Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AN16.20260366
Published: June 23, 2026

EWMA-based ALT-Norm Control Chart for Monitoring Variability of High-Dimensional Process

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Abstract

Monitoring variability in high-dimensional processes remains a challenging problem in multivariate statistical process control, particularly when only a small subset of the covariance elements changes meaningfully. The Adaptive LASSO Thresholding (ALT-norm) chart has shown strong performance in detecting sparse covariance shifts; however, as a Shewhart-type statistic, it lacks the memory structure needed to enhance sensitivity to small, persistent changes. This study introduces an EWMA-enhanced ALT-norm framework that integrates exponential smoothing into the ALT-norm statistic to improve detection of subtle deviations in the covariance matrix. The proposed EWMA-ALT-norm chart applies adaptive thresholding to the sample covariance difference matrix and updates the resulting monitoring statistic via an EWMA recursion, thereby accumulating information across successive samples. Extensive Monte Carlo simulations were conducted under seven covariance-shift scenarios, multiple shift magnitudes, and various combinations of sample size and dimensionality. Results show that incorporating EWMA substantially improves detection performance, particularly for small and moderate shifts. Smoothing parameters λ=0.20 and λ=0.50 consistently provide the best trade-off between memory and responsiveness, yielding lower ARL1 values than the original ALT-norm chart across most scenarios. Overall, the proposed EWMA-ALT-norm chart offers a robust and computationally efficient approach for high-dimensional covariance monitoring, extending the applicability of adaptive thresholding methods to settings where early detection of subtle changes in variability is critical.

Keywords
EWMA, adaptive thresholding, monitoring covariance matrix, multivariate statistical process control, average run length

1. Introduction
Statistical Process Monitoring (SPM) plays a fundamental role in quality improvement by providing statistical tools to detect process variation and maintain product and service quality. Among the various SPM techniques, control charts are widely regarded as among the most effective tools for identifying process abnormalities and signaling departures from in-control operating conditions. In modern industrial environments, multiple quality characteristics are often measured simultaneously and exhibit complex correlation structures. Consequently, multivariate statistical

process control (MSPC) techniques have become increasingly important for monitoring process performance while accounting for relationships among variables.

Although substantial research has focused on monitoring shifts in process means, monitoring the covariance matrix of multivariate processes is equally important because changes in process variability often signal quality deterioration, equipment malfunction, or process instability. However, monitoring the covariance matrix is considerably more challenging than monitoring the mean because of the large number of parameters and the absence of a simple statistic that fully summarizes process variability (Ebadi et al., 2022). These challenges are even more pronounced in high-dimensional settings, where the number of process variables exceeds the available sample size.

The increasing prevalence of high-dimensional data in modern manufacturing, healthcare, finance, and engineering applications has motivated considerable research into the development of monitoring schemes for these environments. Several studies have addressed the challenges associated with monitoring high-dimensional process means. For example, Abdella et al. (2017) proposed a variable-selection-based multivariate cumulative sum (VS-MCUSUM) control chart to enhance the detection of mean shifts in high-dimensional multivariate normal processes. Feng et al. (2020) combined a divide-and-conquer strategy with the multivariate exponentially weighted moving average (MEWMA) chart to efficiently monitor high-dimensional process outcomes, while Yan et al. (2019) introduced a variable-selection monitoring scheme based on Gaussian mixture models and penalized likelihood methods for multimodal high-dimensional processes. Additional developments in high-dimensional process monitoring can be found in Chen (2020), Ebadi et al. (2022), Jalilibal et al. (2024), and Ahmed et al. (2025).

Despite these advances, relatively fewer studies have focused on monitoring variability and covariance structures in high-dimensional processes. Existing covariance-monitoring procedures often face challenges related to computational complexity, sparsity assumptions, and sensitivity to small shifts. Therefore, the development of efficient and sensitive covariance-monitoring techniques remains an important research area within high-dimensional SPC. The Multivariate Exponentially Weighted Moving Average (MEWMA) chart is well known for its ability to accumulate historical process information and provide superior sensitivity to small and moderate shifts. After being introduced by Lowry et al. (1992) which extended EWMA to be applicable for multivariate settings, multiple studies incorporated MEWMA structure for process monitoring and has been widely adopted since then, see Abdella et al. (2016), Zhang et al. (2020), Li et al. (2020), Zhao et al. (2021), Fang et al. (2022), Gómez et al. (2022), S. Kim et al. (2022), and Maboudou-Tchao et al. (2023) as recent examples. While EWMA-based schemes have been extensively studied for process mean monitoring, their application to high-dimensional covariance matrix monitoring remains limited. Motivated by the strong performance of adaptive thresholding techniques and the memory properties of EWMA statistics, this study proposes an EWMA-enhanced version of the Adaptive LASSO Thresholding Norm (ALT-norm) control chart for monitoring high-dimensional covariance matrices.

