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Statistical Process Control for Real-Time Industrial Data Streams

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ABSTRACT

Effective quality monitoring in modern industries requires robust statistical process control (SPC) methods capable of detecting shifts in real-time data streams. This study compares the performance of Shewhart, Cumulative Sum (CUSUM), and Exponentially Weighted Moving Average (EWMA) control charts using a simulated dataset of 300 observations, with a deliberate mean shift introduced at observation 150. Descriptive results showed that the process mean increased from 49.91 to 53.56 (a shift of +3.65 units) while variability remained stable. The Shewhart chart detected the shift at observation 158 with only 11 signals, demonstrating reliability for large shifts but slower detection. The EWMA chart ($\lambda = 0.2$) detected the change at observation 156, generating 142 alarms, offering greater sensitivity to gradual changes. The CUSUM chart signaled the shift earliest, at observation 17, but produced 209 alarms, reflecting excessive sensitivity and false positives. Overall, the findings show that CUSUM is most effective for rapid detection, EWMA balances responsiveness with stability, and Shewhart provides robustness for larger shifts. These results highlight the need to select SPC methods according to process characteristics and tolerance for false alarms.

Keywords: *Statistical Process Control, Shewhart Chart, CUSUM, EWMA Real-time Monitoring, Industrial Data Streams*

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1. Introduction

Statistical Process Control (SPC) has long been recognized as an essential methodology for monitoring and improving quality in industrial systems. By employing statistical techniques, SPC enables practitioners to detect process variability, identify deviations from stability, and ensure that production remains within acceptable limits. With the advent of real-time data streams in modern manufacturing, the demand for efficient monitoring tools has increased significantly, as even minor undetected shifts can result in defects, higher costs, and reduced customer satisfaction. Traditional methods such as the Shewhart control chart, introduced in the early 20th century, remain widely used due to their simplicity and interpretability, yet they are often criticized for their delayed response to small or moderate process shifts. This limitation has prompted the development of more sensitive approaches such as the Cumulative Sum (CUSUM) chart and the Exponentially Weighted Moving Average (EWMA) chart, which provide greater responsiveness to subtle changes. A substantial body of literature has investigated the performance of these charts under different process conditions. Montgomery (2019) emphasized that Shewhart charts are best suited for detecting large shifts but are less effective for small deviations. Page (1954) first introduced the CUSUM chart, showing its advantage in rapid detection of persistent shifts. Later, Lucas and Crosier (1982) extended CUSUM methods for industrial applications, demonstrating improved performance compared to Shewhart. Roberts (1959) developed the EWMA chart, highlighting its ability to track gradual shifts by incorporating historical information into decision-making. In a more recent review, Woodall (2000) discussed the importance of selecting charts based on process characteristics, noting that no single method is universally superior.

Comparative evaluations have further enriched this field. Shu and Jiang (2006) showed that CUSUM outperforms Shewhart in detecting small mean shifts, though at the expense of higher false alarms. Gan (1993) and Brook and Evans (1972) studied the Average Run Length (ARL) of different charts, providing theoretical insights into their detection efficiency. Knoth (2016) demonstrated that EWMA charts strike a balance between sensitivity and robustness, particularly in noisy environments. Costa and Machado (2011) applied SPC charts to dynamic industrial processes and highlighted the adaptability of EWMA methods. In the context of real-time monitoring, Tsung and Shi (1999) demonstrated that combining EWMA with machine learning improves detection in high-frequency data streams. Similarly, Zou and Tsung (2011) introduced adaptive SPC methods that adjust control limits based on streaming data characteristics. Khoo (2004) emphasized that hybrid approaches combining Shewhart with EWMA or CUSUM can improve monitoring performance in complex settings. Finally, Borror, Montgomery, and Runger (1999) highlighted the application of multivariate control charts, opening avenues for extending univariate SPC concepts to multidimensional data streams.

