Research Article

An Enhanced Performance to Monitor Process Mean with Modified Exponentially Weighted Moving Average – Sign Control Chart

Rattikarn Taboran
Department of Mathematics, Faculty of Science and Technology, Muban Chombueng Rajabhat University, Ratchaburi, Thailand

Saowanit Sukparungsee*
Department of Applied Statistics, Faculty of Applied Science, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand

* Corresponding author. E-mail: saowanit.s@sci.kmutnb.ac.th DOI: 10.14416/j.asep.2021.10.013
Received: 11 June 2021; Revised: 25 June 2021; Accepted: 14 July 2021; Published online: 29 October 2021

Abstract
The purpose of this research is to enhance performance for detecting a change in process mean by combining modified exponentially weighted moving average and sign control charts. This is a nonparametric control chart which effective alternatives to the parametric control chart, so called MEWMA-Sign. The nonparametric control chart can serve when process observations are deviated from normal distribution assumption. Generally, the performance of control charts is widely measured by average run length (ARL) divided into two cases; in control ARL (ARL_0) and out of control ARL (ARL_1). In this paper, the performance comparison is investigated when processes are non-normal distributions. The performance of the MEWMA-Sign is compared EWMA-Sign control chart by considering a minimum value of ARL_1. The numerical results found that the MEWMA-Sign performs better than EWMA-Sign in order to detect a very small shift of mean process. Additionally, the real application of the MEWMA-Sign and EWMA-Sign are presented.

Keywords: Distribution free control chart, Mixed control chart, Monte Carlo simulation, Average run length

1 Introduction

As a result of the 20-years national development policy in Thailand, it has resulted in increased competition in the market share. Especially in the manufacturing industry, the quality control of manufacturing processes in industrial factories or enterprises is intensive aware of the quality and service of various products. Therefore, it is important to implement a statistical quality control (SQC) tool to control, monitor, detect as well as improve the quality of the process. By statistical quality control, there are popular seven quality control tools; check sheet, histogram, Pareto chart, cause and effect diagram, scatter diagram and control chart, which are powerful statistical tools for detecting changes in the manufacturing process [1]. The most effective tools is the control chart because the results can be clearly displayed and is widely implemented. An important objective in using control charts is the ability to quickly detect changes in process parameters. Ideally, the false alarm rate must be minimum when the process is in- control and the true alarm rate must be large when the process is out of control. Statistical process control charts are commonly used in industrial production [2], communication engineering [3], epidemiology [4], [5], economics, finance and insurance [6], [7], environmental [8], chemistry and biology [9].

The control chart is divided into two types; 1) variables control chart and 2) attributes control chart. The former is a chart used to control the production process when the properties of the quality characteristic can be measured, such as the diameter of the workpiece, average volume of drinking water, average quantity, and average lifetime of the product. For example, x-bar control chart, range (R chart), standard deviation (S chart), which is considered a standard control chart. It is proposed for the first time by Shewhart [10] on 1931 for processes that have normal distribution and are effective at detecting large changes.

However, the standard control charts do not focus on historical data. As a result, the small past changes that accumulated over time could not be recognized, so the alternative control charts were studied, which weighted to previous data and corrected flaws from the traditional control chart. By focusing on historical weighted data such as the Cumulative Sum control chart (CUSUM chart) first proposed by Page [11]. Later in 1959, Roberts [12] proposed a weighted moving average control chart, namely Exponentially Weighted Moving Average control chart (EWMA chart) with a focus on historical data with exponential weight loss, two of which are widely popular. Due to their excellent ability to detect small process dynamics (Montgomery [1], later in 1994, Butler and Stefani [13] presented the Double Exponentially Weighted Moving Average control chart (DEWMA chart). Recently, Khoo [14] developed the Moving Average control chart (MA chart), a control chart that calculates the moving average with the moving average period (w) in order to smooth the trend. Later in 2008, Khoo and Wong [15] jointly developed the Double Moving Average control chart (DMA chart), a control chart that brings the statistics of MA control chart comes to find one more repeating moving average. The MA and DMA charts can detect small to medium changes well. In addition, they can be applied to both continuous and discrete distribution data. In 2013, Alkahtani [16] presented a comparison of the EWMA chart and DEWMA under non-normal distribution process. The results of the study concluded that the DWMA chart performed better than the EWMA chart, and the DMA chart was also compared with the MA, CUSUM, and EWMA charts when the process takes a small change (δ), the EWMA and the CUSUM control charts will be of the best at detecting change when the process of medium variation (δ) occurs, the DMA control chart is performing the best [17], [18].

