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Comparison of Efficiency Between Classical And Modified EWMA Control Charts Using Different Robust Estimators

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ABSTRACT

Quality control is a crucial practice across various industries to ensure that products and services meet specific standards and fulfill customer expectations. Statistical process control (SPC) is a quality control method that utilizes statistical techniques to monitor and manage a process. This study focuses on EWMA control charts along with robust estimators for monitoring the process mean. The EWMA control chart is particularly effective in detecting small shifts in a process. By implementing SPC, it is usually assumed that the data follows a normal distribution. However, in real-life scenarios, this assumption may not always hold true, and the actual distribution of the data might be unknown. Therefore, in this study, we propose the use of Qn and Biweight Midvariance estimators for constructing EWMA Control Charts. Two data sets, one with heavy skewed and one is slightly skewed, were used in this study. As a result, the EWMA-Qn Control Chart is deemed the most efficient, as it can detect out-of-control points more quickly, regardless of whether the data is heavy skewed or slightly skewed. This method is especially useful in fields such as finance and economics, healthcare and manufacturing where process stability and early detection of shifts are critical. Consequently, the efficiency of the EWMA-Qn Control Chart results in better process monitoring, fewer false alarms, and better decision-making in practical situations, which results in better quality control and utilization of resources in different industries.

Keywords: EWMA Control Chart; robust estimator; Qn estimator; Biweight Midvariance estimator; quality control; skewness

INTRODUCTION

Statistical Process Control (SPC) involves graphical representations of a process's stability. As reported by Saeed et al. (2021), traditional SPC techniques, including EWMA Control Chart, are highly sensitive to deviations from normality and the presence of outliers. This sensitivity can result in incorrect conclusions about the stability and performance of the process. Additionally, classical EWMA control charts are particularly vulnerable to outliers, which can cause lasting effects and false alarms due to the influence of past observations. They rely on the assumption of normality and if this assumption is not met, then the performance of the method may deteriorate and result in false alarms or failure to detect process shifts. Furthermore, according to Riaz et al. (2020), the fixed smoothing parameter in classical EWMA charts limits flexibility, making them prone to excessive false alarms when detecting small shifts, especially in variable processes. While traditional SPC techniques are commonly employed for quality monitoring, these methods are not well suited for data that are heavy tailed or contain outliers. This research aims at dealing with the problem of monitoring process mean using control charts that are resistant to non-normality especially when the distribution is non-normal.

To address these limitations, robust estimators like Qn and Biweight Midvariance offer a solution to the limitations of traditional SPC methods by providing more reliable estimates of process parameters in the presence of outliers and non-normal data distributions. These estimators improve the reliability and efficiency of control charts, thus making them more appropriate for various industries. Razmy and Peiris (2013) emphasize the EWMA Control Chart's ability to detect small process shifts, positioning it as a valuable alternative to the Shewhart control chart for identifying subtle changes. Montgomery (2009) suggests that the parameter performs well within the interval $0.05 \leq \lambda \leq 0.25$, with popular choices being $\lambda = 0.05, 0.10$, and 0.20. He highlights that control charts yield better results when smaller values of are used to detect smaller shifts in the process. One of the most recent uses of EWMA Control Chart in real-life applications is demonstrated by Yupaporn and Rapin (2021), who utilized Exponentially Weighted Moving Average (EWMA) control charts to analyze COVID-19 case numbers across different regions, including Karkh General Hospital in Iraq, aiding in tracking virus transmission and pinpointing potential outbreaks.