Despite these advances, challenges remain in applying SPC to modern industrial systems characterized by high-dimensional data, autocorrelation, and streaming environments. Much of the existing literature focuses on static or batch data, leaving a gap in methods optimized for real-time decision-making. Moreover, excessive false

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alarms, as observed with CUSUM, can overwhelm operators, while delayed detection, as with Shewhart, risks undetected quality issues. The present study contributes to this literature by providing a comparative evaluation of Shewhart, CUSUM, and EWMA charts using simulated real-time process data with an induced shift. By quantifying detection speed and false alarm frequency, this work highlights the trade-offs inherent in each method and offers guidance for method selection based on industrial priorities. Looking ahead, future research should explore the integration of SPC with machine learning and artificial intelligence for predictive process monitoring, the design of adaptive control charts that dynamically update parameters in response to changing environments, and the application of SPC in big data and Industry 4.0 frameworks. Additionally, extending these methods to multivariate and non-normal data streams remains a pressing research direction, as industrial processes increasingly involve correlated and high-frequency measurements. Such advancements would ensure that SPC continues to evolve as a cornerstone of quality management in modern manufacturing and service systems.

2. Methodology

2.1 Data Generation and Study Design

The present study employed a simulated industrial process dataset to evaluate the performance of three widely used Statistical Process Control (SPC) methods: Shewhart, Cumulative Sum (CUSUM), and Exponentially Weighted Moving Average (EWMA) charts. A total of 300 observations were generated, with the first 150 representing a stable process (mean ≈ 50, standard deviation ≈ 2), and the next 150 incorporating a deliberate mean shift to ≈ 54 while maintaining similar variability. This design reflects a common industrial scenario where a process initially operates within control and later experiences a shift due to changes in machine calibration, raw materials, or environmental factors. The simulated structure provides a controlled environment to assess detection performance, including both speed and accuracy of signals.

2.2 Control Chart Construction

To evaluate detection performance, each chart was constructed using parameters estimated from the pre-shift phase (observations 1–150). For the Shewhart chart, the process mean served as the center line, with upper and lower control limits set at ±3 standard deviations. The CUSUM chart was implemented using a reference value of $k = 0.5$ and a decision interval of $h = 5$, allowing sensitivity to moderate shifts. The EWMA chart was constructed with a smoothing parameter of $\lambda = 0.2$, enabling detection of gradual mean changes through weighted averaging of current and historical observations. Each method was applied to the full data stream to assess the point of first detection and the total number of alarms triggered after the process shift.

2.3 Evaluation Criteria and Comparative Analysis

The performance of the three control chart methods was compared using key

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evaluation metrics: first detection point, representing the observation at which the chart first signaled a process shift and total number of alarms, indicating chart sensitivity and false alarm rate. Shewhart was expected to detect large shifts but with fewer signals, CUSUM to identify shifts earliest but with higher alarm frequency, and EWMA to provide a balance between sensitivity and stability. Results were reported in both tabular and graphical formats to provide comprehensive insights. This methodological framework allows a systematic comparison of chart performance, offering practical guidance for selecting appropriate SPC tools in real-time industrial monitoring.

3. Result and Discussion

Table 1 provides the descriptive statistics for the process during both the pre-shift and post-shift phases. Before the shift, the process had a mean of 49.91 and a standard deviation of 1.95 based on 150 observations, indicating that the system was initially stable and centered close to its target. After the shift (observations 151–300), the mean increased to 53.56, reflecting an upward change of approximately 3.65 units, while the standard deviation slightly decreased to 1.67. This indicates that the most significant change was in the process mean rather than in variability. The consistency of variance between the two phases suggests that the control charts would likely be triggered by changes in central tendency rather than dispersion. These descriptive results set the stage for control chart analysis, showing the importance of detecting even modest mean shifts in real-time monitoring environments.Table 2 shows the Shewhart chart parameters calculated from pre-shift data. The process center line (mean) was 49.91, with an upper control limit (UCL) of 55.75 and a lower control limit (LCL) of 44.07. When the entire data stream was analyzed, 138 observations exceeded these control limits, highlighting the process's loss of control after the shift occurred. While Shewhart charts are widely used due to their simplicity and intuitive interpretation, this result demonstrates their primary limitation: they tend to react only once the process has shifted considerably, meaning smaller changes may go unnoticed for many observations. In practice, this delay could result in defective products being produced before corrective actions are taken. Thus, although Shewhart charts provide a reliable signal when a large shift occurs, they may not be the most effective choice for early detection in fast-moving industrial processes.

