where A_0 and A_1 are the in-control intercept and slope, respectively. The term ε is an independent random variable, which is normally distributed with mean 0 and variance σ^2. $\boldsymbol{\mu} = (A_0, A_1)^T$is the mean vector of the regression coefficients a_{0j} and a_{1j}. The covariance matrix ($\boldsymbol{\Sigma_0}$) of the intercept and the slope of the simple linear profile is described as below:

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

The least square estimators are calculated at each sampling point using $a_{0j} = \bar{Y} - a_{1j}\bar{X}$ and $a_{1j} = S_{xy(j)}S_{xx}^{-1}$. To calculate the variances and covariance of the least square estimators, we use $\sigma_0^2 = (\sigma^2 n^{-1} + \bar{x}^2\sigma^2 S_{xx}^{-1})$, $\sigma_1^2 = \sigma^2 S_{xx}^{-1}$, and $\sigma_{01}^2 = -\sigma^2\bar{x}S_{xx}^{-1}$. The transformation model proposed Kim *et al.* (2003) is as follows:

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

where the new in control intercept and slope of the simple linear profile (B_0, B_1) are $A_0 + A_1 * \bar{X}$ and A_0, respectively. The codes explanatory variable is set as $x_i^* = (x_i - \bar{X})$. 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 (Kim *et al.* 2003)

Below, we present the dEWMA statistic for the intercept, slope, and error (Alkahtani and Schaffer 2012):

Intercept:

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

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

Slope:

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

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

where $Z_0^{(b_0)}$, $Z_0^{(b_1)}$, $W_0^{(b_0)}$, and $W_0^{(b_1)}$ are set at zero-value. $\lambda_1^{(b_0)}$, $\lambda_1^{(b_1)}$, $\lambda_2^{(b_0)}$, and $\lambda_2^{(b_1)}$are the smoothing constants. In this paper, we calculate the exact and asymptotic variance of the dEWMA statistics in a similar way to Zhang and Chen (2005). For further details, see Alkahtani (2013). The exact variances of the three model parameters when $\lambda_1^{(.)} = \lambda_2^{(.)} = \lambda^{(.)}$ are simply calculated as follows:

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

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

where $\Lambda^{(b_0)}$=(1-$\lambda^{(b_0)}$) and$\Lambda^{(b_1)}$=(1-$\lambda^{(b_1)}$). Similar to Kang and Albin (2000), this paper uses the average residuals statistic to estimate the error variance. The residual is calculated 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 sample size. Under the profile-monitoring context, the sample size represents the number of explanatory variables. The dEWMA statistic and the exact variance for the error variance are calculated as follows (Alkahtani and Schaeffer 2012):

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

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

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

In this paper, we use $\Lambda^{(e)}$=(1-$\lambda^{(e)}$) and $\sigma_e^2 = \sigma^2/n$. The control limits of the three individual dEWMA control charts are calculated 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.

2.2 The dMEWMA Method

The dMEWMA method proposed in this section is an extension of the work by Alkahtani and Schaffer (2012). The dEWMA statistic was modified to fit for the multivariate case reported below:

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

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

The vectors $\boldsymbol{W}_j = (w_j^{(a_0)},\ w_j^{(a_1)})$, and$\boldsymbol{Z}_j = (z_j^{(a_0)},\ z_j^{(a_1)})$ represents the first and second MEWMA vectors of intercept and slope of the *j*th profile, respectively. For not losing generality, we set the initial vectors $\boldsymbol{W}_0$ and $\boldsymbol{Z}_0$ at zero-values. The terms λ_{1M} and λ_{2M}> 0 are the smoothing constants. Let λ_{1M}=λ_{2M}=λ_M, then the exact and asymptotic covariance matrix (Alkahtani and Schaffer 2012) of the dMEWMA are as follows:

The exact covariance matrix:

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

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 statistic of the dMEWMA control chart is as follows:

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

The dMEWMA chart signals when $Q_j^2 > h$, where h is set to maintain a specific zero-state in-control ARL.