Applying control charts to real data usually contradicts normality assumptions. Hence, robust estimators are introduced. A robust estimator is considered good when it performs well under various conditions, including in the presence of outliers, nonnormality, or other departures from the assumptions of the statistical model. The identified robust estimators used in this study are Qn and Biweight Midvariance estimators. Rousseeuw and Croux (1993) introduced the Qn estimator as a robust alternative to the Median Absolute Deviation (MAD). The Qn estimator is particularly suitable for estimating the standard deviation and constructing dispersion charts for skewed and heavy-tailed data under various distributions, such as the Weibull and Chi-Square distributions (Adekeye et al., 2021). The Biweight midvariance, as reported by Goldberg and Iglewicz (1992), demonstrates a finite sample breakdown point of approximately 0.5. These characteristic underscores its robustness, as it can accommodate a significant proportion of outliers without influencing its performance. The main objective of this paper is to compare classical and modified EWMA control charts using Qn and Biweight Midvariance estimators by assessing their ARL values under various conditions and to construct classical and modified EWMA control charts using real data.

METHODOLOGY

EWMA Control Chart

In this study, data with a rational subgroup of sample size, $n > 1$ is used. The mean is defined as $\bar{x}_i = \frac{\sum_{i=1}^{n} x_i}{n}$ where the EWMA statistics is defined as $z_i = \lambda \bar{x}_i + (1-\lambda) z_{i-1}$ while σ is replaced with $\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$ resulting in control limits

$$UCL = \mu_0 + L \frac{\sigma}{\sqrt{n}} \sqrt{\frac{\lambda}{(2-\lambda)} (1 - (1-\lambda)^{2i})} \tag{1}$$

$$UCL = \mu_0 - L \frac{\sigma}{\sqrt{n}} \sqrt{\frac{\lambda}{(2-\lambda)} (1 - (1-\lambda)^{2i})}. \tag{2}$$

where $0 < \lambda \leq 1$ is the smoothing parameter, L is the width of the control limit and the process goal is the initial value (needed with the first sample at $i = 1$), thus $z_0 = \mu_0$.

Qn Estimator

Qn is a robust measure of dispersion introduced by Rousseeuw and Croux in 1993 and it is defined as a rank-based estimator with an absolute k statistic. The Qn estimator can be computed as follows:by a qudrature formula as follows:

$$Q_n = 2.2191\{|x_i - x_j|;\ i < j\}_{(k)}; i, j = 1, 2, \dots, n. \quad (3)$$

where $k = \binom{h}{2} = \frac{h(h-1)}{2}$ and $h = \left[\frac{h}{2}\right] + 1$. The unbiased estimator of σ for Q_n is $\hat{\sigma} = d_n\overline{Q_n}$ where $\overline{Q_n} = \frac{\sum_{i=1}^{m} Q_n}{m}$ and m is the number of subgroup while d_n proposed by Rousseeuw and Croux (1993) is a constant factor depends on the sample size n given is as follows:

Table 1: Constant factor

n	2	3	4	5	6	7	8	9
d_n	0.399	0.994	0.512	0.844	0.611	0.857	0.669	0.872

when $n > 9$, d_n can be calculated as

$$d_n = \begin{cases} \frac{n}{1+1.4}, & \text{if } n \text{ is odd} \\ \frac{n}{n+3.8}, & \text{if } n \text{ is even.} \end{cases} \quad (4)$$

Biweight Midvariance Estimator

The Biweight Midvariance estimator is not only resistant and robust but also highly efficient. For initial exploration across various scenarios with moderate efficiency requirements, Mosteller and Tukey (1977) suggest using the MAD or interquartile range. However, in cases demanding superior performance such as in skewed distributions, the Biweight Midvariance estimator is a suitable choice as it is less influenced by outliers.

$$s_{bi}^2 = \frac{\sum_{i=1}^{n} (y - y')^2 (1 - \mu_i^2)^4}{\left[\sum_{i=1}^{n} (1 - \mu_i^2)^2 5(1 - \mu_i^2)\right]^2} \quad (5)$$

where y' is the median of y, $\mu_i = \frac{y_i - y'}{9MAD}$ and $MAD = 1.4826 median(|x_i - median(x)|)$. The unbiased estimator of σ for Biweight Midvariance is $\hat{\sigma} = \overline{B\imath M\imath d}$ where $\overline{B\imath M\imath d} = \frac{\sum_{i=1}^{m} Biweight\ Midvariance}{m}$ and m is the subgroups.