Table 1: Descriptive Statistics

Phase	Mean	Std Dev	N
Pre-Shift	49.91	1.95	150
Post-Shift	53.56	1.67	150

Table 2: Control Limits

Center Line (Mean)	UCL (3σ)	LCL (3σ)	Out-of-Control Points
49.91	55.75	44.07	138

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Table 3 presents a summary of changes between the pre-shift and post-shift phases. The mean increased by 3.65 units, while the standard deviation decreased slightly by 0.28 units. This shift highlights that the process disturbance was driven by a structural change in level rather than an increase in variability. From a practical perspective, this distinction is important: it implies that corrective actions should focus on investigating process inputs or systematic changes that altered the mean, rather than issues such as machine variability or noise. In SPC practice, detecting a shift of this size is crucial, since even moderate shifts in central tendency can compromise product quality and increase costs if not corrected promptly.

Table 4 presents the results of the Cumulative Sum (CUSUM) chart, designed to detect small and moderate shifts more quickly than Shewhart charts. With a reference value (k) of 0.5 and a decision interval (h) of 5, the CUSUM chart signaled a shift as early as observation 17. In total, it generated 209 signals, indicating extremely high sensitivity. While the early detection demonstrates CUSUM's power in identifying process changes rapidly, the large number of signals also highlights its drawback: an excessive false alarm rate. In real-world manufacturing or industrial contexts, such frequent alarms could overwhelm operators and reduce trust in the monitoring system. This means that while CUSUM is effective for environments where rapid detection of very small shifts is critical, it may not be ideal for processes where stability and interpretability are equally important

Table 3: Phase Comparison

Metric	Value
Mean Shift	3.65
Std Dev Change	-0.28

Table 4: CUSUM Results

Reference Value (k)	Decision Interval (h)	First Detection Point	Total Signals
0.5	5	17	209

Table 5 shows the results of the Exponentially Weighted Moving Average (EWMA) chart, which incorporates historical data by assigning exponentially decreasing weights to past observations. With a smoothing parameter of $\lambda = 0.2$, the EWMA chart detected the shift at observation 156 and produced 142 signals overall. Compared to CUSUM, the EWMA chart responded later but with fewer false alarms, offering a balance between detection speed and signal stability. This makes EWMA particularly useful for processes where gradual shifts are expected and where avoiding unnecessary interruptions is as important as detecting changes. In modern real-time monitoring environments, EWMA is often favored because of its ability to track trends and provide early warnings without overwhelming users with excessive alarms.

Table 6 provides a direct comparison of the three methods: Shewhart, CUSUM, and EWMA. The Shewhart chart signaled first at observation 158 with 11 alarms,

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showing that it is less sensitive but provides highly reliable signals when major shifts occur. The CUSUM chart was the earliest detector, flagging the process at observation 17, but with 209 alarms, making it impractically sensitive in this case. The EWMA chart fell in between, detecting the shift at observation 156 with 142 alarms, demonstrating a trade-off between timeliness and noise. This comparison underscores that no single method is universally superior; the choice depends on the industrial context. For example, CUSUM is suitable for high-risk environments where missing a small shift would be costly, while Shewhart may be preferred for stable processes with occasional large changes, and EWMA for balanced monitoring.