In practice, however, processes may not be subjected to normal distribution or the population distribution of the process may not be known. Therefore, using a basic, parameter-based control chart may result in false conclusions and not applicable because the assumption is not met. Given these limitations, choosing to use a nonparametric control chart without parameters is a viable solution to this problem. The non-parameterized control chart is called Nonparametric control chart for example, the use of the Sign statistic or Arcsine statistic is applied to an efficient control chart for detecting change, such as EWMA chart, CUSUM chart, Modified Exponentially Weighted Moving Average (MEWMA chart). Thongrong *et al.* [19] studied the effectiveness of the EWMA-Sign control chart as one of the non-parameterized charts. Later in 2017, Prarisudtipong *et al.* [20] studied the estimation of the average run length of the Arcsine EWMA Sign control chart without parameters using the Markov chain method. It was found that the Markov chain method was as efficient and accurate as of the Monte Carlo method, which took longer to process. Both control charts can be used to monitor a process when the quality characteristics are subjected to normal distribution or process quality characteristics not under normal distribution. The control schemes using sign statistic will be performed to adjust observations from the process to have a binomial distribution. In 2014, Aslam *et al.* [21] presented a control chart for the MEWMA chart using the Sign statistic, called "MEWMA-Sign chart" using the average run length (ARL) as the benchmark to measure performance. The results showed that the MEWMA-Sign chart was more effective at detecting change than the EWMA-Sign chart and EWMA chart, but did not detect when process changes in the case of a right-skewed distribution and the change size of the parameter are reduced ($\delta < 0$). Aslam *et al.* [22] presented the MEWMA-Sign chart using the ARL as a criterion for measuring performance. The results showed that the MEWMA-Sign chart had better performance than the EWMA-Sign chart.

Therefore, in this research, a new control chart was proposed by using the MEWMA chart to be applied in conjunction with the Sign statistics, which brings the advantages of both charts together. This gives the control chart a non-parameterized style. This can be used for processes where the distribution of observations is not known or may not be able to estimate the parameter. The common control chart does not resolve the limitation on this issue. The proposed control chart has better detection performance of small to medium changes than the EWMA-Sign control chart, considering the performance of the control chart from its lowest value.

2 Control Charts and Properties

This section introduces the background of the Exponentially Weighted Moving Average - Sign (EWMA-Sign) control chart first introduced by Yang *et al.* [23] on 2011 and Modified Exponentially Weighted Moving Average - Sign (MEWMA-Sign) control chart proposed by Alsam *et al.* [22] in 2019. Assuming $\{X_{it}, 1 \le i \le n\}$ is an independent and identically distributed sequence of observations drawn from X at time t, which follows a certain continuous distribution. In order to monitor the mean process deviation from the target value T, let $Y = X - T$ be the difference between the quality characteristic of interest and the target value, and $p = P(Y > 0)$ be the process proportion. If the process is in control, then $p = p_0 = P(Y \le T) = P(Y > T) = 0.50$. Otherwise, the process is out of control, $p = p_1 \neq 0.50$. The statistic Y can define as follows:
$Y_{it} = X_{it} - T$, for $i = 1, 2, \ldots, n$ and $t = 1, 2, \ldots$

and indicator variable $I_{it} = \begin{cases} 1, \text{ if } Y_{it} > 0 \\ 0, \text{ otherwise} \end{cases}$.

Therefore, the total number of observations for $Y_{it} > 0$, is $S_t = \sum_{i=1}^{n} I_{it}$ which follows the binomial distribution with parameter (n, p_0) for the case of in control process.

2.1 *Exponentially Weighted Moving Average-Sign (EWMA-Sign) control chart*

The EWMA-Sign control chart is combined between the classical parametric EWMA chart and nonparametric sign chart. On 2011, Yang *et al.* [23] proposed the EWMA-Sign control chart which its statistic can be formulated as Equation (1)

$$EWMA_{S_t} = \lambda S_t + (1-\lambda) EWMA_{S_{t-1}}, \; t = 1, 2, \ldots \tag{1}$$

Where λ is the smoothing constant, $0 < \lambda \le 1$ When the process is in control, the mean and variance of $EWMA_{S_t}$ are $E(EWMA_{S_t}) = np_0$
and

$$Var(EWMA_{S_t}) = \frac{\lambda\left(1-(1-\lambda)^{2t}\right)\left(np_0(1-p_0)\right)}{2-\lambda}. \tag{2}$$

From Equation (2), when $t \to \infty$ $Var(EWMA_S) = \frac{\lambda(np_0(1-p_0))}{2-\lambda}$. Then, the asymptotic upper and lower control limits for the EWMA-Sign control chart are given by Equation (3) as follows:

$$np_0 \pm h_1 \sqrt{\frac{\lambda}{2-\lambda}\left(np_0(1-p_0)\right)}, \tag{3}$$

where h_1 is a control limit coefficient of the EWMA-Sign control chart. This value can be determined by Monte Carlo simulation to correspond the desired ARL_0. The EWMA-Sign statistics will signal to an out of control process when $EWMA_S > UCL$ or $EWMA_{S_t} < LCL$.

