2	ARL	138.9	95.9	63.3	41.70	27.8	13.2	6.9	**2.1**	**1.2**	**1.0**	**1.0**
	SDRL	137.1	96.4	61.9	41.4	27.1	12.9	6.3	1.6	0.5	0.1	0.05
EWMA/R	ARL	66.8	31.8	17.6	**11.6**	**8.3**	**5.4**	**3.9**	2.5	1.9	1.6	1.2
	SDRL	63.8	27.0	12.7	7.2	4.5	2.2	1.4	0.7	0.4	0.5	0.4
dMEWMA	ARL	44.2	24.5	16.7	13.2	11.1	8.8	7.4	5.5	4.3	3.5	2.8
	SDRL	32.74	14.1	7.0	4.0	2.6	1.5	1.1	0.7	0.6	0.5	0.3
dEWMA3	ARL	**43.3**	**23.6**	**16.2**	12.7	10.7	8.5	7.2	5.2	4.1	3.3	2.9
	SDRL	31.4	13.5	6.6	3.9	2.5	1.5	1.1	0.7	0.5	0.5	0.4

The results in Table 1 show that the dMEWMA and dEWMA3 methods outperform the T^2 and EWMA/R methods at low and moderate shift values ($0.2 < \theta \leq 0.4$). When the intercept shift takes values between 0.4 and $1(0.4 < \theta < 1)$, the EWMA/R chart performs better than the others do. If the change of intercept increased to reach an amount greater than one time of a process standard deviation, $(\theta = 1\sigma)$, the detection speed of the T^2 charts increases and outperforms the other three methods.

Back to Table 1, the performance of the dMEWMA and dEWMA3 is not significantly different when they are compared with each other. As in the traditional multivariate framework, the T^2control is very quick in detecting high shift values.

Moreover, the dMEWMA and dEWMA3 are strongly recommended when the intercept parameter is slightly changed. This finding is confirmed by the significant difference in ARL values at low shift levels. Figure 2 graphically shows the effectiveness of the dMEWMA and dEWMA3 methods at low shift values.

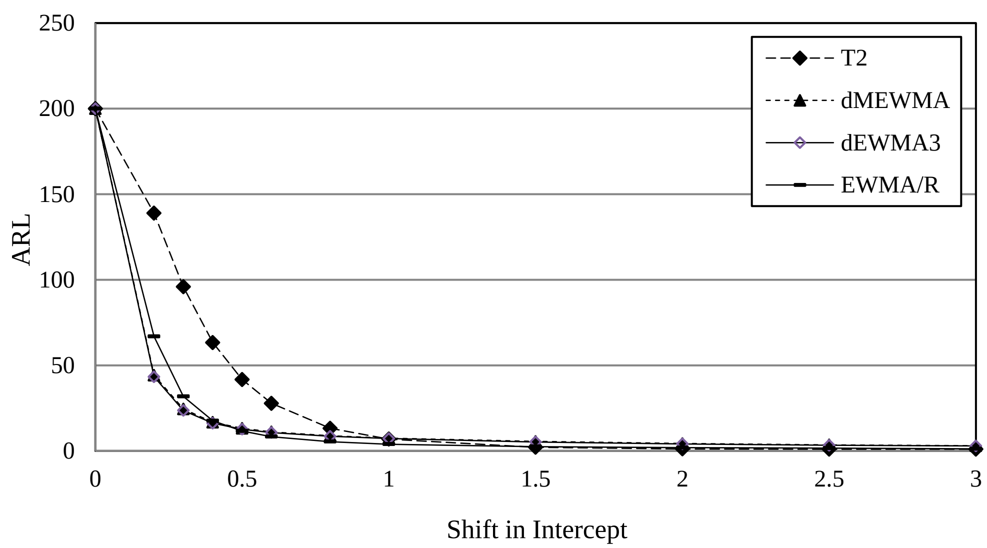

Figure 1 Graphical comparison of zero-state ARL values under shift in intercept

As previously mentioned, this paper considers the three different scenario of positive step shift in the estimates of the quality function. Table 2 shows the result of simulating the situation when the slope (A_1) is positively shifted. It is worthy to mention that, as we are using the transformation model, the shift in (A_1) is equivalent to the shift in the slope of the transformed model (B_1).

