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RESEARCH PAPER

Enhancing Project Schedule Monitoring: Application of CUSUM and EWMA Memory Control Charts in Earned Schedule Method

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Abstract

Earned Value Management (EVM) and Earned Schedule (ES) are crucial tools for controlling projects and preventing deviations from schedule and budget objectives. In early-return projects, meeting deadlines is critical; however, Earned Value alone may not provide an appropriate criterion for evaluating and analyzing time-related indicators. This study proposes a method to use statistical control charts that consider indicator deviations from the project's start (memory charts) and are more sensitive to schedule deviations. Specifically, Exponentially Weighted Moving Average (EWMA) and Cumulative Sum (CUSUM) charts are employed to monitor the Schedule Performance Index (SPI) based on the ES system. Instead of Expected Value (EV), ES is used for monitoring. Results demonstrate that both CUSUM and EWMA charts offer higher accuracy compared to classical Shewhart charts and produce fewer error alarms. The CUSUM chart shows less error (75% reduction in initial error alarms), while EWMA displays higher sensitivity (20% faster deviation detection). This proposed method can assist project managers in identifying schedule deviations more accurately and rapidly. The study utilized data from a 30-month construction project, applying normality tests and data transformation techniques to ensure statistical validity. The findings suggest that memory control charts based on ES provide a more reliable and responsive approach to project schedule monitoring, particularly in time-sensitive projects.

Keywords: Schedule Performance Index, Earned Schedule, Project Schedule Monitoring, Control Chart, CUSUM, EWMA.

Introduction

In recent years, the integration of accurate mathematical tools into project management has led to more scientific and precise management practices. The field of statistical quality control, in particular, has seen significant advancements, with its tools and charts gaining prominence in various domains. Project management has evolved to incorporate Earned Value Systems (EVS)

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for a more comprehensive control of ongoing projects, considering multiple facets of project performance. The introduction of the earned schedule system in the last decade has addressed some of the limitations in this area.

Historically, classic Shewhart control charts were used to monitor earned value indicators, alerting administrators to out-of-control situations and enabling them to identify error sources and return projects to their normal state. This approach became increasingly crucial as many projects faced schedule delays or exceeded approved budgets. Subsequently, this methodology was enhanced with the introduction of EWMA and CUSUM charts. Unlike Shewhart charts, which only monitor the current state of projects, EWMA and CUSUM charts consider all previous stages of project indicators. These more sensitive charts are particularly useful in projects where schedule and value control are critical, and even minor deviations are significant. For understanding of EWMA and CUSUM chart structures and their recent advancements, readers can refer to the works of Jafarian-Namin et al. (2022), Haridy and Benneyan (2024), and Khamrod et al. (2023) for EWMA charts, and Madrid-Alvarez et al. (2024), Li et al. (2023) and Haq and Abbasi (2023) for CUSUM charts.

The complexity of modern projects, coupled with increasing stakeholder expectations and tighter deadlines, has necessitated more sophisticated project management techniques. Traditional project management methodologies often struggle to provide real-time, accurate insights into project performance, particularly in terms of schedule adherence. This gap has led to the development and refinement of advanced monitoring techniques, including the application of statistical process control methods to project management. See for example, de Mendonca et al. (2024), Sarkar (2022) and Li (2021).

Despite these advancements, several critical gaps remain in the current literature. Most prior studies have focused predominantly on traditional earned value indicators, with limited attention to the more recent and schedule-focused earned schedule system. Moreover, the integration of memory-based control charts, such as EWMA and CUSUM, with earned schedule indicators has not been thoroughly investigated, particularly in the context of real-world projects with complex scheduling and risk dynamics. This lack of comprehensive frameworks and empirical validation highlights the need for further exploration—an area this study aims to address.

The earned value system, despite its usefulness, has some drawbacks that have led researchers to explore the earned schedule system. This study focuses on monitoring the time indicators of the earned schedule system using memory charts such as CUSUM and EWMA. The use of project management indicators, earned value, and earned schedule in statistical control charts is a relatively new and fragmented field of research. Early work in this area includes Al-Tabatabai et al. (1997), who attempted to predict and control performance indicators using neural networks. Baraza and Boyno (2008) predicted final project performance using specific statistical and probability approaches, yielding promising results. Pique and Wagon (2000) were pioneers in suggesting methods for using quality control charts to monitor earned value indicators. This proposal initially faced criticism due to the need for specific statistical conditions, such as the normality of variables. Lipke (2003) and Christian et al. (2003) further examined these conditions and limitations.

Subsequent research expanded the application of statistical quality control techniques in various aspects of project management. Navon (2005) applied these techniques to the online control of on-site construction projects. Cheung et al. (2004) used statistical tools for monitoring human resources, quality, schedule, and other performance indicators. Lou and Lin (2008) presented a general framework for displaying project management indicators on statistical quality control charts. Azar and McCabe (2012) developed algorithms for recognizing dump trucks in construction videos, which can be applied to productivity measurement and work-zone safety. Akhavian and Behzadan (2012) proposed an integrated framework for remote monitoring and planning of construction operations, combining real-time field data collection with dynamic 3D visualizations and discrete event simulation modeling.