2.3 ARL Estimations and Comparisons

We dedicate this section to compare the phase II performance of the dEWMA3, dMEWMA, and T^2 in detecting random process shift in the coefficients of simple linear profiles and the process variance. Since this paper considers phase II monitoring, we assume that the in-control coefficients of the linear quality profile are known. The in-control model in this example is assumed to be $Y_i = 3 + 2x_i + \varepsilon_{ij}$, where x is the explanatory variable and its value is limited to $\{2,4,6, 8\}$. The random error ε_{ij} is assumed to be normally distributed with μ_e =0 and σ^2=1.

Each of the three individual dEWMA control charts is designed to have individual in-control ARL equal to 382.5 such that the in-control ARL of the dEWMA control charts when they are used conjunctionally is equal to 200. The transformed model is found to be $y_{ij} = (3 + 2 * 5) + 2x_i^* + \varepsilon_{ij}$. The in-control ARL value of the compared charts is estimated by using a MATLAB code based on more than 15,000 replications.

Table 1 reports the zero-state ARL and standard deviation of the run length distribution (SDRL) when the intercept (A_0) shifts like a normal random variable with a mean μ_θ and variance σ_θ^2 =0.05.

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

Methods		$\theta = N(\mu_\theta, \sigma_\theta$ =0.05)										
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0	2.0
dEWMA3	ARL	**109.96**	**48.15**	**25.14**	**16.77**	**12.94**	**10.79**	**9.49**	**8.50**	**7.79**	7.16	4.11
	SDRL	111.40	45.65	17.49	7.97	4.40	2.80	2.02	1.59	1.33	1.13	0.53
dMEWMA	ARL	113.86	50.25	25.92	17.20	13.37	11.19	9.87	8.88	8.15	7.51	4.36
	SDRL	120.91	49.24	18.57	8.17	4.47	2.82	2.08	1.61	1.35	1.15	0.57
Hotelling T^2	ARL	176.21	136.07	96.03	65.47	43.77	28.25	19.19	13.44	9.57	**6.99**	**1.24**
	SDRL	177.09	139.65	98.57	67.20	44.56	28.44	19.40	13.20	9.21	6.53	0.56

The results in Table 1 and Figure 1 show that the dEWMA3 method outperforms both the dMEWMA and T^2 control charts at low and moderate shift values ($0.1 < \theta \leq 0.9$). As it was expected, at high shift values ($1.0 < \theta$), the T^2 control chart becomes the best choice for the quality practitioner. Table 1 also shows that the dEWMA3 and dMEWMA are performing similarly at $\theta \geq 0.7$. Table 2 reports the ARL values of the compared control charts when the process shift follows an exponential random variable with a mean equal to μ_θ.

Table 2 Zero-state ARL and SDRL comparison under the exponential shift in intercept (A_0)

Methods		$\theta = Exp(\mu_\theta)$									
		0.2	0.4	0.6	0.8	1.0	1.2	1.4	1.6	1.8	2.0
dEWMA3	ARL	**87.86**	**57.76**	**42.55**	**37.21**	31.93	26.04	23.00	21.76	19.15	17.31
	SDRL	120.69	98.25	80.74	77.86	77.27	62.70	58.80	57.67	52.62	49.92
dMEWMA	ARL	92.08	59.19	46.10	**35.00**	**29.93**	**25.35**	**22.35**	**20.36**	**18.99**	**15.49**
	SDRL	124.63	100.21	91.46	71.79	66.75	64.25	67.12	61.58	62.03	54.36
Hotelling T^2	ARL	144.7	99.7	82.0	67.3	55.8	48.4	43.3	38.2	34.8	31.7
	SDRL	166.2	136.4	128.4	118.1	110.7	105.1	96.5	89.2	88.5	83.6

Table 2 and Figure 2 show that the dEWMA and DMEWMA control charts are the best choice at all levels of the exponential shift in the intercept of the simple linear profiles. More specifically, the dEWMA3 performs well at low and moderate shift values, while the dMEWMA is the best to detect large shift values. One general finding here is that the T^2 control chart is not appropriate to detect this kind of shift when it compared with the dEWMA and dMEWMA control charts.