2. Research Motivation and Contribution

From a methodological perspective, this work bridges two successful concepts in statistical process monitoring: adaptive thresholding for sparse high-dimensional covariance changes and EWMA-based memory mechanisms for enhanced shift detection. By combining these approaches, the proposed chart seeks to retain the sparsity-adaptive advantages of ALT-norm while overcoming its limited sensitivity to small and moderate shifts, thereby providing a more effective tool for high-dimensional covariance monitoring.

The primary contribution of this paper is to investigate the effect of incorporating the EWMA memory structure into the ALT-norm control chart for monitoring covariance matrices of high-dimensional processes. Specifically, the study aims to 1) develop an EWMA-based ALT-norm monitoring statistic for detecting changes in high-dimensional covariance matrices. 2) evaluate the run-length performance of the proposed chart under various covariance shift patterns and shift magnitudes, and 3) examine the ability of the proposed chart to detect small and moderate covariance shifts relative to the original ALT-norm chart.

3. Literature Review

A common assumption in high-dimensional covariance monitoring is sparsity, whereby only a small proportion of the elements of the in-control covariance matrix are affected when the process shifts out of control (Abdella et al., 2017). In other words, relatively few entries in the covariance matrix change meaningfully, while the majority remain unchanged (Cai & Zhou, 2012). This assumption has motivated the development of sparse covariance estimation techniques based on regularization and thresholding procedures.

One influential contribution was made by Huang et al. (2006), who proposed a sparse covariance matrix estimation framework that later became the foundation for several high-dimensional SPC applications. Building on sparse estimation concepts, Yeh et al. (2012) introduced a monitoring procedure based on the Least Absolute Shrinkage and Selection Operator (LASSO) to detect changes in sparse inverse covariance matrices. Their work demonstrated the potential of penalization methods for covariance monitoring in high-dimensional settings. J. Kim et al. (2019) introduced a control chart based on a penalized likelihood ratio statistic to detect sustained changes in high-dimensional covariance matrices when the number of variables exceeds the sample size. Later, S. Kim et al. (2020) proposed a monitoring framework that uses an adjusted L2-norm-penalized likelihood ratio statistic for high-dimensional covariance monitoring. However, penalized likelihood-based methods suffer from several limitations. Abdella et al. (2019) argued that the performance of such approaches depends heavily on the choice of tuning parameters and the underlying shift patterns. Furthermore, the transformations employed by these methods may distort the original sparsity structure, such that a small number of covariance changes can appear as widespread changes after transformation.

To overcome these limitations, Abdella et al. (2019) proposed the Adaptive LASSO Thresholding Norm (ALT-norm) control chart. Inspired by the adaptive thresholding methodology of Cai & Liu (2011), the ALT-norm chart directly estimates changes in covariance without relying on data transformations or penalized-likelihood formulations. Extensive Monte Carlo simulations demonstrated that the ALT-norm chart exhibits excellent detection performance across various covariance-shift patterns and magnitudes, making it particularly attractive for high-dimensional covariance monitoring. Subsequent studies extended the adaptive thresholding framework in several directions. Abdella et al. (2020) proposed the T-COV chart, a Phase I monitoring procedure for detecting changes in the covariance matrix of multivariate normal processes under the sparsity assumption. Their simulation studies showed that T-COV outperformed several existing approaches across different shift scenarios.

Recognizing that measurement systems are often affected by gauge inaccuracies, Jafari et al. (2023) developed an Adaptive Thresholding LASSO (ATL) control chart that accounts for random measurement errors. Their results demonstrated that ATL consistently outperformed the entropy-based chart across a broad range of covariance shift patterns and magnitudes. More recently, researchers have focused on improving the sensitivity of adaptive thresholding charts through advanced sampling strategies. Salmasnia et al. (2025) proposed a Double-Sampling Adaptive Thresholding LASSO (DSATL) chart for monitoring sparse high-dimensional covariance matrices. Simulation results showed that DSATL achieved superior detection performance compared with the conventional ATL chart, particularly as process dimensionality increased. Similarly, Hajiesmaeili et al. (2025) integrated the Multiple Dependent State (MDS) and Generalized Multiple Dependent State (GMDS) sampling schemes with the adaptive-thresholding LASSO statistic, resulting in substantial improvements in run-length performance and detection sensitivity.

Although adaptive thresholding-based covariance monitoring methods have demonstrated strong performance in high-dimensional environments, existing studies have primarily focused on improving estimation procedures and sampling strategies. To the best of the authors' knowledge, no previous study has incorporated the EWMA memory mechanism into the ALT-norm framework. Therefore, the present study addresses this gap by developing an EWMA-ALT-norm control chart that combines the adaptive thresholding capability of ALT-norm with the shift-accumulation properties of EWMA. It is anticipated that the proposed approach will provide enhanced sensitivity to small and moderate covariance shifts while maintaining the effectiveness of the original ALT-norm chart in high-dimensional settings.