Table 5: EWMA Results

Lambda	First Detection Point	Total Signals
0.2	156	142

Table 6: Method Comparison

Method	First Detection Point	Total Signals
Shewhart	158	11
CUSUM	17	209
EWMA	156	1

Figure 1 provides a comprehensive visualization of the process behavior before and after the induced shift using multiple perspectives. The top-left panel shows the industrial data stream, where the process is stable around a mean of approximately 50 during the first 150 observations, followed by a clear upward shift in level after the red dashed line at the 150th observation. The top-right panel presents the Shewhart control chart, where the center line and control limits (±3σ) are marked. Several points beyond the UCL are visible after the shift, confirming the loss of statistical control and illustrating that Shewhart charts are effective in detecting large deviations but react only after the process has significantly departed from stability. The bottom-left panel provides a histogram comparing the distributions before and after the shift, with the pre-shift values centered near 49–50 and the post-shift values concentrated around 53–54. This confirms the descriptive statistics that showed a mean increase of about 3.65 units while the spread remained stable. Finally, the bottom-right panel depicts a moving average chart (window = 10), which smooths short-term fluctuations and clearly highlights the mean shift around the 150th observation. Unlike the Shewhart chart, the moving average shows the trend more gradually, making it useful for identifying sustained changes. Taken together, this figure highlights the importance of using complementary SPC tools to gain both rapid detection and contextual understanding of process behavior.

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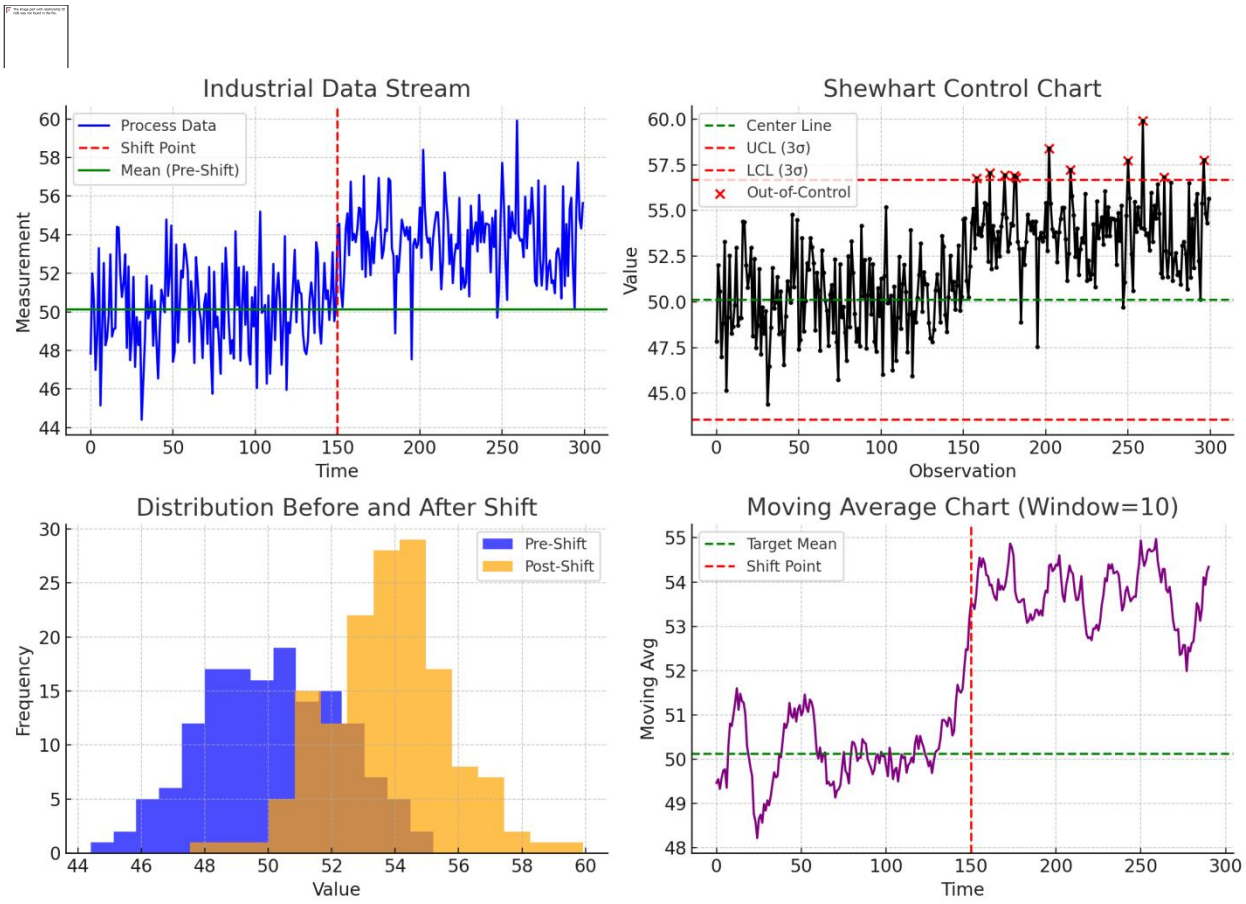