Table 2 Initial-state ARL and SDRL comparison study under shift in slope (A_1)

Methods		$A_1 = A_1 + \beta\sigma$									
		0.03	0.04	0.05	0.075	0.10	0.15	0.20	0.25	0.30	0.35
T^2	ARL	153.5	128.8	105.9	61.3	34.3	12.3	5.3	2.7	**1.7**	**1.3**
	SDRL	151.9	128.1	105.1	59.3	34.0	11.8	4.7	2.1	1.1	0.6
EWMA/R	ARL	97.4	64.2	44.0	19.7	**11.4**	**5.7**	**3.9**	**3.0**	2.4	2.1
	SDRL	92.0	58.8	39.1	14.7	7.2	2.6	1.4	0.9	0.7	0.5
dMEWMA	ARL	**58.8**	**38.7**	**27.7**	**16.2**	12.0	8.6	7.0	5.9	5.1	4.3
	SDRL	46.5	27.0	16.7	6.4	3.2	1.4	1.0	0.8	0.7	0.6
dEWMA3	ARL	61.0	40.4	28.90	16.8	12.4	8.9	7.1	6.0	5.2	4.5
	SDRL	47.6	28.7	17.2	6.8	3.5	1.6	1.1	0.9	0.7	0.6

According to the out-of-control values estimated and presented in Table 2, the performance of the dMEWMA is better than the T^2, EWMA/R, and dEWMA3 methods over a wide range of change in the slope ($0.03 \leq \beta \leq 0.075$). At high shift levels ($0.075 < \beta < 0.25$), the EWMA/R combination is the fastest. Again, the dMEWMA and dEWMA3 methods performance is very close at all shift levels. Figure 2 shows a graphical comparison of the effectiveness of the four methods.

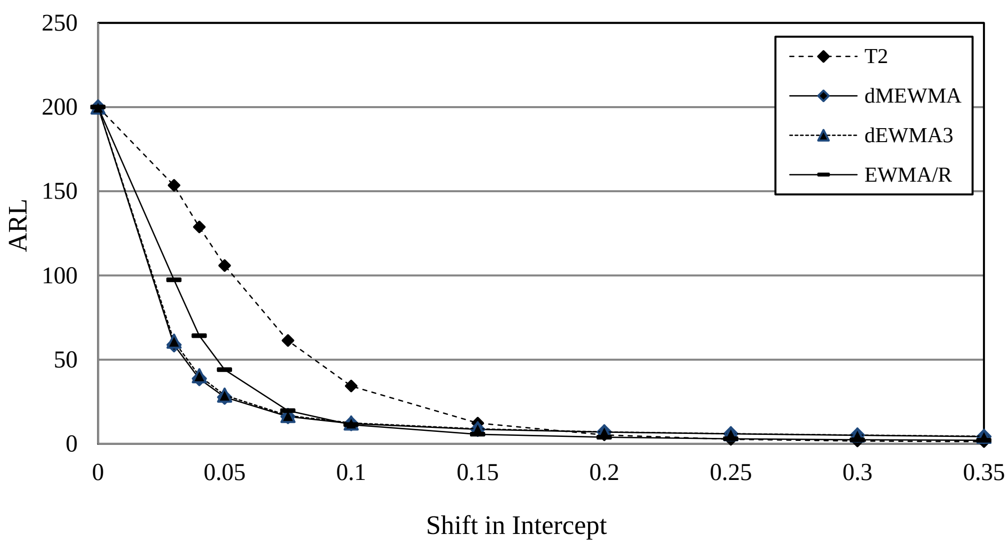

Figure 2 Graphical comparison of initial-state ARL values under shift in slope

As it is known, the performance of the EWMA control chart is affected by the value of the smoothing factor ($0 < \lambda < 1$). Different values of λ is recommended for further analysis. This work considered only the case when λ equals 0.2.

The third scenario of shift considered in this paper is the simultaneous changes in the variance of the error. As the EWMA statistic is insensitive to changes in variability around the regression line (Kang and Albin (2000), Kim *et al.* (2003)). The third dEWMA control chart is replaced by the R-chart suggested and used by Kang and Albin (2000). The new combination is named as dEWMA2/R method. At each profile the statistic R_j is calculated as $R_j = \max(e_{ij}) - \min(e_{ij})$, where e_{ij} is the residual around the point i in the j^{th} profile.

The dMEWMA and dEWMA3 are excluded from this comparison to the reason early mentioned. Under shift of process variance, it is expected that dEWMA/R competes the EWMA/R method as the R control chart dedicated for observing and capturing abnormal changes in the process variability. Each chart (dEWMA2 and R) is designed to have false alarm of approximately 400 when used individually.