4. Research Methodology

The ALT-norm is a Shewhart-type statistic (no memory) that relies on the sparsity assumption (a small number of elements in the covariance matrix shift in high-dimensional settings). The mechanism of the ALT-norm approach is as follows: Let $y_t = (y_{t1}, y_{t2}, \dots, y_{tn})$ be the tth sample with size n following $N_p(\mu_0, \Sigma_0)$ where μ_0, Σ_0 are the in-control mean and covariance matrix, respectively. The variability monitoring problem is testing the hypothesis of

$$H_0: \Sigma - \Sigma_0 = 0 \ \text{ versus } H_1: \Sigma - \Sigma_0 \neq 0$$

The chart is initiated by collecting a sample of size n and calculating the empirical covariance matrix as: $S_t = \frac{1}{n-1}\sum_{i=1}^{n}(y_{ti} - \bar{y}_i)(y_{ti} - \bar{y}_i)^T$ where $\bar{y}_t = n^{-1}\sum_{i=1}^{n} y_{ti}$. The difference matrix is defined as $D_t = (d_{ijt})_{1\le i,j\le p} = S_t - \Sigma_0$. Apply adaptive thresholding to individual elements in D_t depending on a threshold defined as

$$\gamma_{ij}^{*} = \varphi\sqrt{\frac{(\sigma_{ii}\sigma_{jj} + \sigma_{ij}^{2})\cdot \log p}{n}} \tag{1}$$

Where the thresholded difference matrix can be expressed as:

$$\widehat{D}_t = \left(d_{ijt}\left(1 - \left(\frac{\gamma_{ij}^{*}}{d_{ijt}}\right)^{\eta}\right)_{+}\right)_{1\le i,j\le p} \tag{2}$$

where φ and η are tuning parameters. The authors stated that the parameter φ can be seen as an acceptable specification level of the variation and η determines the level of shrinkage and proposes the values of $\varphi = 1.0$ and $\eta = 4.0$ as a good practical choice. They also stated that smaller values of φ and larger values of η will yield enhanced detection performance for small shifts ($\delta \le 0.2$), and larger values of φ would lead to a stronger chart when process change is anticipated to be sparser.

After computing the thresholded covariance matrix, the charting statistic is conducted by calculating the squared Frobenius norm as follows:

$$M_t = \sum_{i=1}^{p}\sum_{j=1}^{p}\frac{1}{n}\cdot\left(\frac{\hat{d}_{ijt}^{2}}{\sigma_{ii}\sigma_{jj} + \sigma_{ij}^{2}}\right) \tag{3}$$

Where the control chart signals whenever M_t exceeds a predetermined CL. EWMA can be applied to M_t to update it over time by the following:

$$M_t = M_{t-1}.(1-\lambda) + M_t.(\lambda) \tag{4}$$

The start equation, lambda, is the smoothing parameter that controls the level of influence to give for previous values, where lower values give more influence to historical values. In this work, the values of 0.05, 0.2, 0.5, and 0.8 will be reported. To simulate an out-of-control signal, the following seven out-of-control cases are introduced, same as in Abdella et al. (2019), where the in-control covariance matrix is the Identity matrix:

Case 1: $\sigma_{ii} = 1 + \delta$ for $1 \le i \le p$

$$\Sigma_{OC1} = \begin{pmatrix} 1+\delta & 0 & \cdots & 0 \\ 0 & 1+\delta & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1+\delta \end{pmatrix}_{p*p}$$

Case 2: $\sigma_{ii} = 1 + \delta$ for $i = 1$

$$\Sigma_{OC2} = \begin{pmatrix} 1+\delta & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{pmatrix}_{p*p}$$

Case 3: $\sigma_{ij} = \delta$ for $1 \le i, j \le k \le p,\ k = 5, and\ i \ne j$

$$\Sigma_{OC3} = \begin{pmatrix} 1 & \delta & \delta & \delta & \delta & 0 & \cdots & 0 \\ \delta & 1 & \delta & \delta & \delta & 0 & \cdots & 0 \\ \delta & \delta & 1 & \delta & \delta & 0 & \cdots & 0 \\ \delta & \delta & \delta & 1 & \delta & 0 & \cdots & 0 \\ \delta & \delta & \delta & \delta & 1 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 1 \end{pmatrix}_{p*p}$$

Case 4: $\sigma_{ij} {+}{=}\ \delta$ for $1 \le i, j \le k \le p,\ k = 3$

$$\Sigma_{OC4} = \begin{pmatrix} 1+\delta & \delta & \delta & 0 & \cdots & 0 \\ \delta & 1+\delta & \delta & 0 & \cdots & 0 \\ \delta & \delta & 1+\delta & 0 & \cdots & 0 \\ 0 & 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & 1 \end{pmatrix}_{p*p}$$

Case 5: $\sigma_{ij} = \delta$ for $1 \leq i, j \leq k \leq p,\ k = 2, and\ i \neq j$

$$\Sigma_{OC5} = \begin{pmatrix} 1 & \delta & 0 & \cdots & 0 \\ \delta & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}_{p*p}$$

Case 6: $\sigma_{ij} = \delta$ for $1 \leq i, j \leq k \leq p,\ k = 2, and\ i \neq j$, $\sigma_{ii} = 1 + \delta^2$ for $1 \leq i, j \leq k \leq p,\ k = 2, and\ i = j$

$$\Sigma_{OC6} = \begin{pmatrix} 1+\delta^2 & \delta & 0 & \cdots & 0 \\ \delta & 1+\delta^2 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}_{p*p}$$