2.2 *Modified Exponentially Weighted Moving Average-Sign (MEWMA-Sign) control chart*

Recently, the MEWMA-Sign control chart was proposed by Alsam *et al.* [21], which shown the comparison performance with EWMA-Sign control chart. The MEWMA-Sign statistic can be written as Equation (4)

$$MEWMA_{S_t} = \lambda S_t + (1-\lambda) MEWMA_{S_{t-1}} + k(S_t - S_{t-1}), \; t = 1, 2, \ldots \tag{4}$$

where k is a constant and given equal to 1 and it coincides to the form of Patel and Divecha [24] when set up $k = 1$. Furthermore, Equation (4) reduces to the EWMA-Sign control chart when given $k = 0$. The mean and variance of $EWMA_{S_t}$ are as follows:
$E(MEWMA_{S_t}) = np_0$
and

$$Var(MEWMA_{S_t}) = \left[\frac{(\lambda + 2\lambda k + 2k^2) - \lambda(1-\lambda-k)^2(1-\lambda)^{2(t-1)}}{2-\lambda}\right] np_0(1-p_0). \tag{5}$$

From Equation (5), when $t \to \infty$, $Var(MEWMA_{S_t}) = \frac{\lambda + 2\lambda k + 2k^2}{2-\lambda}$. Then, the asymptotic upper and lower control limits for the MEWMA-Sign control chart are given by Equation (6) as follows:

$$np_0 \pm h_2 \sqrt{\frac{\lambda + 2\lambda k + 2k^2}{2-\lambda}\left(np_0(1-p_0)\right)}, \tag{6}$$

where h_2 is a control limit coefficient of the MEWMA-Sign control chart corresponding to the target of ARL_0 based on Monte Carlo simulation. The MEWMA-Sign statistics will signal to an out of control process when $MEWMA_{S_t} > UCL$ or $MEWMA_{S_t} < LCL$.

3 Performance Measurement and Properties

Generally, the goal performance of control chart is the ability of detection of a change in a process as soon as possible. Ideally, the excellent control chart should not give a false alarm signal that a process is out of control when it is still in control, however it should quickly give a true alarm signal when a process does go out of control. The former and latter are the same manner of probability of type I and type II error, respectively. The procedure widely used to measure the performance of an SPC chart is called "Average Run Length" (ARL). The ARL is the expected number of runs to an alarm and is expressed depending on the case in hand. According to the expectations of the stopping time, the ARL is classified into ARL_0 and ARL_1, respectively. ARL_0 shows that the performance of the SPC chart is in-control. ARL_0 is defined as the measure of time before a process that is on target when a process is falsely signaled as being out-of-control, and then is defined as:

$ARL_0 = E_\theta(\tau) = T, \ \theta = \infty$

where $E_\theta(\tau)$ is the expectation of the distribution $F(x, \alpha)$, when the change-point occurs at point θ

τ is the stopping time

θ is the change-point time

T is a constant (should be large enough).

ARL_1 arises when the process becomes out of control, where the performance of the control chart is usually used as ARL_1. ARL_1 is defined as a measure of the time before the process that has gone out of control when a process is signaled as being out of control. This time should minimize the quantity. Ideally, ARL_1 is minimal, and then is defined as:

$$ARL_1 = E_\theta\left(\tau - \theta + 1 \middle| \tau \geq \theta\right), \tag{7}$$

where $E_\theta(\tau)$ is the expectation of an assumption that a change-point $F(x, \alpha \neq \alpha_0)$ has occurred in time θ. Note that, the form in Equation (7) is usually determined when $\theta = 1$ is applied. In this paper, the ARL can be evaluated by using Monte Carlo simulation with m replications and calculated as:

$$ARL = \frac{\sum_{j=1}^{m} RL_j}{m}. \tag{8}$$

The ARL are computed the aforementioned RL properties of EWMA-Sign and MEWMA-Sign control charts. The numerical results are addressed on Tables 1–4 in the form of ARL_1 when given ARL_0 = 370 by varying the magnitudes of shifts in mean parameter.