Performance Evaluation

The average number of points that must be plotted before a point indicates an out-of-control condition is referred to as average run length (ARL). It is used to compare the performance of two or more control charts and to measure control chart performances. The two most prevalent varieties of ARL are ARL for in control process (ARL_0) and ARL for out-of-control process (ARL_1). Given that the process is under control, ARL_0 signifies the average number of samples until a control chart notifies a false alarm. Because the process is in command, the ARL_0must be as large as possible to reduce the number of false alarms. Contrast to that, given that the process is out-of-control, ARL_1 is the average number of samples until a control chart shows that the mean has shifted. Because the process is out-of-control, the ARL_1 must be as minimal as possible in order to identify the out-of-control points as quickly as possible.

Each control chart will be tested by seven level of δ times standard deviation for shifting process mean ($\delta = 0, 0.25, 0.5, 0.75, 1.0, 2.0$ and 3.0). Hence, for the seven different shifts, the ARL_1 values acquired from the classical control chart and the modified control chart (EWMA-Qn and EWMA-Biweight Midvariance) control charts will be tabulated. The simulation will be performed using R programming.

The simulations will be carried out by varying three conditions which are weighing constant (λ), the width of the control limit (L) and the type of population distribution. The width of the control limit which is between $2.1 \leq L \leq 3.5$ will be used to identify the appropriate combination (λ, L) to obtain $ARL_0 \approx 500$ for data with normal distribution. Whereas the width of the control limit $4.5 \leq L \leq 5.0$ with $ARL_0 \approx 500$ will be utilized for skewed data by varying g and h distributions based on a study by Hoaglin D.C. (2006) which g represents skewness, while h represents kurtosis. The table below distinguishes the different distributions.

Table 2: g and h properties for each distribution

g	h	Distribution
0.0	0.0	Normal
0.0	0.225	Mild Skewness
0.5	0.5	Heavy Skewness

The selection of an $ARL_0 \approx 500$ for an EWMA control chart is done to ensure that while the chart is sensitive to process shifts, it does not give many false alarms. This means that on average the chart will give a false alarm once in every 500 observations when the process is still in control. This ARL_0 offers a reasonable compromise because if set higher, it would minimize false alarms but might take time to detect actual shifts, and if set lower, it would produce many false alarms and hence many unnecessary interventions (Huang, 2022). In many industrial applications, the $ARL_0 \approx 500$ is typical because it provides a reasonable frequency of false alarms while at the same time is sensitive enough to detect small shifts. This value is normally derived under the assumption that the process data is normally distributed and that the control limits are set in that regard. For non-normal distributions, the $ARL_0 \approx 500$ may not be valid because of the dissimilarities in the distribution of data such as skewness or kurtosis (Graham et al., 2011). In such cases, the actual

ARL_0 may be lower or higher and hence the rate of false alarms and the chart's performance. To achieve an $ARL_0 \approx 500$, modifications of the control limits or the use of robust estimators are required to make the chart functional with non-normal data (Koshti and Kalgonda, 2011).

In this study, two datasets were used to investigate the performance of the control charts. The first dataset was obtained from Harvard Dataverse by Spatial Data Lab (2020) on Air Quality: Maximum Nitrogen Content. This dataset includes the measurements from cities in China, starting from January 1, 2020, and updated to March 24, 2021. The data features daily measurement of maximum, minimum, and standard deviation values for indicators such as AQI, CO, NO_2, O_3, PM10, PM2.5, and SO_2. The data's variability and potential outliers make it an excellent candidate for testing the robustness and sensitivity of different control charts, particularly in detecting shifts that could signal changes in air quality conditions. Meanwhile, the second dataset was obtained from the U.S Geological Survey (2005) on Water Quality: Suspended Sediment Mean Concentration. The data was collected at Brewster Creek Near Valley View, IL and features daily mean discharge, mean concentration and sediment discharge from October 2004 to September 2005. It is used for evaluating water quality and the processes of sedimentation which are important for the evaluation of water environments and water treatment. This is useful for testing control charts and for detecting shifts and controlling the environment where sediment changes are important for ecology and operations. These datasets were used to construct the Classical EWMA Control Chart and modified EWMA Control Chart which are EWMA-Qn Control Chart and EWMA-Biweight Midvariance Control Chart.