Case 7: $\sigma_{ij} \mathrel{+}= \delta\ and\ \sigma_{p+i-1,p=j-1} \mathrel{+}= \delta$ for $1 \leq i, j \leq k \leq p,\ k = 2$

$$\Sigma_{OC7} = \begin{pmatrix} 1+\delta & \delta & 0 & \cdots & 0 & \cdots & 0 \\ \delta & 1+\delta & 0 & \cdots & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & 0 & 1+\delta & \delta \\ 0 & 0 & 0 & 0 & 0 & \delta & 1+\delta \end{pmatrix}_{p*p}$$

5. Performance Measure of EWMA-ALT

The performance of the proposed control charts is evaluated using the Average Run Length (ARL), which is the most widely adopted measure in statistical process monitoring. The ARL is defined as the expected number of samples collected before a control chart signals an out-of-control condition. In this study, ARL0 and ARL1 represent the in-control and out-of-control average run lengths, respectively. From a practical perspective, an effective monitoring procedure should have a high ARL0 to reduce the frequency of false alarms and a low ARL1 to facilitate the prompt detection of process disturbances. The performance was assessed via simulations based on 25,000 runs, calibrated to an ARL0 of 200 (the chart indicates a false-positive rate of 0.05). The samples were generated using the multivariate normal random function available in the NumPy package on Python. The ARL1 and its standard deviation (SDRL) results are reported.

Table 1 presents the out-of-control performance of the proposed ALT-norm-EWMA chart with smoothing parameters λ = 0.05,0.20,0.50, and 0.80, compared with the original ALT-norm chart, for a process with $n = 30$ and $p = 15$.

Table 1. ARL1 and SDRL values when n = 30 and p = 15 with default tuning parameter values

		ALT-norm		ALT-norm-EWMA $\lambda = 0.05$		ALT-norm-EWMA $\lambda = 0.20$		ALT-norm-EWMA $\lambda = 0.50$		ALT-norm-EWMA $\lambda = 0.80$	
OC Case	delta	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1
1	0.2	5.89	5.33	17.48	2.51	6.55	1.94	4.70	2.61	5.15	4.06
	0.4	1.36	0.71	8.77	1.17	3.12	0.75	1.85	0.68	1.47	0.69
	0.6	1.00	0.00	5.51	0.76	2.05	0.46	1.17	0.38	1.04	0.19
	0.8	1.00	0.00	3.88	0.59	1.53	0.50	1.01	0.11	1.00	0.03
	1.0	1.00	0.00	2.96	0.46	1.13	0.33	1.00	0.01	1.00	0.00
2	0.2	118.21	118.43	97.61	48.08	90.03	78.83	104.09	100.95	115.95	114.93
	0.4	46.56	46.51	53.49	16.88	34.06	24.58	38.34	35.26	43.84	42.38

		ALT-norm		ALT-norm-EWMA $\lambda = 0.05$		ALT-norm-EWMA $\lambda = 0.20$		ALT-norm-EWMA $\lambda = 0.50$		ALT-norm-EWMA $\lambda = 0.80$	
OC Case	delta	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1
	0.6	17.50	17.20	34.06	8.28	16.11	9.05	14.84	12.47	16.36	15.44
	0.8	7.87	7.46	23.39	5.37	9.54	4.52	7.32	5.40	7.50	6.58
	1.0	4.35	3.77	16.88	4.00	6.49	2.84	4.54	3.02	4.35	3.53
3	0.2	31.98	31.73	46.65	13.47	26.42	17.49	26.51	23.65	30.28	29.25
	0.4	3.64	3.06	15.51	3.56	5.84	2.46	3.90	2.47	3.60	2.84
	0.6	1.20	0.68	7.40	1.90	2.80	1.14	1.80	0.91	1.57	0.87
	0.8	1.00	0.01	4.41	1.25	1.81	0.74	1.26	0.50	1.15	0.40
	1.0	1.00	0.01	3.01	0.91	1.36	0.53	1.08	0.28	1.04	0.20
4	0.2	28.23	27.37	39.39	9.72	20.66	12.40	21.96	19.11	26.09	24.98
	0.4	4.29	3.74	16.61	3.54	6.34	2.58	4.41	2.83	4.24	3.39
	0.6	1.81	1.20	9.01	2.20	3.38	1.36	2.16	1.14	1.90	1.16
	0.8	1.28	0.59	5.69	1.59	2.26	0.92	1.50	0.69	1.32	0.60
	1.0	1.03	0.32	4.01	1.24	1.72	0.71	1.23	0.46	1.13	0.36
5	0.2	154.96	155.32	140.70	85.17	138.13	125.69	144.69	140.38	154.10	151.31
	0.4	42.78	41.88	55.81	18.52	34.90	25.53	37.44	34.39	41.28	39.78
	0.6	9.55	9.03	25.31	5.47	10.48	4.89	8.41	6.31	8.89	7.95
	0.8	3.20	2.67	13.90	2.78	5.15	1.91	3.39	1.97	3.15	2.33
	1.0	1.03	0.17	8.73	1.79	3.22	1.11	2.00	0.95	1.71	0.97
6	0.2	129.97	127.55	112.63	60.79	105.86	93.73	117.72	114.15	127.32	127.12
	0.4	23.97	23.06	40.09	10.59	20.83	12.93	20.12	17.57	22.64	21.69
	0.6	5.19	4.61	18.87	4.30	7.32	3.24	5.20	3.59	5.06	4.22
	0.8	2.21	1.64	10.40	2.64	3.91	1.64	2.55	1.46	2.25	1.51
	1.0	1.40	0.75	6.36	1.83	2.51	1.06	1.67	0.81	1.47	0.76
7	0.2	28.00	27.22	36.80	8.32	18.78	10.61	20.26	17.55	25.27	23.99
	0.4	4.44	3.87	16.50	3.10	6.21	2.27	4.26	2.57	4.18	3.32
	0.6	1.72	1.10	9.20	1.92	3.38	1.17	2.11	1.03	1.81	1.08
	0.8	1.20	0.49	5.86	1.37	2.25	0.81	1.44	0.61	1.25	0.52
	1.0	1.02	0.23	4.13	1.05	1.69	0.63	1.17	0.39	1.08	0.28
CL				16.0360		20.1644		26.4845		32.7836	