4 Numerical Results

The performance comparison of EWMA-Sign and MEWMA-Sign control charts are studied by given ARL_0 = 370. The numerical results for ARL_0 and ARL_1 were calculated via Equation (8) by Monte Carlo simulation with 10^5 replications which evaluated by R programming [25]. The process distribution that studied the performance in order to detect a change in mean parameter is Laplace and logistic defined as symmetric distributions and exponential and Weibull defined as asymmetric distributions. The in control parameter of process distributions are defined as following; Laplace(1,1), logistics(6,2) Exponential(1) and Weibull(2,2), sample sizes is 5 and 10, the smoothing parameter of EMWA-Sign and MEWMA-Sign control chart is 0.05 and 0.10. The out of control parameter of the process distribution, α_1, was set as $\alpha_0(1+\delta)$, where δ is a value of changed parameter magnitudes was varied as 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.7, 1.0 and 1.5. The coefficients of control limit of EWMA-Sign and MEWMA-Sign control charts are determined to meet the desired ARL_0=370 by the Monte Carlo simulation method for all values of λ. On Table 1, the numerical results found that the MEWMA-Sign performs better than EWMA-Sign control chart when a shift size is less than 0.05, otherwise the EWMA-Sign is superior to MEWMA-Sign control chart on the case of Laplace(1,1) distribution and λ = 0.1 for both n = 5 and 10. Beside, on the case of logistic(6,2) distribution the performance of MEWMA-Sign can detect a small shift (δ = 0.05) better than EWMA-Sign control chart with λ = 0.05 as shown on Table 2. Furthermore, the performance of EWMA-Sign and MEWMA-Sign control charts will enhance in order to detect a change when smoothing parameter (λ) is raised for moderate and large magnitudes of shift. For the asymmetric processes, the performance of EWMA-Sign control chart is better than MEWMA-Sign control chart for all magnitudes of shift when λ = 0.1 and both n = 5 and 10 for the case of exponential and Weibull distribution are presented in Tables 3 and 4, respectively. Furthermore, the performance comparison can be clearly graphical viewed as Figures 1–4 which presented the performance

Table 1: Comparison of ARL of EWMA-Sign and MEWMA-Sign charts for Laplace(1,1)

δ	$n = 5$				$n = 10$			
	EWMA-Sign		**MEWMA-Sign**		**EWMA-Sign**		**MEWMA-Sign**	
	$\lambda = .05$ $h_1 = 13.883$	$\lambda = 0.1$ $h_2 = 9.74$	$\lambda = .05$ $h_1 = 4.02$	$\lambda = 0.1$ $h_2 = 3.683$	$\lambda = .05$ $h_1 = 19.54$	$\lambda = 0.1$ $h_2 = 13.74$	$\lambda = .05$ $h_1 = 5.672$	$\lambda = 0.1$ $h_2 = 5.203$
.05	336.386	335.589	338.930	**334.485**	325.085	324.290	324.728	**323.981**
.10	304.979	**302.741**	310.190	304.782	286.000	**282.813**	289.505	283.725
.15	280.059	**275.707**	286.027	278.451	254.529	**248.568**	260.276	250.733
.20	258.670	**251.772**	264.742	255.180	230.446	**220.255**	237.245	223.951
.25	239.575	**230.832**	247.968	233.349	211.274	**198.341**	219.404	202.311
.30	224.551	**213.829**	232.682	217.165	194.428	**178.965**	203.803	183.516
.70	156.437	**133.570**	168.360	138.778	132.147	**103.836**	144.896	110.406
1.0	135.026	**108.194**	148.062	114.392	114.908	**83.124**	128.253	90.386
1.5	117.734	**88.132**	131.265	94.798	101.649	**68.124**	115.386	75.525

Note: The bold number is minimum value of ARL_1

Table 2: Comparison of ARL of EWMA-Sign and MEWMA-Sign charts for Logistic(6,2)

δ	$n = 5$				$n = 10$			
	EWMA-Sign		**MEWMA-Sign**		**EWMA-Sign**		**MEWMA-Sign**	
	$\lambda = .05$ $h_1 = 13.388$	$\lambda = 0.1$ $h_2 = 9.57$	$\lambda = .05$ $h_1 = 3.951$	$\lambda = 0.1$ $h_2 = 3.655$	$\lambda = .05$ $h_1 = 18.663$	$\lambda = 0.1$ $h_2 = 13.33$	$\lambda = .05$ $h_1 = 5.551$	$\lambda = 0.1$ $h_2 = 5.132$
.05	341.132	341.327	**340.321**	340.720	329.034	329.791	**325.878**	328.168
.10	**312.561**	315.538	314.286	315.319	**289.154**	291.001	295.932	293.463
.15	**287.474**	288.465	290.017	289.723	**259.968**	260.460	266.206	262.515
.20	**265.613**	266.275	268.841	268.211	233.741	**233.355**	241.909	236.142
.25	**245.192**	246.878	251.458	248.775	212.199	**209.880**	221.870	213.968
.30	227.928	**227.678**	235.395	230.567	195.366	**189.055**	205.489	194.426
.70	148.044	**135.528**	159.534	141.326	121.765	**102.400**	135.406	109.290
1.0	120.701	**103.597**	133.447	110.274	100.290	**76.527**	114.403	83.775
1.5	97.046	**75.417**	110.750	82.469	82.601	**56.501**	97.042	64.112