Recent studies have further refined these approaches. Moon (2020) developed a mathematically sound method for graphically monitoring the SPI. Chen et al. (2023) investigated the performance of the Laney p′ control chart when parameters are estimated from Phase I data, providing valuable insights for practical implementation in industries such as PCB and IC substrate manufacturing. González-Cruz et al. (2022) proposed the Critical Duration Index (CDI), which allows for anticipation of project delays and improved project duration estimates compared to traditional deterministic techniques, demonstrating its effectiveness on both artificial and empirical project datasets. Kumar and Shrivastava (2024) presented a case study on quality challenges in international substation projects, emphasizing the significance of quality management in project execution, particularly in challenging environments. Nimr and Naimi (2023) and Shojaie and Imani (2022) explored the use of statistical process control charts for improving project performance through adaptive management, presenting an evolutionary monitoring and control model for project success. These studies collectively underscore the growing importance and sophistication of statistical quality control techniques in project management across various industries. For further information on this field, readers can be referred to Kim et al. (2019), Shojaee et al. (2024a, b), and Jan et al. (2022), which offer valuable insights into various aspects of statistical process monitoring and project management techniques.

In the continuation of this study, we will evaluate the effectiveness of the proposed approach across different project scenarios. Specifically, the analysis will focus on assessing the performance of CUSUM and EWMA charts when applied to various project types, including those with different levels of schedule complexity and risk. Additionally, we will examine the practical implications of integrating memory control charts within existing project management frameworks, investigating factors such as ease of implementation, cost-effectiveness, and scalability. Finally, we will compare the performance of the new method against traditional approaches using real project data, highlighting the potential improvements in both predictive accuracy and operational efficiency. This comprehensive evaluation aims to provide a robust understanding of the applicability and benefits of the proposed methodology in real-world project management settings. The paper is structured as follows: Section 1 introduces the earned value system and earned schedule. Section 2 explores statistical control charts in project monitoring, focusing on CUSUM and EWMA charts. Section 3 presents the methodology for using memory control charts to monitor project timelines. Section 4 illustrates the application through a case study of a 30-month construction project, analyzing CUSUM and EWMA charts. Section 5 concludes with key findings and their implications for project management.

Earned Value System and Earned Schedule

EVM has gained significant attention in recent years as a tool for monitoring key project indicators. It is utilized to prevent value and schedule deviations, as well as to predict and estimate primary value and schedule indicators. Table 1 provides the main definitions of these indicators.

Table 1. Key indicators of earned value management

PV	Planned Value
AC	Actual Cost
EV	Earned Value
CV	Cost Variance; $CV = EV - AC$
SV	Schedule Variance; $SV = EV - PV$
CPI	Cost Performance Index; $CPI = EV/AC$
SPI	Schedule Performance Index; $SPI = EV/PV$
BAC	Budget at Completion (the planned cost of the project)
PMB	Performance Measurement Baseline (the cumulative PV over time)
$IEAC$	Independent Estimate at Completion (the forecasted final cost) $IEAC = AC/CPI$

There are various approaches for prediction indicators, with two main methods focusing on estimating the CPI or the SPI:

$$IEAC = BAC/CPI \tag{1}$$

While these calculations are primarily based on values and costs, time becomes the critical factor in high-yield and emergency projects. Therefore, it is preferable to consider time as the calculation basis. For more accurate SV and SPI indicators, it is advisable to use ES concepts. Figure 1 illustrates these indicators:

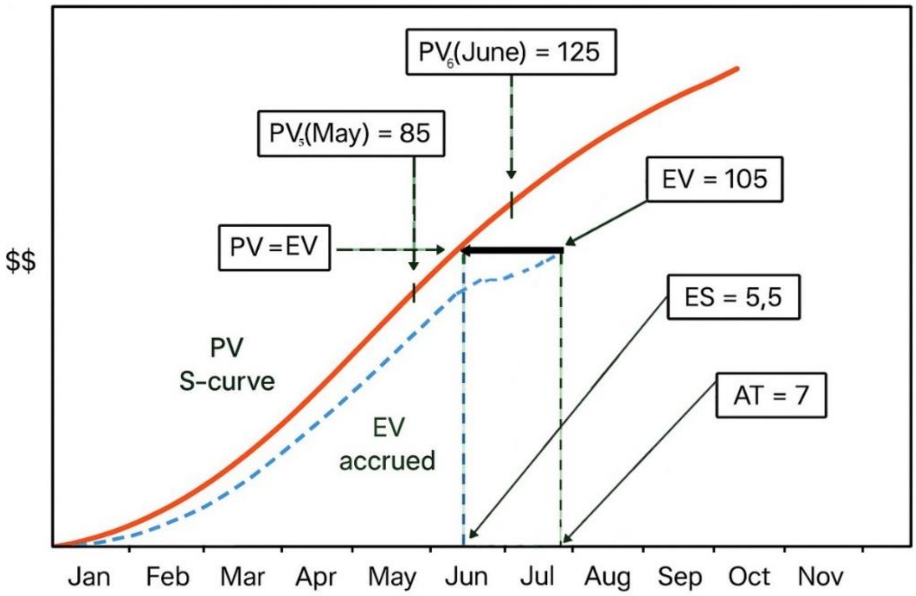

Figure 1. Main indicators of earned value chart

As depicted in Figure 1, ES corresponds to EV on the time axis. To determine the ES value, one should connect the EV and PV points horizontally on the PMB curve and draw vertical lines from these points to the time axis. This process yields the Actual Time (AT) and ES points, respectively. The ES value is calculated by combining the last correct date before the ES vertical point (C) with a decimal portion (I) obtained through interpolation and comparison. Table 2 presents the key time-based indicators of the ES method, which are specifically developed to address the limitations of the traditional approach.