Initially, the data is subjected to a normality test using two different methods, namely the QQ-plots and Shapiro-Wilk test. Subsequently, a Classical EWMA Control Chart and modified EWMA Control Charts are constructed using the data. The Upper Control Limit (UCL) and Lower Control Limit (LCL) for each of the three control charts are calculated. The statistics for each sample are then computed and plotted on the EWMA control charts. If the plotted statistics fall beyond the control limits, the process is identified as out-of-control; otherwise, it is considered in control. Finally, the control chart with the smallest ARL for out-of-control ARL_1 is selected as the best-performing chart.

RESULTS AND DISCUSSION

The simulated data sets are being tested for classical EWMA and modified EWMA Control Chart (EWMA-Qn and EWMA-Biweight Midvariance) and the performance of each control chart are measured using their ARL values. The simulation is conducted using R programming iteratively until the optimal combination of $(\lambda, L)$and $ARL_0 \approx$ 500 are obtained. The results are as follows:

Table 3: ARL_0 Setup for each distribution

Type of Distribution	Classical	Qn	Biweight Midvariance
Normal	505.285	501.199	472.697
Mild Skewed	507.008	499.407	491.016
Heavy Skewed	460.026	506.338	509.859

Table 4: Combination of (λ, L) for each distribution

Type of Distribution	Classical		Qn		Biweight Midvariance	
	λ	L	λ	L	λ	L
Normal	0.1	2.9	0.1	3.43	0.1	3.5
Mild Skewed	0.1	3.5	0.1	4.7	0.1	4.8
Heavy Skewed	0.03	5	0.001	6	0.01	8

This observation holds true across all distributions analysed, indicating a consistent trend. While there are subtle differences among the distributions, they generally exhibit similar patterns in terms of ARL behaviour with increasing shifts. Consequently, these findings suggest that the three control charts under study demonstrate comparable efficiency in detecting deviations from the expected process behaviour.

Simulation Results for Normal Distribution

Figure 1 shows the simulation results under normal distribution with prefix $ARL_0 \approx 500$ and n = 5 by varying values of width of control limit between L = 2.1 and L = 3.5 with fixed λ = 0.1 under parameters $g = 0$ and $h = 0$. It is observed that ARL values decrease as the magnitude of shifts in the normal distribution increases. The results of the analysis conducted under the standard normal distribution revealed a consistent pattern across the control charts, indicating comparable performance and efficiency among them. This similarity in results suggests that all three control charts are equally effective in monitoring and detecting deviations from the expected process behavior when applied to data following a standard normal distribution.

Simulation Results for Mild Skewed Distribution

Figure 2 shows the simulation results under mild skewed distribution with prefix $ARL_0 \approx 500$ and n = 5 by varying values of width of control limit between L = 3.0 and L = 5 with fixed λ = 0.1 under parameters $g = 0.225$ and $h = 0$. It is observed that as the shift mean increases, there is a clear trend of decreasing ARL values for EWMA-Qn and EWMA-Biweight Midvariance control charts. However, there is a slight increase for Classical EWMA Control Chart at shift = 3.

EWMA Control Chart is designed to be more responsive to small, persistent shifts in the mean rather than large, sudden changes. Its emphasis on recent observations, controlled by the smoothing parameter λ means that it might not react as strongly to outliers or large shifts, especially in distributions with skewness. If a large shift occurs in a mild skewed distribution, the EWMA chart might not exhibit the rapid response typically associated with detecting such shifts in more symmetric distributions. Notably, the robust Qn method stands out significantly in swiftly detecting out-of-control (OOC) points within a shorter time frame when a shift occurs.