Note: The bold number is minimum value of ARL_1

Table 3: Comparison of ARL of EWMA-Sign and MEWMA-Sign charts for Exponential(1)

δ	$n = 5$				$n = 10$			
	EWMA-Sign		**MEWMA-Sign**		**EWMA-Sign**		**MEWMA-Sign**	
	$\lambda = .05$ $h_1 = 5.67$	$\lambda = 0.1$ $h_2 = 4.84$	$\lambda = .05$ $h_1 = 2.961$	$\lambda = 0.1$ $h_2 = 2.861$	$\lambda = .05$ $h_1 = 7.23$	$\lambda = 0.1$ $h_2 = 5.918$	$\lambda = .05$ $h_1 = 3.874$	$\lambda = 0.1$ $h_2 = 3.764$
.05	**181.172**	194.952	208.001	210.214	**146.036**	153.047	197.675	198.879
.10	**107.125**	112.238	129.990	127.945	81.643	**78.103**	132.661	122.832
.15	74.065	**73.228**	96.437	87.112	56.049	**48.809**	103.379	87.025
.20	56.264	**52.280**	78.851	65.893	43.319	**34.800**	86.739	67.574
.25	45.789	**39.976**	68.284	52.985	35.793	**27.074**	75.445	55.875
.30	38.374	**32.318**	61.226	45.164	30.721	**22.279**	67.132	47.716
.70	19.647	**13.691**	42.094	24.337	16.395	**10.331**	38.494	23.631
1.0	15.584	**10.382**	35.769	20.109	13.173	**8.032**	31.681	18.462
1.5	12.629	**8.133**	30.732	16.947	10.769	**6.396**	26.585	14.895

Note: The bold number is minimum value of ARL_1

of EWMA-Sign and MEWMA-Sign for both cases of n = 5 and 10. Nevertheless, the performance of EWMA-Sign as well as MEWMA-Sign were shown in the same manner that the small value of λ will suit when the magnitudes of change δ are small for all symmetric and asymmetric distributions. Figures 1 and 2 show the performance comparison when process observation are from symmetric distribution as Laplace(1,1) and logistic(6,2). Besides, the asymmetric distributions such Exponential(1) and Weibull(2,2) are investigated and compared the performance which EWMA-Sign is superior to MEWMA-Sign for both λ = 0.05 and 0.1. In addition, when sample sizes are large then the ARL_1 will decrease for all case studies.

Table 4: Comparison of ARL of EWMA-Sign and MEWMA-Sign charts for Weibull(2,2)

δ	*n* = 5				*n* = 10			
	EWMA-Sign		**MEWMA-Sign**		**EWMA-Sign**		**MEWMA-Sign**	
	$\lambda = .05$ $h_1 = 13.849$	$\lambda = 0.1$ $h_2 = 9.74$	$\lambda = .05$ $h_1 = 4.02$	$\lambda = 0.1$ $h_2 = 3.683$	$\lambda = .05$ $h_1 = 19.472$	$\lambda = 0.1$ $h_2 = 13.72$	$\lambda = .05$ $h_1 = 5.66$	$\lambda = 0.1$ $h_2 = 5.198$
.05	276.653	**274.034**	283.617	274.910	251.090	**246.262**	257.657	248.312
.10	218.887	**208.608**	227.019	212.806	187.087	**173.333**	197.897	177.725
.15	182.135	**164.584**	192.676	170.833	153.477	**132.047**	165.176	137.514
.20	158.189	**137.353**	169.720	143.101	132.830	**106.727**	145.640	112.787
.25	141.905	**117.616**	154.000	124.409	119.549	**90.587**	132.916	97.345
.30	130.187	**104.184**	142.896	111.172	110.582	**80.058**	124.178	86.944
.70	98.342	**67.850**	112.229	75.526	86.731	**53.819**	100.807	61.059
1.0	94.115	**63.173**	108.077	71.144	83.755	**50.780**	97.790	57.848
1.5	93.043	**62.046**	107.034	70.041	83.028	**50.029**	97.027	57.030

Note: The bold number is minimum value of ARL_1

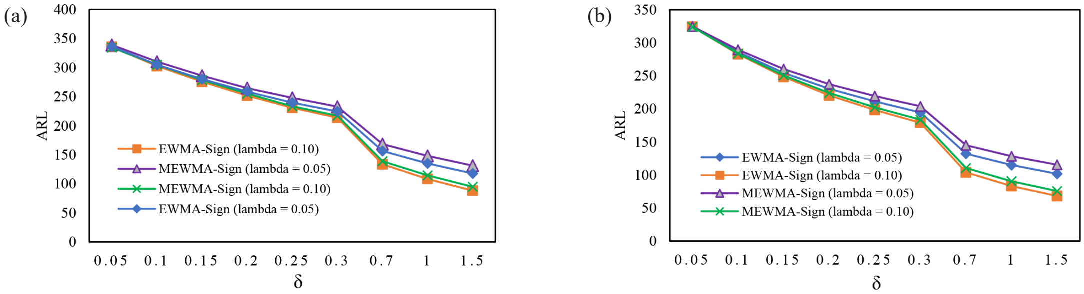

Figure 1: ARL of EWMA-Sign and MEWMA-Sign charts for Laplace(1,1) distribution by varying *n*: (a) *n* = 5 and (b) *n* = 10.