Table 3 Initial-state ARL and SDRL comparison study under shift in $\sigma = \gamma\sigma$

Methods		γ									
		1.2	1.4	1.6	1.8	2.0	2.4	2.6	2.8	3.0	3.5
T^2	ARL	39.2	14.8	8.1	5.1	3.8	2.5	2.2	2.0	1.8	1.5
	SDRL	38.2	14.3	7.7	4.5	3.2	1.9	1.6	1.4	1.2	0.9
EWMA/R	ARL	**34.2**	**12.0**	**6.2**	**4.0**	**2.9**	**1.9**	**1.7**	**1.5**	**1.4**	**1.2**
	SDRL	32.9	11.3	5.5	3.3	2.3	1.3	1.1	0.9	0.8	0.5
dEWMA2/R	ARL	39.8	15.0	7.6	4.8	3.3	2.4	2.1	1.9	1.7	1.4
	SDRL	37.4	13.4	6.8	4.1	2.7	2.0	1.6	1.2	1.1	0.9

The results in Table 3 show the outstanding performance of the EWMA/R method in detecting the deviations in process variability, such performance can be referred to that the EWMA/R method uses two control schemes based on an estimator of the process variance (e_{ij}).

However, the dEWMA2/R performance is satisfied if one considered that the dEWMA chart is insensitive to the variability shift. The dEWMA2/R outperforms the traditional T^2 in detecting medium and high shift values and performs the same at low shift levels.

The simultaneous shift scenario in intercept and slope investigated by Zou *et al.*(2007) is applied in this section, and the out-of-control ARL shown in the following Table. According to the results, the dEWMA3 control chart is faster than the multivariate T^2 method. This finding is only valid at small and medium shift values. When the shift of intercept and slope are high for instance (θ=0.8 and β=0.1), the T^2 statistic exhibits a better performance in quickly detecting the simultaneous drifts in the quality profiles (see the shaded area).

Table 4 Zero-state ARL comparison study under simultaneous shift in intercept and slope

β	Method	θ						
		0.2	0.4	0.6	0.8	1	1.5	2.0
0.01	T^2	114.5	77.4	52.0	34.0	22.6	**6.0**	**2.0**
	dEWMA3	**30.9**	**19.2**	**14.1**	**11.5**	**10.0**	6.9	4.7
0.04	T^2	60.3	40.4	26.9	18.5	13.0	**3.9**	**1.6**
	dEWMA3	**16.2**	**12.8**	**10.8**	**9.4**	**8.5**	6.2	4.6
0.06	T^2	38.4	26.4	18.0	12.6	9.2	**3.1**	**1.4**
	dEWMA3	**12.6**	**10.7**	**9.4**	**8.5**	**7.8**	5.9	4.5
0.08	T^2	25.4	17.1	12.2	9.0	**6.5**	**2.5**	**1.3**
	dEWMA3	**10.7**	**9.4**	**8.5**	**7.7**	7.2	5.5	4.3
0.1	T^2	16.2	12.0	8.7	**6.4**	**4.9**	**2.1**	**1.2**
	dEWMA3	**9.4**	**8.5**	**7.7**	7.1	6.7	5.2	4.1

3. Conclusions and Remarks

This work aims to provide further assessment for the performance of some of profiling techniques based on the dEWMA statistic in observing the process performance when the quality is modeled as a simple linear function. The first method is an extension of the dMEWMA method to the profile monitoring research area; see Alkhatani and Schaffer (2015) and Abdella (2016). The second method is a combination of three dEWMA control charts; see Abbas *et al.* 2017). Two of these control charts are individual dEWMA for intercept and slope. The third is the dEWMA chart for average residual statistic suggested by Kang and Albin (2000). In order to be able to use a combination of three individual dEWMA charts, the transformation method suggested by Kim *et al.* (2003) is applied. The last method examined in this work is the dEWMA/R. This method uses two individual dEWMA charts in conjunction with one R control chart of average residual. The reason the R control chart is integrated with dEWMA is to overcome the deficiency of the EWMA statistic in capturing the variability changes. All the compared methods exhibit a competitive performance in detecting changes in regression parameters and error variance. Integrating other control charts to be conjunctionally applied with the suggested methods could enhance their efficiency and effectiveness.

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