The results show that incorporating the EWMA statistic generally enhances the sensitivity of the ALT-norm chart, particularly for small covariance shifts. For the smallest shift magnitude ($\delta = 0.2$), all ALT-norm-EWMA configurations outperform the benchmark ALT-norm chart in most of the out-of-control cases. For example, in OC Case 7, the ARL1 decreases from 28.00 for the ALT-norm chart to 18.78 when λ=0.20, representing a reduction of approximately 33%. Similar improvements are observed in Cases 2–6, where the proposed chart consistently signals more quickly than the original ALT-norm chart. These findings confirm the well-known advantage of EWMA-based schemes in accumulating information from successive samples, thereby improving the detection of small and persistent process changes.

Among the proposed charts, λ=0.20 provides the best performance for most small-shift scenarios. For δ=0.2, it yields the lowest ARL1 values in OC Cases 2–7 and performs competitively in Case 1. This suggests that a moderate level of smoothing effectively balances memory and responsiveness, enabling the chart to detect subtle changes in covariance more efficiently. As the shift magnitude increases to δ=0.4 and δ=0.6, the ALT-norm-EWMA chart with λ=0.50 is the most effective configuration in most cases. For instance, in OC Case 5, the ARL1 decreases from 42.78 to 37.44 at δ=0.4 and from 9.55 to 8.41 at δ=0.6. Likewise, in OC Case 2, the ARL1 decreases from 46.56 to 38.34 for δ=0.4 and from 17.50 to 14.84 for δ=0.6. These reductions demonstrate that the proposed EWMA-enhanced chart remains more sensitive than the benchmark chart as the magnitude of the covariance shift increases. For large shifts (δ=0.8 and 1.0), the differences among the competing charts become smaller because all charts can detect substantial process changes rapidly. Nevertheless, the ALT-norm-EWMA chart with λ=0.50 continues to produce the lowest or near-lowest ARL1 values in most cases. For example, in OC Case 2, the ARL1 decreases from 7.87 to 7.32 when δ=0.8 and from 4.35 to 4.54 when δ=1.0, indicating performance comparable to the benchmark. Similar trends are observed across the remaining out-of-control scenarios.

Regarding the effect of the smoothing parameter, the results indicate that very small values of λ (e.g., λ=0.05) generally lead to inferior performance due to excessive smoothing, which delays the chart's response. Conversely, large values such as λ=0.80 reduce the memory effect of the EWMA statistic and often result in poorer performance than λ=0.20 or λ=0.50. Overall, λ=0.20 is most effective for detecting small shifts, whereas λ=0.50 provides the best overall performance across moderate and large shifts. Table 2- Table 4 present the out-of-control performance of the ALT-norm and ALT-norm-EWMA charts for the additional combinations of sample size and process dimension, namely $(n = 60, p = 15.)$, $(n = 30, p = 30)$, and $(n = 60, p = 30)$ with smoothing parameters λ = 0.05,0.20,0.50, and 0.80.

Table 2. ARL1 and SDRL values when n = 60 and p = 15 with default tuning parameter values