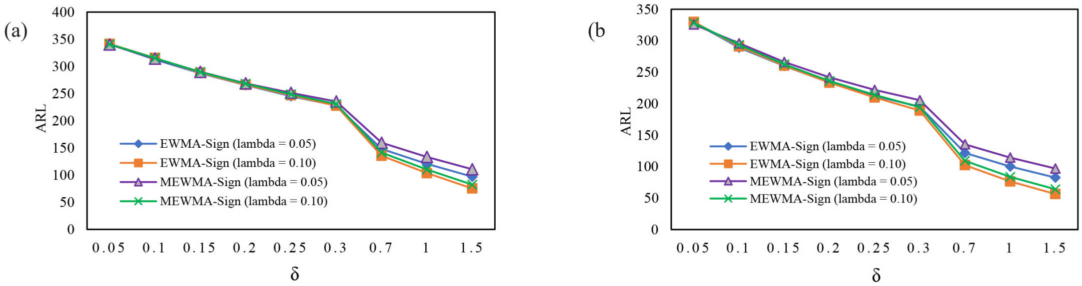

Figure 2: ARL of EWMA-Sign and MEWMA-Sign charts for Logistic(6,2) distribution by varying *n*: (a) *n* = 5 and (b) *n* = 10.

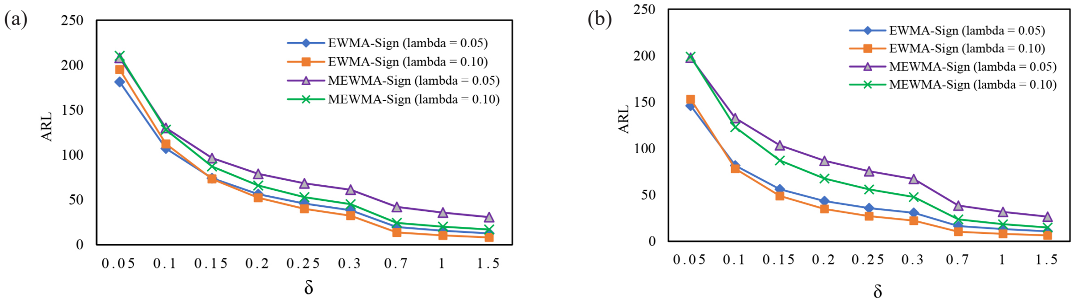

Figure 3: ARL of EWMA-Sign and MEWMA-Sign charts for Exponential(1) distribution by varying *n*: (a) *n* = 5 and (b) *n* = 10.

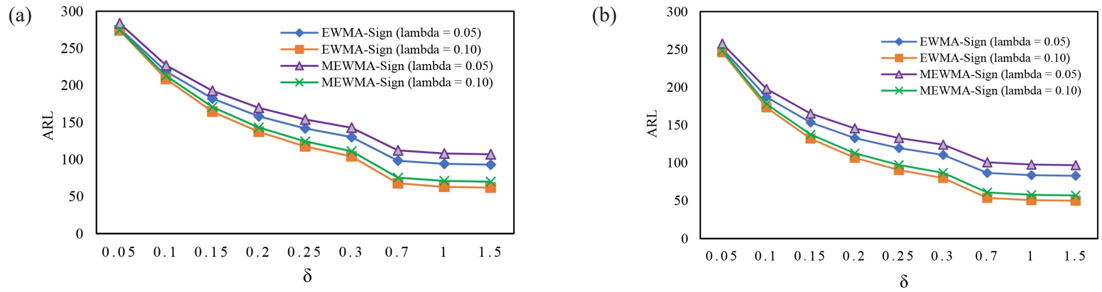

Figure 4: ARL of EWMA-Sign and MEWMA-Sign charts for Weibull(2,2) distribution by varying *n*: (a) *n* = 5 and (b) *n* = 10.

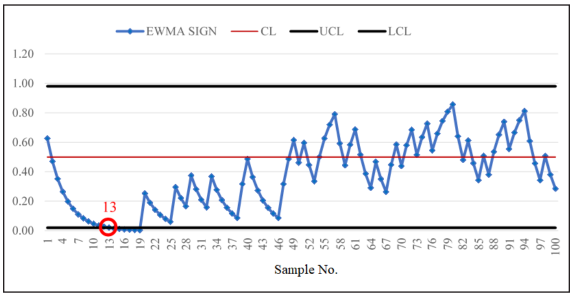

Figure 5: Graphical displays of the illustrative of the mine explosion period in the UK during 1875–1951 of EWMA-Sign control chart.