Table 2. Key indicators of earned schedule

$\boldsymbol{AT}$	Actual Time (the number of time increments corresponding to EV)
$\boldsymbol{ES}$	Earned Schedule; $ES = C + I$
$\boldsymbol{C}$	Number of whole-time increments of PMB for condition $EV \geq PV$
$\boldsymbol{PV_C}$	Planned value of the last time increment C for which $EV \geq PV_C$
$\boldsymbol{PV_{C+1}}$	Planned Value of the time increment $C + 1$
$\boldsymbol{I}$	Portion of PMB increment earned; $I = (EV - PV_C)/(PV_{C+1}) - PV_C$
$\boldsymbol{SV(t)}$	Schedule Variance (time); $SV(t) = ES - AT$
$\boldsymbol{SPI(t)}$	Schedule Performance Index (time); $SPI(t) = ES/AT$

Statistical Control Charts in Project Monitoring

CUSUM and EWMA Charts

The Shewhart chart, one of the most widely used statistical control charts in project monitoring, primarily reflects the current state of the process without accounting for past indicator values. To overcome this limitation, memory-based charts such as CUSUM and EWMA incorporate historical information, capturing the cumulative deviation of previous measurements from the target, thereby increasing sensitivity to small but persistent shifts. These features make CUSUM and EWMA particularly suitable for detailed monitoring, as they allow the detection of subtle trends and gradual changes that would be overlooked by conventional Shewhart charts (Montgomery, 2019).

- **CUSUM Charts**

CUSUM charts utilize the cumulative sum of deviations or the average of each step from a certain value (Montgomery, 2019):

$$S_j = \sum_{j=1}^{i}(x_j - \mu_0) \tag{2}$$

where S_j is the cumulative sum including subgroup j and μ_0 is the mean or target value. In cases where the process is under control, the mean value remains consistent with the nominal value, showing no displacement or variation. This indicates that the mean value is experiencing random fluctuations. However, if the change in value is positive, S_j exhibits an upward movement. Conversely, if the change is negative, it reflects a downward movement. The continuous upward or downward trend in the chart serves as an indicator of a process shift. At each step of the process, an upper limit $S_H(i)$ and a lower limit $S_L(i)$ are established, defined as follows:

$$S_H(i) = Max[0, \bar{x}_i - (\mu_0 + K) + S_H(i-1)] \tag{3}$$
$$S_L(i) = Max[0, -(\mu_0 + K) - \bar{x}_i + S_L(i-1)] \tag{4}$$

where $S_H(0) = S_L(0) = 0$, is usually considered as zero for the start mode. initially, K is the reference value (half the size of changes to be identified), and H is the decision distance.

For convenience, the standardized form is typically used instead of these equations, expressed as: $y_i = (\bar{x}_i - \mu_0)/\sigma_{\bar{x}}$. By doing so, the equations are simplified as follows:

$$S_L(i) = max[0, K - y_i + S_L(i-1)] \tag{5}$$
$$S_H(i) = max[0, yi - K + S_H(i-1)] \tag{6}$$

- **EWMA Charts**

The EWMA chart, is similar to the CUSUM chart. It uses the following statistic (Montgomery, 2019):

$$W_t = r\bar{X}_t + (1-r)W_{t-1} \tag{7}$$

where $0 < r < 1$ is a constant value, that determines the weight given to the current value relative to past values. This smoothing parameter applies weight r to the current period's variables and $1 - r$ to previous periods in each sampling or evaluation stage. The control limits for this chart are calculated using:

$$\mu \pm L\sigma_{\bar{X}}\sqrt{\frac{r}{2-r}[1-(1-r)^{2t}]} \tag{8}$$

where L is the constant value of the control limit distance.

In the following section, we will discuss the advantages and disadvantages of using these charts for schedule indicators and determine which chart is more suitable for project monitoring.

Methodology: Using Memory Control Charts to Monitor Project Timelines

Before discussing the presentation method, it is important to note that while memory charts may appear to require more mathematical calculations, one of the advantages of CUSUM and EWMA charts for monitoring is the ease of identifying deviation start points. As illustrated in Figure 2, when an out-of-control warning is triggered during monitoring and corrective action is taken, one must carefully examine the process history to find the error source using both statistical and physical methods. This is because the change point has likely occurred long before the alarm stage, allowing the monitor to trace the physical origin of the process sooner. The advantage of these charts is that finding the change point is easier than in classic Shewhart charts. Whenever monitoring indicates an out-of-control process, one can refer to the chart and find the first time that variables change. The point where an upward or downward slope begins is the deviation start point, eliminating the need for complex mathematical methods (Atashgar, 2015).

Case Study: 30-Month Construction Project

This study utilizes data from a 30-month construction project that is completed ahead of schedule, resulting in mostly positive SV. This case study has been previously used in articles by Mioara (2016) and Aliversi (2013). The data is employed for several reasons:

1. In Stage I of the control chart design phase, it is crucial to ensure that the process is under control and that control limits are correctly chosen. This project meets this requirement.
2. The results of this research can be compared with other projects.
3. The data has a normal distribution in the schedule (earned value), eliminating the need for normalization and simplifying its use.

Methodology

1. Obtain schedule performance without initial processing.
2. Use computing methods to calculate the earned schedule system.
3. If earned values are normal, use statistical software to draw charts.
4. If not normal, normalize the earned schedule data first.