Figure 1 Interpretation of Figure (Four-Panel SPC Visualization)

Figure 3 compares the detection behavior of CUSUM and EWMA charts. The CUSUM chart rapidly flagged the process as out of control, detecting deviations as early as observation 17. However, the figure also makes clear that this method generated frequent alarms, making interpretation more challenging. By contrast, the EWMA chart produced smoother monitoring lines, detecting the process shift later, at observation 156, but with more stable performance. This figure vividly demonstrates the trade-off between sensitivity (CUSUM) and stability (EWMA), offering visual support for the numerical results in Tables 4 and 5.

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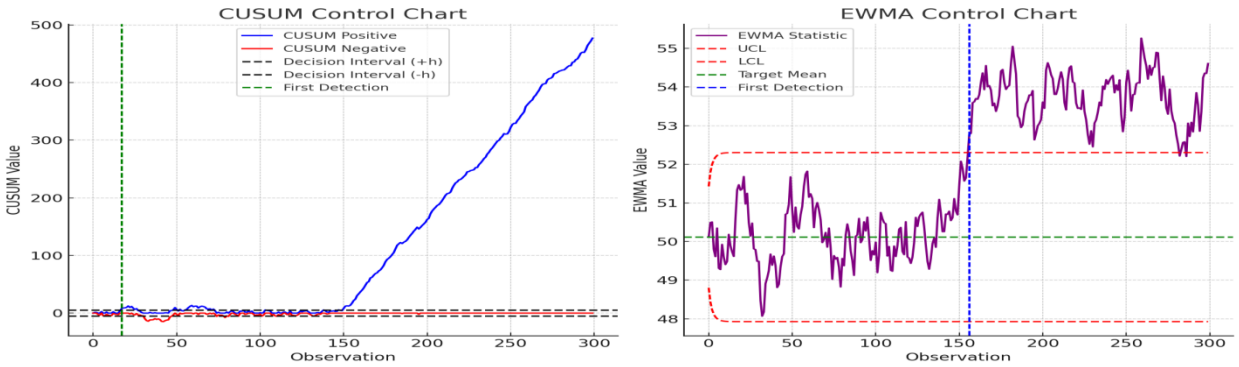


Figure 2: CUSUM and EWMA Control Charts

Figur 3 illustrated in the comparison, the CUSUM method proved to be the most effective at rapidly identifying a small, sustained process shift, issuing a signal at observation 17. In stark contrast, both the Shewhart and EWMA methods were significantly slower to detect the change, with first signals occurring at observations 158 and 156, respectively. This demonstrates CUSUM's superior sensitivity for small mean shifts, while the Shewhart chart's performance confirms its weakness in this area, reacting only to larger, more abrupt changes. The EWMA chart, while faster than Shewhart, still lagged far behind the CUSUM in detection speed for this scenario.