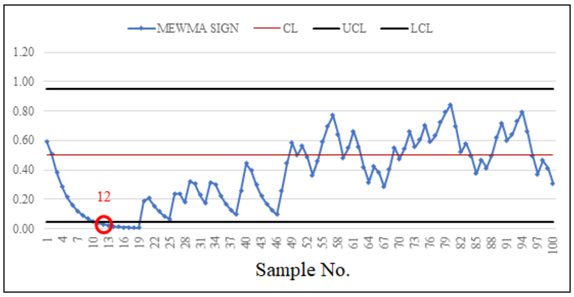

Figure 6: Graphical displays of the illustrative of the mine explosion period in the UK during 1875–1951 of MEWMA-Sign control chart.

5 Practical Applications

In this section, the mine explosion period in the UK during 1875–1951 was selected to study of the comparison performance as the real world application. The 100 data sets were collected and distributed as exponential process. When the mean process of mine explosion was 129 days/time then there is no change in mean. At the 51st change of the process, it showed 339 days/time [26].

The data sets: 378, 36, 15, 31, 215, 11, 137, 4, 15, 72, 96, 124, 50, 120, 203, 176, 55, 93, 59, 315, 59, 61, 1, 13, 189, 345, 20, 81, 286, 114, 108, 188, 233, 28, 22, 61, 78, 99, 326, 275, 54, 217, 113, 32, 23, 151, 361, 312, 354, 58, 275, 78, 17, 1205, 644, 467, 871, 48, 123, 457, 498, 49, 131, 182, 255, 195, 224, 566, 390, 72, 228, 271, 208, 517, 1613, 54, 326, 1312, 348, 745, 217, 120, 275, 20, 66, 291, 4, 369, 338, 336, 19, 329, 330, 312, 171, 145, 75, 364, 37, 19.

The performance in detecting a mean of the mine explosion period in the UK from 1875–1951 of EWMA-Sign and MEWMA-Sign control charts are presented, which the graphical displays of these control charts along with the data are provided in Figures 5 and 6. The performance of the benchmark chart can detect a mean change of the mine explosion period in the 12th and it is superior to EWMA-Sign control chart, which can detect at 13th. Consequently, it could be concluded that the MEWMA-Sign control chart was the quickest detection control chart to detect the change of the mine explosion period in the UK between 1875–1951.

6 Discussion and Conclusions

In general, the performance of control chart are measured by minimal value of ARL_1 given the desired ARL_0. The performance of MEWMA-Sign is enhanced by adding the last term of $k(S_t - S_{t-1})$, which made the MEWMA-Sign statistics are higher than EWMA-Sign control chart for the same data sets. Then, this point can enhance the ability of detection of a change of MEWMA-Sign control chart shown as the Monte Carlo simulation as well as the real practical data set.

In addition, the performance of EWMA-Sign control chart based on a smoothing parameter (λ), however, the MEWMA-Sign control chart are depended on two parameters λ and k. Consequently, in order to enhance the performance of detection of a change of MEWMA-Sign control chart need to investigate how to choose the value of k as well as λ in the sense of optimal control chart. Especially, the study investigated in the effect of k can enhance the detected properties of MEWMA-Sign control chart by raising the value of k, then it could be detect a change faster than $k = 1$. Furthermore, the nonparametric statistic studied in this research is Sign statistics, thus there are several nonparametric statistics can raise the performance of control chart such as Arcsine, Sign-Rank.

Acknowledgments

The authors gratefully acknowledge the editor and referees for their valuable comments and suggestions which greatly improve this paper. Besides, we would like to express the gratitude to the Department of Applied Statistics for allowance and financial support the Faculty of Applied Science, King Mongkut's University of Technology North Bangkok, Thailand for supporting research grants with contract no. 642046.

References

[1] D. C. Montgomery, *Introduction to Statistical Quality Control Case Study*. New York: John Wiley and Sons, 2008.

[2] B. Mason and J. Antony, "Statistical process control: An essential ingredient for improving service and manufacturing quality," *Managing Service Quality: An International Journal*, vol. 10, pp. 233–238, 2000.

[3] J. Kim, G. M. Abdella, S. Kim, K. N. Al-Khalifa, and A. M. Hamouda, "Control charts for variability monitoring in high-dimensional processes," *Computers & Industrial Engineering*, vol. 130, pp. 309–316, Feb. 2019, doi:10.1016/j.cie.2019.02.012.