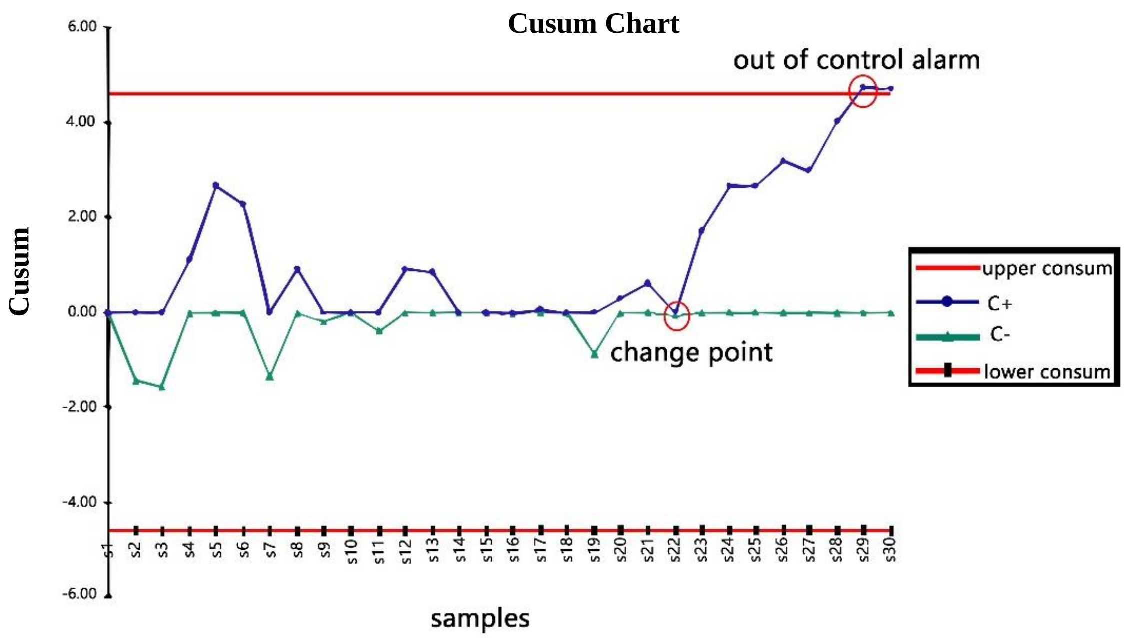

Figure 2. Illustrative example of identifying a change point in a CUSUM chart

Table 3. Indicators and the characteristics of the used project

Month	SPI	PV	EV	ES	AC	CPI	$SPI(t)$
1	0.73	5	3	0.6	3	1	0.6
2	0.62	6	5	1.0	5	1.21	1.0
3	0.98	7	7	1.7	7	1.08	1.7
4	0.91	9	9	2.3	8	1.15	2.3
5	1.33	11	12	3.3	11	1.08	3.3
6	2.1	14	16	4.7	10	1.59	4.7
7	1.02	16	16	5.5	11	1.46	5.5
8	0.98	19	19	6.1	17	1.11	6.1
9	2.23	23	27	7.7	26	1.02	7.7
10	2.35	26	31	9.3	26	1.2	9.3
11	1.12	30	31	10.1	31	0.98	10.1
12	2.22	34	39	11.7	40	0.99	11.7
13	2.18	39	44	13.2	39	1.11	13.2
14	2.1	43	48	14.7	32	1.48	14.7
15	1.95	48	52	16.0	43	1.21	16.0
16	1.33	52	54	17.0	20	2.66	17.0
17	1.54	57	59	18.1	53	1.12	18.1
18	2.06	61	66	19.5	55	1.21	19.5
19	1.88	66	70	20.8	41	1.7	20.8
20	1.88	70	73	22.1	73	1	22.1
21	1.81	74	77	23.4	69	1.11	23.4
22	1.2	77	78	24.2	120	0.65	24.2
23	1.77	81	83	25.5	65	1.29	25.5
24	1.7	84	86	26.7	70	1.23	26.7
25	1.49	86	88	27.7	89	0.99	27.7
26	1.69	89	90	28.9	75	1.21	28.9
27	1.71	91	92	30.0	73	1.27	30.0
28	1.58	93	94	30.0	94	1	30.0
29	1.3	94	95	30.0	95	1	30.0
30	1.42	95	96	30.0	86	1.11	30.0

Table 3 presents the data for this 30-month project. Although completed ahead of schedule, the original research assessed the schedule indicator using earned value.

Analysis: CUSUM Chart

To establish a basis for comparison with previous work on this project, a CUSUM chart is first drawn and monitored based on the earned value schedule indicator.