Simulation Results for Heavy Skewed Distribution

Figure 3 shows the simulation results under heavy skewed distribution with prefix $ARL_0 \approx 500$ and n = 5 by varying values of λ and L under parameters $g = 0.5$ and $h = 0.5$. It is observed that as the shift mean increases, there is a clear trend of decreasing ARL values for EWMA-Qn and EWMA-Biweight Midvariance Control Charts. However, at larger shifts, there is an increase in the ARL values for Classical EWMA Control Chart. This is because, in a heavily skewed distribution, the tail of the distribution contains a significant portion of the data, and extreme values can exert a substantial influence on the mean. The EWMA chart's sensitivity to these extreme values might be limited due to its design, which prioritizes the detection of small, persistent shifts. Notably, the robust Qn method stands out significantly in swiftly detecting OOC points within a shorter time frame when a shift occurs.

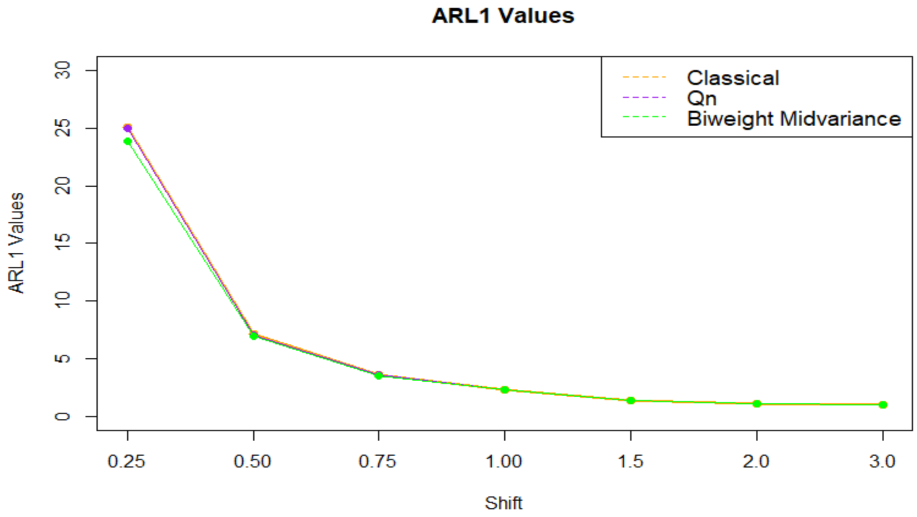

Figure 1: Simulation Results under Normal Distribution

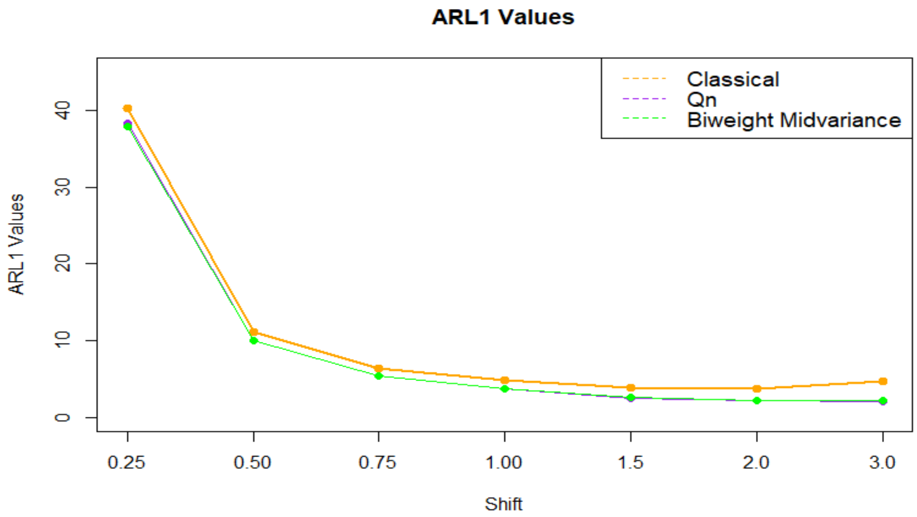

Figure 2: Simulation Results under Mild Skewed Distribution

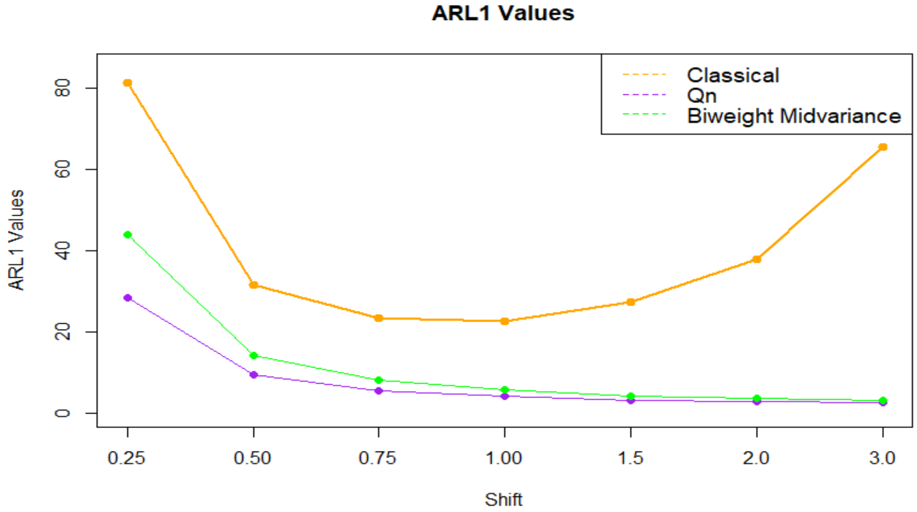