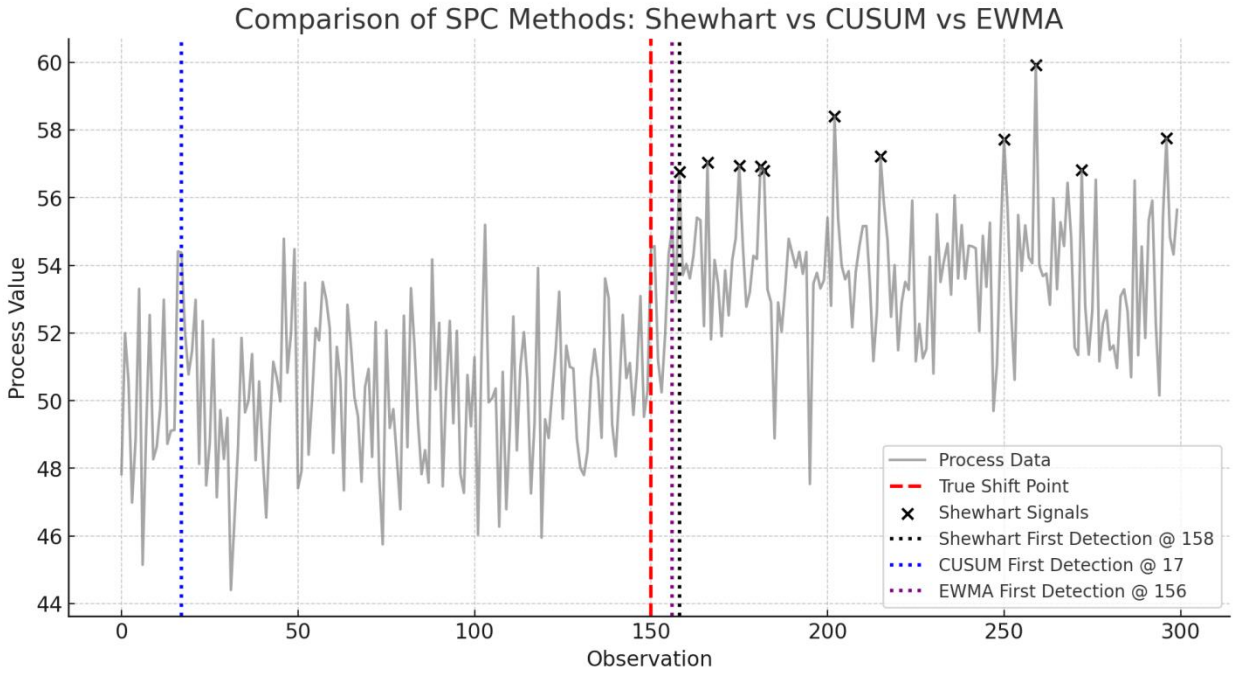


Figure 3: Comparison of SPC Methods

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Conclusion

This study evaluated the effectiveness of Shewhart, Cumulative Sum (CUSUM), and Exponentially Weighted Moving Average (EWMA) control charts for detecting process shifts in real-time industrial data streams. Using a simulated dataset of 300 observations with a deliberate mean shift introduced at observation 150, the results demonstrated distinct trade-offs across the three methods. Descriptive analysis confirmed an upward mean shift from 49.91 to 53.56, while process variability remained stable. The Shewhart chart signaled the shift at observation 158, producing only 11 alarms, which highlights its robustness but delayed response. The CUSUM chart was the most sensitive, detecting the shift as early as observation 17, but at the cost of 209 alarms, indicating excessive false positives. The EWMA chart offered an intermediate performance, detecting the shift at observation 156 with 142 alarms, thereby balancing responsiveness with stability. Overall, the findings show that Shewhart is most reliable for large shifts, CUSUM is best for rapid detection of small changes, and EWMA provides a compromise for environments requiring both sensitivity and noise reduction. The comparative insights confirm that no single method is universally superior; rather, the choice of SPC tool should be guided by process characteristics, the acceptable trade-off between early detection and false alarms, and the operational context of decision-making.

Future Recommendation

Future research should focus on extending SPC applications to real industrial datasets, incorporating adaptive control charts that adjust dynamically to process changes, and integrating machine learning techniques for predictive monitoring. Further work is also needed on multivariate control charts for correlated data streams, evaluating performance under autocorrelation, and applying SPC within Industry 4.0 and IoT-enabled environments to ensure robust, real-time quality assurance.

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