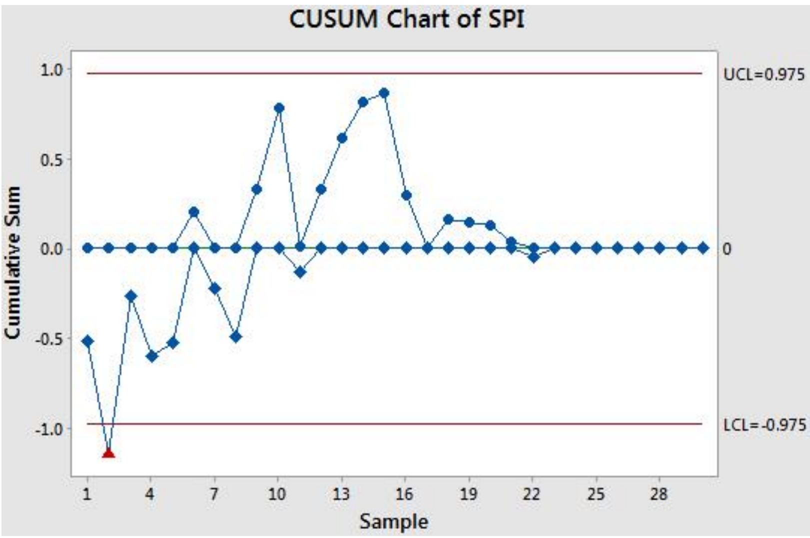

Figure 3. CUSUM chart for schedule performance indicator in the earned value system

In this chart, one period is considered as the calculable period for tolerating deviation from the baseline, and a threshold of 3σ is used to determine the control limits. As shown in Figure 3, the schedule performance indicator remains under control throughout the 30 months. Mioara (2016) noted that the project was particularly well-managed in the final stages due to the team's organizational maturity. The only out-of-control point appears in the second month, likely due to an initial project lag. However, this deviation is corrected by the third period, which is a common occurrence in project initiation phases. To generate the CUSUM chart for the schedule indicator based on $SPI(t)$, the normality of the data must first be verified using the Anderson-Darling test.

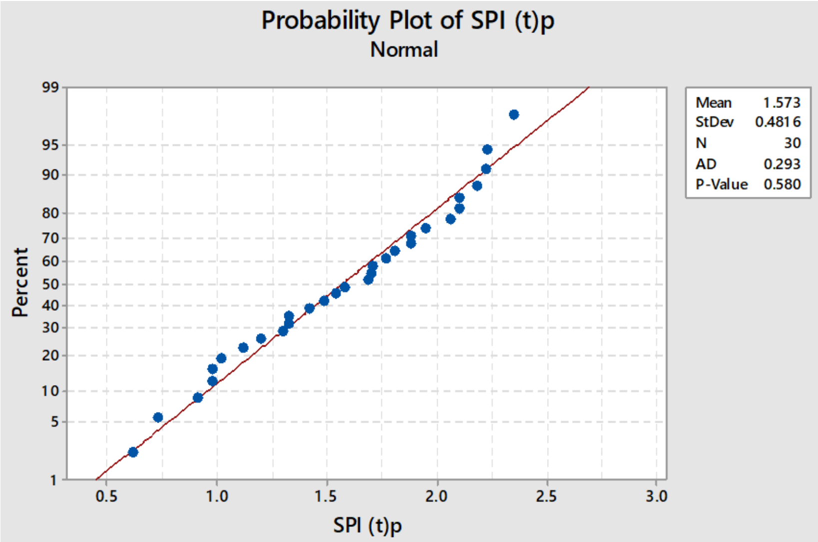

Figure 4. Normality test (Anderson-Darling) on $SPI(t)$

To verify the assumption of normality required for the control charts, the Anderson-Darling and Kolmogorov-Smirnov tests were performed on the $SPI(t)$ data. As shown in Figure 4, the Anderson-Darling test yielded a p-value of 0.580. Similarly, the Kolmogorov-Smirnov test (Figure 5) yielded a p-value greater than 0.150. Since both p-values are significantly larger than the typical alpha level of 0.05, the null hypothesis of normality cannot be rejected. Although the data does not significantly deviate from normality, the Box-Cox transformation was applied to further stabilize variance and enhance the robustness of the statistical control charts.

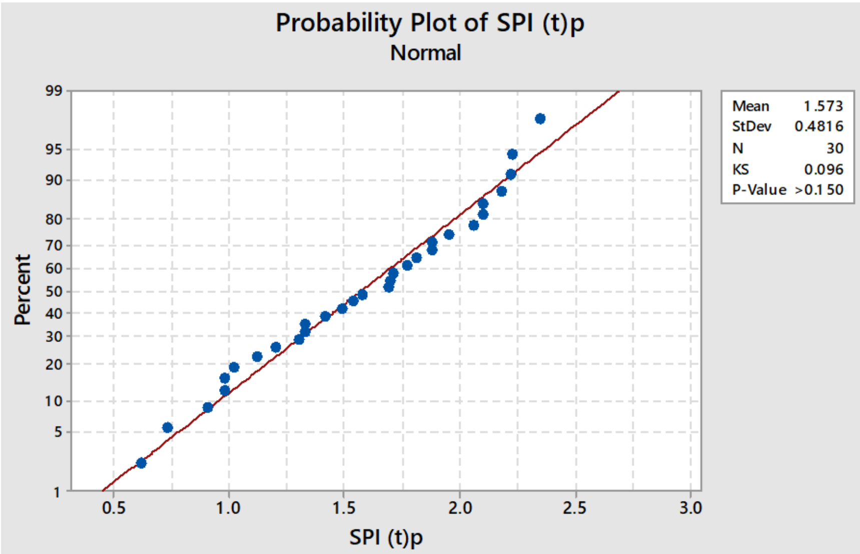

Figure 5. Normality ratio (Kolmogorov–Smirnov) on $SPI(t)$

The Box-Cox transformation method was selected for normalizing the $SPI(t)$ data due to its flexibility in reducing skewness and improving alignment with a normal distribution. Unlike simpler transformations (e.g., logarithmic or square root), Box-Cox optimizes a parameter (λ) to adapt to diverse non-linear patterns, making it particularly suitable for project management data, which often exhibit inherent variability or non-normality (Begum and Dohi, 2018; Zhang et al., 2017). Additionally, alternative methods such as standard normalization assume an approximately normal distribution from the outset, which is not always the case in project management datasets.