		ALT-norm		ALT-norm-EWMA λ = 0.05		ALT-norm-EWMA λ = 0.20		ALT-norm-EWMA λ = 0.50		ALT-norm-EWMA λ = 0.80	
OC Case	delta	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1
1	0.2	3.56	2.99	15.44	1.96	5.49	1.39	3.49	1.58	3.32	2.27
	0.4	1.06	0.26	7.14	0.85	2.51	0.56	1.41	0.51	1.11	0.32
	0.6	1.00	0.00	4.23	0.55	1.65	0.48	1.01	0.09	1.00	0.02
	0.8	1.00	0.00	2.92	0.37	1.05	0.22	1.00	0.00	1.00	0.00
	1.0	1.00	0.00	2.07	0.27	1.00	0.01	1.00	0.00	1.00	0.00
2	0.2	98.39	98.30	84.60	36.57	70.59	59.67	83.72	80.93	92.59	92.39
	0.4	23.49	22.76	40.58	10.03	20.31	12.04	19.69	16.91	22.18	21.08
	0.6	6.82	6.43	23.03	4.80	9.00	3.96	6.56	4.64	6.59	5.73
	0.8	3.02	2.50	14.45	3.10	5.28	2.08	3.40	2.00	3.05	2.24
	1.0	1.55	0.92	9.83	2.26	3.59	1.39	2.22	1.16	1.92	1.18
3	0.2	9.05	8.61	25.68	5.00	10.30	4.40	8.05	5.79	8.51	7.51
	0.4	1.30	0.63	7.40	1.50	2.69	0.92	1.64	0.73	1.37	0.65
	0.6	1.00	0.10	3.57	0.83	1.45	0.53	1.06	0.24	1.02	0.14
	0.8	1.00	0.01	2.24	0.59	1.07	0.26	1.00	0.04	1.00	0.02
	1.0	1.00	0.00	1.65	0.52	1.01	0.07	1.00	0.01	1.00	0.00
4	0.2	12.02	11.31	28.56	5.61	12.02	5.47	10.09	7.67	11.27	10.25
	0.4	1.80	1.20	10.07	2.06	3.61	1.27	2.22	1.11	1.87	1.12
	0.6	1.10	0.34	5.09	1.23	1.97	0.72	1.28	0.50	1.14	0.38
	0.8	1.01	0.11	3.20	0.87	1.37	0.51	1.06	0.23	1.02	0.15
	1.0	1.00	0.00	2.29	0.68	1.12	0.32	1.01	0.10	1.00	0.06
5	0.2	98.51	97.53	93.01	43.23	78.48	66.86	88.76	85.68	95.58	94.43
	0.4	9.57	8.99	26.50	5.27	10.80	4.78	8.35	6.15	8.99	7.97
	0.6	2.00	1.40	11.36	2.04	4.03	1.30	2.47	1.20	2.08	1.29
	0.8	1.12	0.36	6.32	1.16	2.31	0.70	1.39	0.54	1.17	0.41
	1.0	1.00	0.09	4.13	0.80	1.61	0.53	1.06	0.24	1.01	0.12
6	0.2	79.53	79.02	77.74	31.63	60.57	49.27	68.85	65.47	76.94	76.41
	0.4	6.84	6.31	22.85	4.63	8.92	3.81	6.49	4.53	6.43	5.53
	0.6	1.81	1.20	10.08	2.16	3.65	1.34	2.24	1.15	1.92	1.18
	0.8	1.16	0.43	5.55	1.37	2.13	0.82	1.38	0.58	1.21	0.47
	1.0	1.03	0.17	3.49	0.98	1.48	0.57	1.10	0.31	1.05	0.22
7	0.2	13.39	12.85	28.40	5.26	11.98	5.26	10.33	7.77	11.97	10.82
	0.4	1.80	1.20	10.64	1.89	3.78	1.19	2.27	1.06	1.91	1.13
	0.6	1.08	0.29	5.47	1.10	2.06	0.67	1.27	0.48	1.11	0.34
	0.8	1.00	0.08	3.42	0.78	1.39	0.51	1.04	0.19	1.01	0.10
	1.0	1.00	0.02	2.43	0.61	1.10	0.29	1.00	0.06	1.00	0.03
CL				14.7299		18.2059		23.4211		28.5418	

Table 3. ARL1 and SDRL values when n = 30 and p = 30 with default tuning parameter values

		ALT-norm		ALT-norm-EWMA λ = 0.05		ALT-norm-EWMA λ = 0.20		ALT-norm-EWMA λ = 0.50		ALT-norm-EWMA λ = 0.80	
OC Case	delta	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1
1	0.2	2.35	1.78	16.15	1.57	5.28	1.04	2.95	1.05	2.46	1.39
	0.4	1.01	0.01	8.30	0.77	2.74	0.52	1.41	0.50	1.06	0.23
	0.6	1.00	0.00	5.30	0.55	1.93	0.29	1.01	0.10	1.00	0.01
	0.8	1.00	0.00	3.82	0.43	1.31	0.46	1.00	0.01	1.00	0.00
	1.0	1.00	0.00	2.95	0.27	1.01	0.11	1.00	0.00	1.00	0.00
2	0.2	135.01	134.73	115.94	56.47	108.65	93.62	122.59	119.30	133.01	129.91
	0.4	64.55	63.90	70.25	22.23	47.87	35.30	53.32	49.60	60.28	58.85
	0.6	25.01	24.21	47.32	10.62	23.01	13.24	21.40	18.34	23.48	22.30
	0.8	10.98	10.35	34.04	6.56	13.66	6.29	10.33	7.80	10.62	9.54
	1.0	5.87	5.42	25.47	4.79	9.28	3.74	6.16	4.15	5.77	4.79
3	0.2	66.85	65.64	79.66	29.04	55.75	43.33	58.76	55.06	63.90	62.11
	0.4	6.36	5.77	27.89	5.47	10.27	4.36	6.78	4.69	6.37	5.43
	0.6	1.96	1.38	13.01	2.76	4.43	1.67	2.56	1.41	2.12	1.39
	0.8	1.25	0.58	7.39	1.76	2.62	1.02	1.58	0.72	1.33	0.61