Figure 3: Simulation Results under Heavy Skewed Distribution

Application to Real Data

Prior to determining the most appropriate control chart, the normality of both datasets is evaluated using two methods which are the QQ-plot and the Shapiro-Wilk test. In the QQ-plot analysis, data points should align along a straight line for normal distribution. However, the plot in the Figure 4 and Figure 5 below indicates deviations from this linearity, suggesting that the data is not adhere to a normal distribution due to some points diverging from the expected straight line.

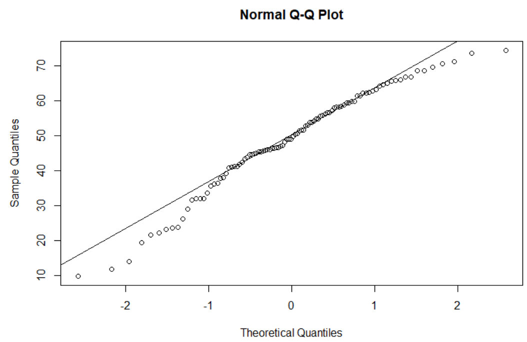

Figure 4: QQ-plot for Data A

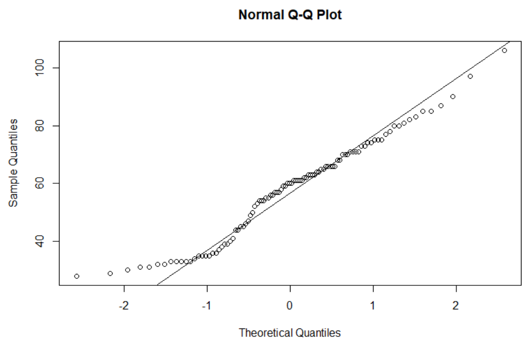

Figure 5: QQ-plot for Data B

The Shapiro-Wilk test, a widely used statistical method for assessing normality, operates by subjecting data to a hypothesis test. This test is designed to determine whether a given dataset conforms to a normal distribution. By comparing observed data to what would be expected under a normal distribution, the Shapiro-Wilk test provides a quantitative measure of how closely the data aligns with normality. The hypothesis tested in this test are:

$$H_0: \text{Data is normally distributed}$$
$$H_1: \text{Data is not normally distributed}$$