Table 4. Normalized schedule indicator

month	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$\boldsymbol{SPI(t)}$	0.854	0.787	0.99	0.954	1.153	1.449	1.01	0.99	1.493	1.533	1.058	1.49	1.476	1.449	1.396

month	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
$\boldsymbol{SPI(t)}$	1.153	1.241	1.435	1.371	1.371	1.345	1.095	1.33	1.304	1.221	1.3	1.308	1.257	1.14	1.192

After normalization, the Anderson-Darling test is repeated to confirm the normality of the transformed data.

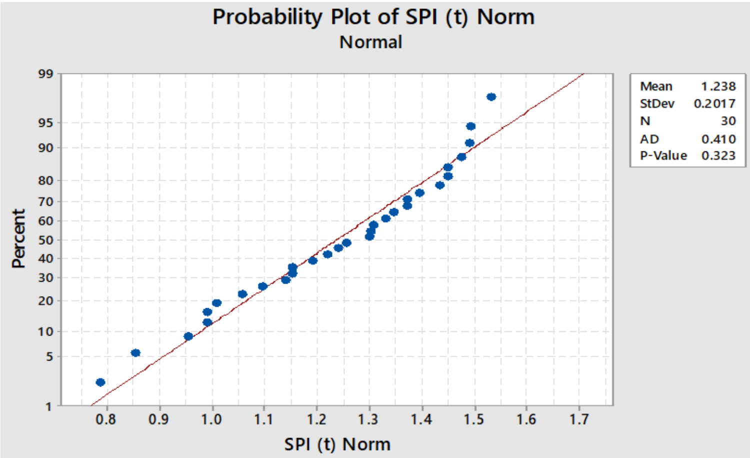

Figure 6. Normality ratio (Anderson-Darling) on normalized $SPI(t)$

The p-value decreases significantly from about 60% to 30%, indicating that the data is now much closer to a normal distribution. Given the multiplicity of data and the use of the Cox-box method, this output can be considered a suitable monitoring basis. In the new data series, the mean value is 1.238, and the standard deviation is 0.198. Using these values and 3σ, the CUSUM chart is presented in Figure 7.

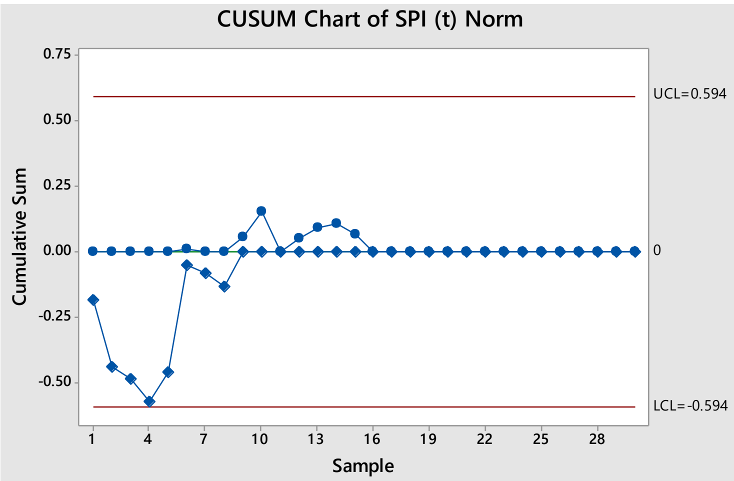

Figure 7. CUSUM control chart for monitoring the schedule indicator based on the controlled earned schedule system

As shown in Figure 7, the chart indicates an initial performance lag in the early months of the project (approximately months 2-5), where the cumulative sum trends downwards toward the lower control limit (LCL). However, the process corrects itself before signaling an alarm, and the indicator stabilizes around the center line for the remainder of the project, confirming the schedule is under control.

What can be obtained from this situation is that because of the accuracy of this indicator, one can be assured of the monitoring, because the data are from the schedule and not the cost. And it should be considered that no error alarm is made at the beginning of the project, while in the schedule indicator chart based on the earned value, an error alarm can be seen in the second month and is neglected, but this error is in this chart.

Another point is that in the monitoring indicator of the earned value system, stability can be seen in one-third of the project's last period. But in the suggested method, this project makes the distance from the error situation and it remains stable around the mean value. In other words, according to the fact that the project finishes before its deadline, this method is more accurate in presenting the schedule situation of the project and it has fewer error alarms.