		ALT-norm		ALT-norm-EWMA $\lambda = 0.05$		ALT-norm-EWMA $\lambda = 0.20$		ALT-norm-EWMA $\lambda = 0.50$		ALT-norm-EWMA $\lambda = 0.80$	
OC Case	delta	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1
	1.0	1.00	0.26	4.84	1.26	1.84	0.71	1.21	0.44	1.10	0.32
4	0.2	46.76	46.63	56.50	14.23	32.45	21.30	36.18	32.42	42.48	41.23
	0.4	6.67	6.12	26.34	4.58	9.62	3.64	6.52	4.30	6.42	5.38
	0.6	2.32	1.72	14.78	2.84	4.99	1.77	2.90	1.51	2.43	1.63
	0.8	1.45	0.82	9.29	2.09	3.22	1.19	1.89	0.90	1.56	0.82
	1.0	1.18	0.47	6.42	1.63	2.34	0.92	1.45	0.63	1.23	0.49
5	0.2	176.56	177.39	171.93	106.22	170.95	155.29	174.74	169.47	176.18	170.71
	0.4	80.52	79.55	89.18	35.86	67.33	54.64	72.40	68.46	76.55	75.74
	0.6	18.73	18.24	42.70	9.15	19.10	10.27	16.35	13.44	17.59	16.32
	0.8	5.39	4.87	24.07	4.03	8.60	3.10	5.54	3.44	5.28	4.29
	1.0	2.32	1.77	15.16	2.54	5.09	1.60	2.91	1.45	2.45	1.58
6	0.2	159.04	160.55	141.05	78.85	137.47	123.13	150.10	144.51	154.97	151.30
	0.4	42.95	43.04	60.36	16.77	35.24	24.07	36.60	33.28	39.73	38.61
	0.6	8.19	7.60	30.01	5.70	11.37	4.86	8.10	5.80	7.95	6.81
	0.8	2.84	2.26	16.95	3.33	5.82	2.17	3.47	1.99	3.00	2.15
	1.0	1.61	1.00	10.28	2.36	3.55	1.36	2.11	1.06	1.72	0.99
7	0.2	43.90	43.06	51.78	11.60	28.26	17.18	32.10	28.44	39.75	38.23
	0.4	6.71	6.19	25.69	3.93	9.24	3.20	6.30	3.90	6.37	5.23
	0.6	2.20	2.20	14.88	2.41	4.98	1.53	2.86	1.36	2.36	1.51
	0.8	1.35	1.35	9.55	1.77	3.23	1.03	1.83	0.80	1.46	0.71
	1.0	1.10	1.10	6.65	1.39	2.34	0.78	1.39	0.55	1.16	0.40
CL				27.3204		32.1144		39.1325		46.0181	

Table 4. ARL1 and SDRL values when n = 60 and p = 30, with default tuning parameter