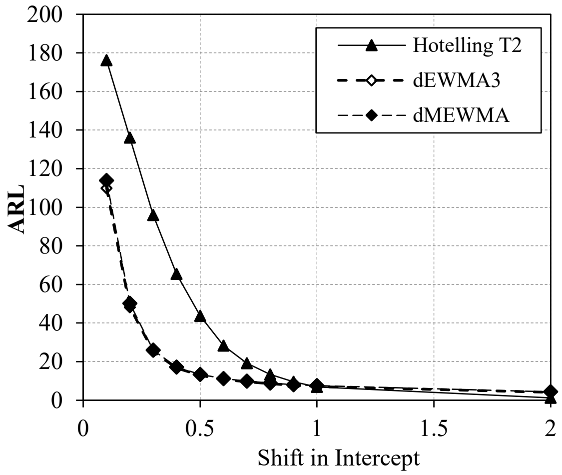

Figure 1 Graphical comparison of zero-state ARL values under shift Normal in intercept

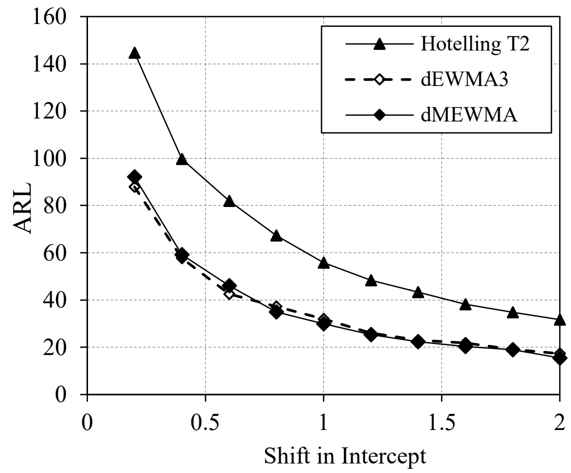

Figure 2 Graphical comparison of zero-state ARL values under Exponential shift in intercept

Table 3 Zero-state ARL and SDRL comparison under the normal shift in slope (A_0)

Methods		$\beta = N(\mu_\beta, \sigma_\beta = 0.05)$								
		0.025	0.05	0.075	0.1	0.15	0.175	0.225	0.275	0.3
dEWMA3	ARL	72.59	57.04	37.25	24.62	11.01	9.02	6.92	5.93	5.41
	SDRL	100.72	93.22	69.83	47.07	15.86	9.63	2.02	1.26	1.09
dMEWMA	ARL	**70.31**	**52.99**	**36.03**	**23.50**	**10.90**	**8.63**	6.68	5.63	5.22
	SDRL	106.55	90.32	70.02	50.21	17.05	6.39	2.11	1.20	1.02
Hotelling T^2	ARL	126.27	106.63	79.04	52.80	21.32	12.81	**5.27**	**2.71**	**2.14**
	SDRL	152.49	135.81	113.37	85.26	43.63	24.17	9.29	3.52	2.39

Table 3 and Figure 3 report the ARL values of under a normally distributed shift in the slope (A_1) of the simple linear profile. The results show that the dMEWMA control chart performs better than the other two control charts, namely dEMA3 and T^2, under both low and moderate shift levels. The T^2 control chart has the advantage of the dEWMA3 and dMEWMA at high shift values.

Table 4 Zero-state ARL and SDRL comparison under the exponential shift in intercept (A_0)

Methods		$\theta = Exp(\mu_\theta)$								
		0.025	0.05	0.075	0.1	0.15	0.175	0.225	0.275	0.3
dEWMA3	ARL	**112.03**	**75.11**	**60.70**	47.87	36.03	32.26	26.93	22.46	20.91
	SDRL	133.78	108.24	102.07	86.06	78.04	71.53	66.37	55.27	53.61
dMEWMA	ARL	111.73	76.29	58.10	**46.38**	**34.50**	**31.17**	**24.20**	**21.41**	**19.85**
	SDRL	135.29	113.61	100.81	87.21	73.39	70.05	67.60	60.78	55.13
Hotelling T^2	ARL	160.82	126.31	101.84	82.80	65.58	56.70	48.69	41.26	38.39
	SDRL	170.55	154.93	141.47	125.23	118.42	110.63	103.51	96.80	96.60