The null hypothesis (H_0) is rejected if the p-value is less than the significance level (α). For Data A (0.01449) and Data B (0.0118), both p-values are below $\alpha = 0.05$, leading to the rejection of H_0 and suggesting significant deviations from normality. This result indicates the data is unlikely to be normally distributed. Additionally, skewness measures the asymmetry of the distribution. Values between -5 and 5 indicate mild skew, while values outside this range suggest heavy skew. Data A, with a skewness of -0.5842719, is categorized as heavily skewed. In contrast, Data B shows mild skewness with a value of 0.09925527. Both datasets thus demonstrate non-normal distributions based on these measures.

Figure 6, Figure 7 and Figure 8 display the results for Data A. From the observed charts, it is evident that deviations from the center line are present. These deviations indicate where large shifts have occurred. Despite these deviations, a majority of the plotted points appear clustered around the center line, suggesting a relatively stable process with minor shifts. Classical EWMA Control Chart is deemed to be in control as no points exceed the control limits. In the case of the EWMA-Qn Control Chart and EWMA-Biweight Midvariance Control Chart, some points exceed the upper and lower control limits. This indicates the occurrence of very large shifts at these points.

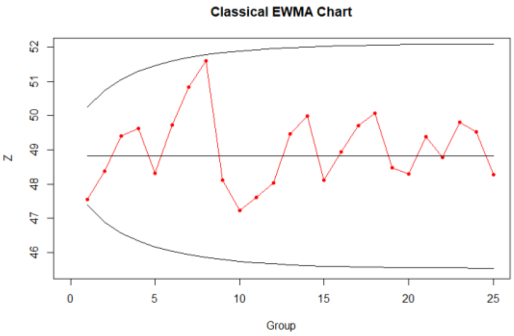

Figure 6: Classical EWMA Control Chart

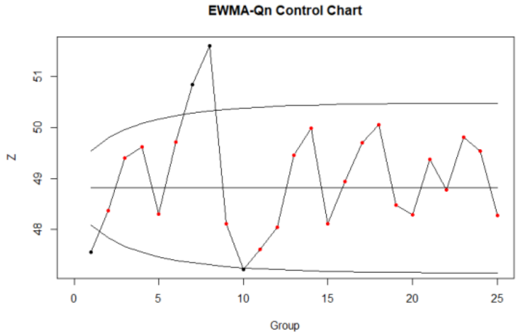

Figure 7: EWMA-Qn Control Chart

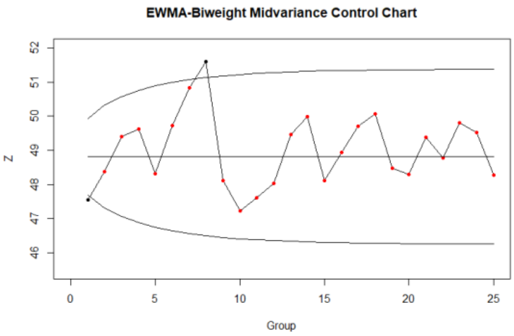

Figure 8: EWMA-Biweight Midvariance Control Chart

Figure 9, Figure 10 and Figure 11 display the results for Data B. From the observed charts, it is evident that deviations from the center line are present. These deviations indicate instances where large shifts have occurred. Despite these deviations, some of the plotted points appear clustered around the center line, suggesting a relatively stable process with minor shifts. Classical EWMA Control Chart and EWMA-Biweight Midvariance Control Chart are deemed to be in control as no points exceed the control limits. However, in the EWMA-Qn chart, some points exceed the upper control limits, indicating very large shifts. Its heightened sensitivity makes it more reliable for maintaining process control. Additionally, the presence of a downward trend in the control chart suggests a consistent movement in one direction over time, indicating a systematic shift potentially due to special cause variation.