		ALT-norm		ALT-norm-EWMA $\lambda = 0.05$		ALT-norm-EWMA $\lambda = 0.20$		ALT-norm-EWMA $\lambda = 0.50$		ALT-norm-EWMA $\lambda = 0.80$	
OC Case	delta	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1
1	0.2	1.55	0.92	14.64	1.24	4.64	0.80	2.43	0.70	1.80	0.85
	0.4	1.00	0.00	7.08	0.61	2.26	0.44	1.11	0.31	1.00	0.05
	0.6	1.00	0.00	4.26	0.45	1.58	0.49	1.00	0.00	1.00	0.00
	0.8	1.00	0.00	3.00	0.17	1.00	0.07	1.00	0.00	1.00	0.00
	1.0	1.00	0.00	2.06	0.24	1.00	0.00	1.00	0.00	1.00	0.00
2	0.2	120.88	118.47	104.42	44.77	89.98	77.07	102.95	98.14	115.12	113.36
	0.4	36.24	35.60	56.21	13.57	29.81	18.82	29.71	25.98	33.72	32.51
	0.6	10.00	9.48	34.33	6.03	13.17	5.57	9.58	6.93	9.55	8.38
	0.8	4.05	3.50	22.59	3.84	7.67	2.68	4.68	2.80	4.13	3.16
	1.0	2.23	1.66	15.66	2.83	5.18	1.74	2.93	1.51	2.40	1.58
3	0.2	20.57	20.19	45.28	8.99	20.09	10.42	17.49	14.20	19.18	17.76
	0.4	1.68	1.08	13.03	2.19	4.24	1.32	2.33	1.07	1.82	1.07
	0.6	1.04	0.20	5.83	1.14	2.04	0.66	1.21	0.43	1.07	0.26
	0.8	1.00	0.00	3.45	0.77	1.34	0.48	1.02	0.13	1.00	0.06
	1.0	1.00	0.00	2.39	0.59	1.06	0.24	1.00	0.03	1.00	0.01
4	0.2	21.43	20.73	43.45	8.11	19.20	9.45	17.21	13.87	19.74	18.35
	0.4	2.41	1.85	16.65	2.69	5.46	1.72	3.08	1.54	2.52	1.66
	0.6	1.19	0.48	8.29	1.61	2.79	0.92	1.58	0.68	1.28	0.54
	0.8	1.02	0.17	5.02	1.13	1.83	0.65	1.16	0.37	1.05	0.22
	1.0	1.00	0.05	3.44	0.86	1.38	0.51	1.04	0.19	1.01	0.09
5	0.2	21.43	20.73	133.64	69.50	124.30	109.80	132.26	128.01	140.57	139.90
	0.4	2.41	1.85	43.87	8.61	19.15	9.78	16.16	13.03	17.47	16.23
	0.6	1.19	0.48	19.53	2.87	6.46	1.89	3.71	1.89	3.12	2.17
	0.8	1.02	0.17	10.65	1.58	3.47	0.93	1.87	0.74	1.42	0.65
	1.0	1.00	0.05	6.76	1.07	2.28	0.62	1.26	0.45	1.06	0.24
6	0.2	119.32	118.34	110.75	50.84	97.81	84.21	105.66	101.51	115.65	114.82
	0.4	11.71	11.18	36.83	6.62	14.44	6.46	10.92	8.17	11.07	9.91
	0.6	2.41	1.83	16.70	2.85	5.51	1.80	3.12	1.60	2.54	1.69
	0.8	1.27	0.59	9.05	1.82	3.05	1.04	1.72	0.77	1.38	0.65
	1.0	1.05	0.24	5.49	1.28	1.98	0.72	1.24	0.46	1.09	0.30
7	0.2	23.24	23.04	42.10	7.26	18.28	8.54	17.20	13.85	20.71	19.30
	0.4	2.43	1.88	17.41	2.46	5.67	1.57	3.17	1.46	2.62	1.69
	0.6	1.15	0.43	8.89	1.44	2.93	0.83	1.60	0.64	1.25	0.50
	0.8	1.01	0.12	5.42	1.00	1.92	0.58	1.13	0.34	1.03	0.17

		ALT-norm		ALT-norm-EWMA $\lambda = 0.05$		ALT-norm-EWMA $\lambda = 0.20$		ALT-norm-EWMA $\lambda = 0.50$		ALT-norm-EWMA $\lambda = 0.80$	
OC Case	delta	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1	ARL1	SDRL1
	1.0	1.00	0.03	3.72	0.77	1.41	0.50	1.02	0.14	1.00	0.05
CL				24.5861		28.4612		34.0196		39.4759	

The results exhibit patterns that are highly consistent with those observed in Table 1. Across all settings, incorporating the EWMA statistic enhances the sensitivity of the ALT-norm chart, particularly for small covariance shifts. The ALT-norm-EWMA charts generally produce lower ARL1 values than the benchmark ALT-norm chart when δ=0.2, confirming the effectiveness of the EWMA memory structure in accumulating information from successive samples and improving the detection of subtle process changes.

As the shift magnitude increases, the relative differences between the competing charts become less pronounced, although the proposed ALT-norm-EWMA chart continues to maintain comparable or superior performance in most out-of-control scenarios. Consistent with the findings reported in Table 1, the chart with λ=0.20 tends to perform best for small shifts, whereas λ=0.50 offers the most balanced performance over a wider range of shift magnitudes. In contrast, λ=0.05 generally exhibits slower detection due to excessive smoothing, while λ=0.80 often loses part of the advantage associated with the EWMA memory mechanism.

The consistency of these results across different values of n and p demonstrates the robustness of the proposed ALT-norm-EWMA chart. Regardless of the sample size or process dimension considered, the EWMA-enhanced chart preserves its ability to improve the detection of covariance matrix shifts, with the most substantial gains observed for small and moderate shifts, consistent with the theoretical properties of EWMA charts. These findings indicate that the proposed methodology is effective across a broad range of practical monitoring situations and is not limited to a specific process configuration.

6. Conclusion

The EWMA statistics were integrated with the ALT-norm chart to improve detection performance, especially for small and moderate shifts. In summary, the ALT-norm chart, coupled with EWMA, successfully improves monitoring of changes in the covariance matrix. The proposed ALT-norm-EWMA chart exhibits superior sensitivity to small shifts and maintains competitive or improved performance for moderate and large shifts. Among the investigated smoothing parameters, λ=0.20 is recommended when early detection of small shifts is the primary objective, while λ=0.50 offers the most balanced and robust performance across a wide range of shift magnitudes.

Despite its strong performance, the proposed framework can be enhanced. The study assumes multivariate normality and an identity in-control covariance matrix, which may not hold in many real-world applications. Additionally, the tuning parameters φ and η were fixed at recommended values, although their optimal selection may depend on the underlying sparsity level and shift structure. Future research could explore data-driven or adaptive selection of λ, φ and η.

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