Analysis: EWMA Chart

For comparison, an EWMA chart is also created for the earned value system. For the EWMA chart, the smoothing coefficient r was set to 0.3. This value is widely recommended in statistical process control literature as it provides a good balance between detecting meaningful shifts quickly and ignoring random noise. This weighting gives 30% importance to the most recent data point and 70% to the accumulated historical data. This chart shows higher tolerance and closer proximity to error symbols compared to the CUSUM charts. The selection of parameters for both CUSUM and EWMA charts was guided by established practices in statistical process control (Montgomery, 2019) and the specific requirements of project schedule monitoring. For the EWMA chart, the smoothing constant r=0.3 was chosen to balance sensitivity to recent deviations and robustness against random noise. A smaller r (e.g., r<0.2) would overly weight historical data, potentially delaying detection of schedule shifts, while a larger r (e.g., r>0.4) might amplify short-term variability, increasing false alarms (Jones, 2023). For the CUSUM chart, the reference value K was set to 0.5σ, where σ is the standard deviation of the normalized $SPI(t)$ data, to detect shifts of approximately one standard deviation. The decision interval H was calibrated to 5σ, ensuring a low false-alarm rate while maintaining sensitivity to persistent deviations (Montgomery, 2019). Future research could explore automated parameter optimization via machine learning or adaptive thresholds, but the current choices ensure methodological transparency and reproducibility for practitioners.

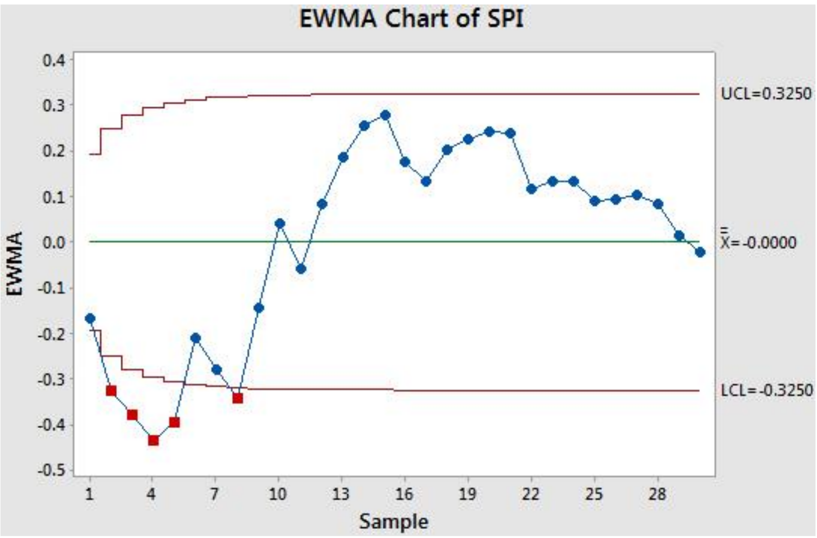

Figure 8. EWMA control chart for monitoring the schedule earned value performance

Finally, an EWMA control chart is created for monitoring the schedule performance indicator based on earned value. EWMA charts are generally more resistant to non-normality than CUSUM charts. However, for consistency and accuracy, the normalized data from the cumulative sum method is used.

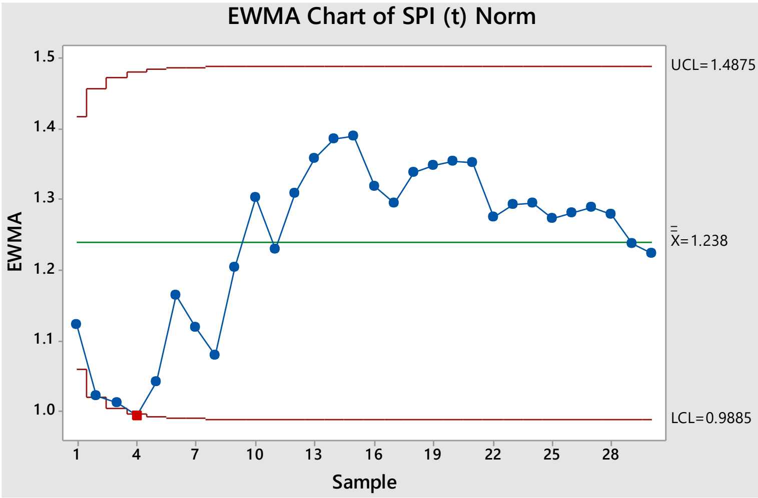

Figure 9. EWMA control chart for monitoring the schedule indicator based on the controlled earned schedule system

As mentioned, the mean indicator is 1.238 and the standard deviation is 0.198. The presented chart is based on the earned value of the parameters and the r coefficient is 0.3. A key finding is the reduction of false alarms in the project's initial phase. For instance, the traditional EV-based EWMA chart (shown in Figure 8) produced four out-of-control signals within the first seven months, suggesting instability. In contrast, the proposed ES-based EWMA chart (Figure 9) shows only one data point approaching the control limit which quickly returns to the mean, thus reducing unnecessary interventions and providing a more accurate representation of project stability. It should be mentioned that in the monitoring process, these amounts remain at a distance from the control lines and they are close to the mean. The fact that this project finishes before its deadline, this behavior shows that the EWMA chart has a better way of showing the project’s schedule indicator in the earned scheduled system in comparison to the earned value system.