Table 4 and Figure 4 reports the ARL values under an exponentially distributed shift in the intercept of the slope (A_1) of the simple linear profile. The dEWMA control chart has shown a better performance comparing with the other two charts at low shift values. The dMEWMA control chart becomes the most preferable control chart when the shift in the slope takes moderate and large values ($0.075 < \theta$)

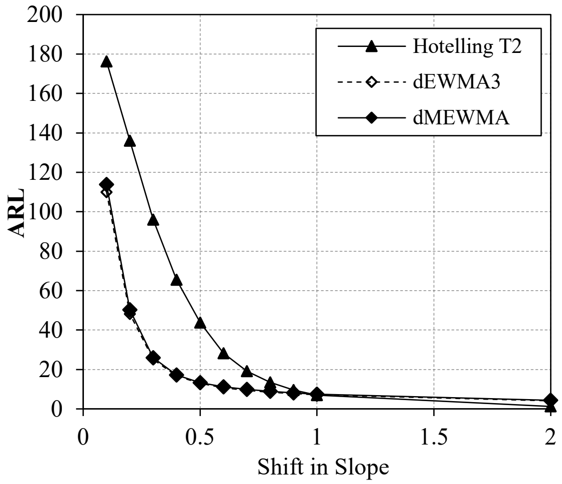

Figure 3 Graphical comparison of zero-state ARL values under shift Normal in Slope

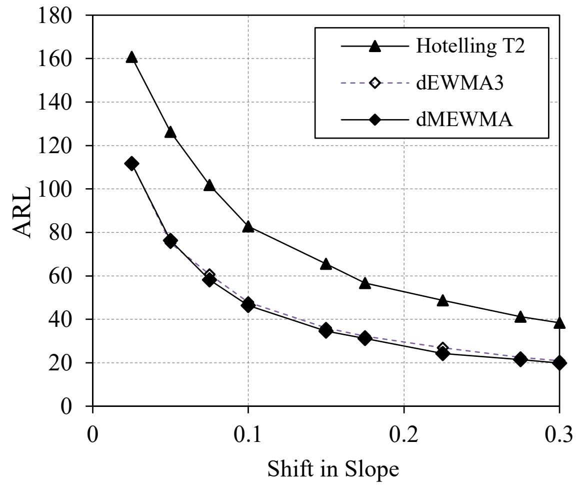

Figure 4 Graphical comparison of zero-state ARL values under Exponential shift in Slope

Table 5 Initial-state ARL and SDRL comparison study under the normal shift in σ

Methods		$\gamma = N(\mu_\gamma, \sigma_\gamma = 0.05)$									
		0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
dEWMA3	ARL	159.63	123.21	99.17	82.58	68.95	59.70	52.21	46.64	42.32	38.76
	SDRL	157.99	119.32	91.11	74.98	60.78	48.99	41.85	35.66	31.97	28.26
dMEWMA	ARL	163.22	124.19	99.04	81.28	69.36	58.77	51.00	46.38	41.90	37.99
	SDRL	162.44	119.17	90.55	72.71	60.33	47.75	41.24	36.56	31.92	27.53
Hotelling T^2	ARL	**143.41**	**89.7**	**59.3**	**42.89**	**31.51**	**23.95**	**18.97**	**15.48**	**12.78**	**10.66**
	SDRL	196.69	105.99	66.9	46.59	33.59	25.16	19.74	15.46	12.55	10.28

Table 5 and Figure 5 report the ARL values when the error variance shifts as a normally distributed variable. The results in Table 5 shows the advantage of the T^2 is detecting several levels of a shift in the variance of error. The advantage of the T^2 becomes more clear at large values of a shift in σ.