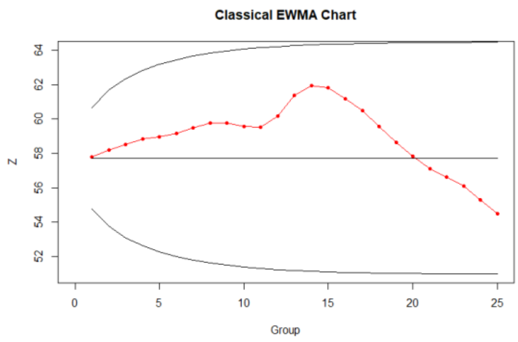

Figure 9: Classical EWMA Control Chart

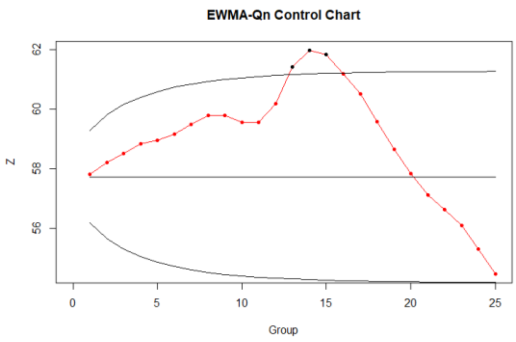

Figure 10: EWMA-Qn Control Chart

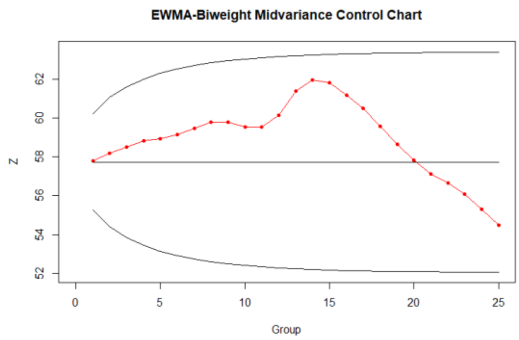

Figure 11: EWMA-Biweight Midvariance Control Chart

Analysis of Data A revealed that the classical EWMA failed to detect OOC points. Given that Data A was heavily skewed, it appears that the classical EWMA was less effective in detecting OOC points in this scenario. In contrast, EWMA-Qn successfully detected three OOC points, beginning at point 1, whereas EWMA-Biweight Midvariance detected two OOC points, also beginning at point 1. Turning to Data B, both the classical EWMA and EWMA-Biweight Midvariance failed to detect any OOC points. This suggests that in the case of mildly skewed data, these methods were less adept at identifying OOC points. However, EWMA-Qn was able to detect OOC points starting at point 13, which occurred later than in the case of heavily skewed data. This consistent ability of EWMA-Qn to detect more OOC points in both heavily and mildly skewed datasets demonstrates its superior robustness and effectiveness compared to the classical EWMA and EWMA-Biweight Midvariance methods.

CONCLUSION

The similarity in results under normal distribution suggests that all three control charts are equally effective in monitoring and detecting deviations from the expected process behavior. In the case of violation of the normality assumption, specifically under mild and heavy skewness. EWMA-Qn generally produced smaller ARL_1 values, indicating its superiority in detecting OOC points.

The second approach involves constructing control charts using real-world data. Upon analysing both Data A and Data B, it was observed that the EWMA-Qn Control Charts demonstrated a superior ability to detect out-of-control points compared to other methods. This finding justifies the use of the EWMA-Qn Control Chart as the preferred and most efficient option for monitoring and maintaining process stability in real-world scenarios.

Upon comparing the results obtained from both the simulation and real data analyses, a consistent pattern emerges, indicating that the EWMA-Qn control chart stands out as the most effective among the control charts studied. This consistency across simulation and real-world application lends strong support to the conclusion that the Qn estimator is the most suitable choice for this study.

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