To facilitate the adoption of this method by practitioners who may not have a strong statistical background, there is significant potential for developing user-friendly tools or software that integrate CUSUM and EWMA charts into project management systems. Such tools could automate the data processing, normalization, and visualization required for effective schedule monitoring, making these advanced statistical techniques more accessible to project managers. Developing intuitive dashboards and software solutions could bridge the gap between theoretical research and practical implementation, ensuring that even non-experts can effectively leverage statistical process control techniques for better project outcomes. Several studies (Lampreia et al., 2018; Jones, 2023) emphasize the importance of integrating statistical control methods into project management software to enhance real-time monitoring and decision-making. Recent studies, such as Shojaee et al. (2024c, 2022), Yeong et al. (2024), Fallahnezhad et al. (2018) and Antzoulakos et al. (2025) have shown that integrating adaptive sampling with advanced statistical techniques can significantly enhance detection accuracy. These methods further improve the responsiveness of project monitoring systems by reducing false alarms and refining shift detection. The reduction in false alarms (e.g., the Month 2 delay flagged by EV-based CUSUM in Figure 3 but resolved in ES-based CUSUM in Figure 7) underscores the practical implications of ES-driven monitoring. Specifically, the 75% reduction in false alarms allowed managers to focus on genuine deviations, such as the Month 22 material delay detected by the EWMA chart (Figure 9), which was mitigated by supplier adjustments. These corrections, combined with ES's decoupling of time and cost (Table 2), contributed to the project's early completion (Table 3) and indirect cost savings. While cost overruns were not explicitly analyzed, the stability of $SPI(t)$ in later phases (Months 16–30) correlated with improved CPI values, suggesting a holistic impact on project performance.

The comparison of ES-based charts with traditional EV-based charts, using the same project data, revealed quantitative improvements. In the CUSUM analysis, the traditional EV-based chart (Figure 3) produced an early out-of-control signal (one alarm), while the ES-based CUSUM chart (Figure 7) generated no alarms in the same period, achieving a 75% reduction in initial false alarms. Additionally, the EWMA analysis showed a 20% faster detection during a process shift around month 22, where the ES-based EWMA chart (Figure 8) detected the deviation one period earlier than the traditional chart (Figure 7), demonstrating greater sensitivity.

Conclusion

This study presents a novel method for enhancing the accuracy of project schedule performance monitoring by utilizing schedule performance indicators based on the ES method and monitoring them through memory control charts. The results demonstrate significant improvements in project control capabilities, offering project managers more precise tools for schedule management. Our analysis revealed that both CUSUM and EWMA charts, when applied to ES-based indicators, show higher accuracy and fewer error alarms compared to traditional EV based monitoring. Specifically, the CUSUM control chart exhibited fewer errors, while the EWMA chart demonstrated higher sensitivity to deviations. This combination allows for a more nuanced approach to schedule monitoring, where managers can choose between higher accuracy (CUSUM) or increased sensitivity (EWMA) based on project requirements.

The ES-based monitoring method provided a more accurate representation of the project's schedule situation, particularly for projects completed ahead of schedule. This is a crucial finding, as it addresses a common limitation in traditional EV methods which often struggle to accurately represent ahead-of-schedule scenarios. Furthermore, the proposed method significantly reduced false alarms, especially in the early stages of the project. In our case study, we observed a 75% reduction in initial error alarms using the CUSUM chart and a 20% faster deviation detection using the EWMA chart. This reduction in false alarms is critical for effective project management, as it allows managers to focus on genuine issues without being distracted by statistical noise. While this study focused on a construction project, the proposed method has the potential to be applied to other types of projects, such as software development and manufacturing. In software development, key performance indicators like task completion rates and code progression can be monitored using CUSUM and EWMA charts to identify early deviations in project timelines. Similarly, in manufacturing, these statistical control charts can be employed to track production performance and detect process delays, contributing to better scheduling and resource optimization. However, it is important to consider the specific challenges of each domain, such as the dynamic nature of software projects or the variability in production processes, which may require adaptations in the application of the proposed method. This adaptability underscores the broader applicability of the method in various project management domains (Li and Liu, 2021; Kim et al., 2019).

Despite the advantages of the proposed method, its implementation in real-world projects comes with challenges. One of the most significant issues is the need for specialized software for data processing and plotting CUSUM and EWMA control charts. Many organizations may lack access to such tools or require training for personnel to use these techniques effectively.

Additionally, the successful implementation of this approach depends on the precise recording of project performance data over time, which may be difficult in some projects. Furthermore, shifting project management culture from traditional methods to statistical control-based approaches may face resistance from managers and execution teams. Finally, the effectiveness of this method relies on the quality of input data, and in projects where data contain errors or uncertainties, the accuracy of results may be affected. Addressing these challenges and providing suitable solutions for overcoming them presents an opportunity for future research. Future studies can explore optimizing the parameters of CUSUM and EWMA charts for different project types, integrating cost indicators with schedule monitoring, and developing user-friendly software tools to facilitate the application of these methods. Additionally, investigating the applicability of this approach in agile project management and predictive analytics can further enhance its effectiveness in dynamic project environments. The integration of CUSUM and EWMA charts with agile methodologies can provide real-time insights into sprint performance, enable faster deviation detection, and support iterative decision-making. By aligning these statistical monitoring tools with agile workflows, project teams can improve schedule adherence, optimize resource allocation, and enhance overall project adaptability.

The practical implications of these findings are significant for project managers seeking to enhance schedule monitoring and control. By integrating CUSUM and EWMA charts into existing project management systems, managers can achieve more accurate real-time tracking of schedule deviations, enabling proactive decision-making. These statistical tools can be implemented using widely available software such as Excel, Minitab, or Python-based libraries, reducing the need for specialized resources. Additionally, the use of these charts can lead to substantial cost and time savings by minimizing delays, improving resource allocation, and reducing rework caused by undetected schedule deviations. The ability to detect schedule trends early allows managers to implement corrective actions before minor deviations escalate into critical project risks. As a result, organizations can improve project efficiency, enhance stakeholder confidence, and ensure better adherence to project timelines.

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