[4] R. R. Sitter, L. P. Hanrahan, D. De Mets, and H. A. Anderson, "A monitoring system to detect increased rates of cancer incidence," *American Journal of Epidemiology*, vol. 132, pp. 123–130. 1990.

[5] M. Frisen, "Evaluations of methods for statistical surveillance," *Statistics in Medicine*, vol. 11, pp. 1489–1502, 1992.

[6] B. A. Ergashev, "On a CAPM monitoring based on the EWMA procedure," presented at the 9th International Conference of the Society for Computational Economics and Finance, Seattle, Jul. 11–13, 2003.

[7] V. Golosnoy and W. Schmid, "EWMA control charts for monitoring optimal portfolio weights," *Sequential Analysis*, vol. 26, pp. 195–224. 2006.

[8] M. Basseville and I. V. Nikiforov, *Detection of Abrupt Changes: Theory and Applications*. New York: Prentice-Hall, 1993.

[9] S. Ozilgen, S. Bucak, and M. Ozilgen, "Improvement of the safety of the red pepper spice with FMEA and post processing EWMA quality control charts," *Chemistry of Food Science and Technology*, vol. 50, no. 3, pp. 466–476, 2011, doi: 10.1007/s13197-011-0371-7.

[10] W. A. Shewhart, *Economic Control of Quality of Manufactured Product*. New York: D. Van Nostrand Company, 1931.

[11] E. S. Page, "Continuous inspection schemes," *Biometrika*, vol. 41, pp. 100–144, 1954.

[12] S. W. Roberts, "Control chart tests based on geometric moving average," *Technometrics*, vol. 1, pp. 239–250, 1959.

[13] S. W. Butlet and J. A. Stefani, "Supervisory run-to-run control of a polysilicon gate etch using in situ ellipsometry," *IEEE Transaction on Semiconductor Manufacturing*, vol. 7, pp. 193–201, 1994.

[14] M. B. C. Khoo, "A moving average control chart for monitoring the fraction nonconforming," *Quality and Reliability Engineering International*, vol. 20, pp. 617–635, 2004.

[15] M. B. C. Khoo and V. H. Wong, "A double moving average control chart," *Communication in Statistics – Simulation and Computation*, vol. 37, pp. 1696–1708, 2008.

[16] S. S. Alkahtani, "Robustness of DEWMA versus EWMA control charts to non-normal processes," *Journal of Modern Applied Statistical Methods*, vol. 12, pp. 148–163, 2013.

[17] N. Abbas, M. Riaz, and R. J. M. M. Does, "Mixed exponentially weighted moving average-Cumulative sum charts for process monitoring," *Quality and*

Reliability Engineering International, vol. 29, pp. 345–356, 2013.
[18] N. Abbas, M. Riaz, and R. J. M. M. Does, "CS-EWMA chart for monitoring process dispersion," *Quality and Reliability Engineering International*, vol. 29, pp.653–663, 2013.
[19] N. Thongrong, S. Sukparungsee, and Y. Areepong, "Evaluation of average run length of nonparametric EWMA sign control chart by Markov chain approach," *The Journal of KMUTNB*, vol. 26, No. 3, pp. 487–497, 2016 (in Thai).
[20] A. Prarisudtipong, Y. Areepong, and S. Sukparungsee, "An approximation of average run length for nonparametric arcsine EWMA sign control chart using Markov chain approach," *The Journal of KMUTNB,* vol. 27, no. 1, pp. 140–146, 2017 (in Thai).
[21] M. Aslam, M. Azam, and C. H. Jun, "A new exponentially weighted moving average sign chart using repetitive sampling," *Journal of Process Control*, vol. 24, no. 7, pp. 1149–1153, 2014, doi: 10.1016/ j.jprocont.2014.05.001.
[22] M. Aslam, M. A. Raza, M. Azam, L. Ahmad, and C. H. Jun, "Design of a sign chart using a new EWMA statistic," *Communications in Statistics - Theory and Methods*, vol. 49, no. 6, pp. 1299–1310, 2019, doi: 10.1080/03610926. 2018.1563163.
[23] S. F. Yang, J. S. Lin, and S. W. Cheng, "A new non parametric EWMA sign control chart," *Expert Systems with Applications*, vol. 38, no. 5, pp. 6239–6243, 2011, doi: 10.1016/ j.eswa.2010.11.044.
[24] A. K. Patel and J. Divecha, "Modified exponentially weighted moving average (EWMA) control chart for an analytical process data," *Journal of Chemical Engineering and Materials Science*, vol. 2, no. 1, pp. 12–20, 2011.
[25] R. C. Team, "R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria," (2020). [Online]. Available: http://www.R-project.org/
[26] Y. Wu, *Inference for Change-point and Post-change Means after a CUSUM Test*. New York: Springer, 2005.