Table 6 Initial-state ARL and SDRL comparison study under the exponential shift in σ

Methods		$\gamma = Exp(\mu_\gamma)$									
		0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
dEWMA3	ARL	157.98	134.92	115.24	106.97	96.67	89.15	81.80	76.72	73.61	70.01
	SDRL	152.23	138.12	122.06	117.52	111.98	106.56	99.65	96.85	96.00	91.67
dMEWMA	ARL	158.40	131.70	118.98	105.28	97.15	90.32	82.42	75.19	72.38	70.03
	SDRL	151.05	132.66	126.11	115.57	112.63	109.02	99.64	94.28	92.93	94.28
Hotelling T^2	ARL	**136.57**	**104.91**	**82.59**	**72.53**	**65.10**	**58.29**	**50.58**	**47.48**	**43.51**	**40.68**
	SDRL	149.13	126.09	110.43	104.97	99.82	97.21	85.67	85.01	77.89	79.23

Table 6 and Figure 6 shows the ARL values under an exponential shift in the error variance. Similar to the normally distribute shift, the Hotelling T^2 still the best chart for quickly detecting this shift.

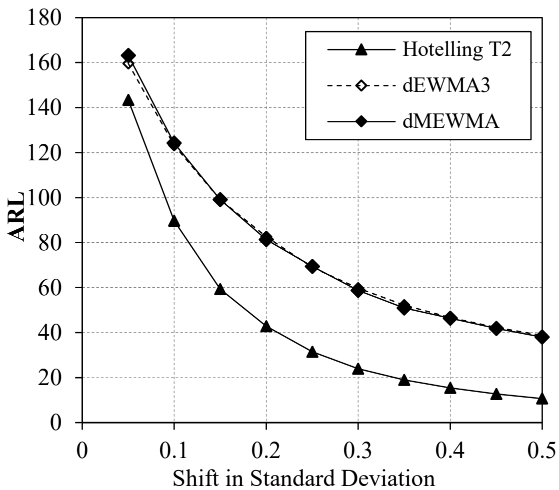

Figure 5 Graphical comparison of zero-state ARL values under shift Normal in the Standard Deviation

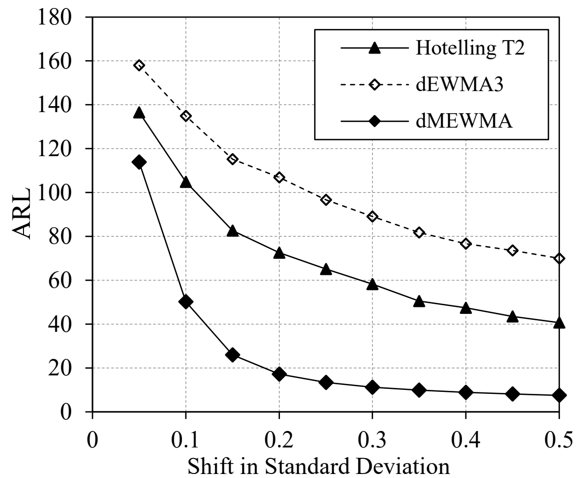

Figure 6 Graphical comparison of zero-state ARL values under Exponential shift in the Standard Deviation

2. Conclusions

This paper aims to investigate the zero-state ARL performance of the dEWMA and dMEWMA control charts in detecting a random shift in the parameters of the simple linear profile and the error variance. Three different methods for monitoring process performance were investigated when the quality of a process or product is characterized by a simple linear function. The comparative simulation studies have shown the advantage of the dEWMA statistic-based control charts over the Hotelling T^2 when the shift in the slope and intercept is normally or exponentially distributed. The simulation results have shown that under normally or exponentially distributed shift in the error variance, the Hotelling T^2 performs better than the dEWMA-based control charts. This study recommends the integration of other control charts with the dEWMA and dMEWMA, such as R chart, when they are used to detect shifts in the error variance.

Acknowledgments

This paper was made possible by internal grant No. QUSD-CENG-2018\2019-5 from Qatar University, Doha-Qatar. The authors of this paper would like to thank the anonymous reviewers for their helpful comments that highly contributed to enhancing the quality of this paper

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