Journal of Science and Technology in Civil Engineering, HUCE, 2025, 19 (2): 62–77

RISK-BASED EARNED VALUE MANAGEMENT WITH COST–TIME MUTUAL EFFECT TO ENHANCE CONSTRUCTION FORECASTS AND MANAGEMENT

Nguyen Anh Duc[a,*]

[a] *Faculty of Building and Industrial Construction, Hanoi University of Civil Engineering, 55 Giai Phong road, Hai Ba Trung district, Hanoi, Vietnam*

Article history:

Received 28/02/2025, Revised 14/4/2025, Accepted 05/6/2025

Abstract

Earned Value Management (EVM) traditionally provides single-value forecasts of project cost and schedule that often underestimate real-world complexities—particularly the correlation between delays and cost overruns, as well as the evolution of risk over time. This paper introduces an augmented EVM approach that incorporates (i) a monthly correlation factor linking extended task durations to higher expenditures, and (ii) interval-based risk factors driving probability distributions of final cost and schedule. By merging Monte Carlo simulation with traditional EVM metrics (planned value, earned value, actual cost), this method produces robust forecast bands instead of single-value estimates, enabling proactive contingency planning. Two actual construction projects—one with 10-month planned vs. 12-month actual duration, another with 18 vs. 22 months—demonstrate how the augmented EVM captures worst-case scenarios significantly better than traditional EVM, while clarifying the likelihood of potential overruns. Though sometimes conservative, the distribution-based outputs give project managers a fuller picture of uncertainty, improving resource allocation and stakeholder communication in high-volatility construction environments.

Keywords: EVM; risk-based; forecasts; construction management; cost; schedule.

https://doi.org/10.31814/stce.huce2025-19(2)-05

1. Introduction

Large-scale engineering and construction projects are significantly influenced by cost and schedule dynamics, which are often monitored through Earned Value Management (EVM) [1, 2]. EVM integrates scope, schedule, and budget data to produce performance indices such as the Cost Performance Index (CPI) and Schedule Performance Index (SPI), which are critical for forecasting final costs and completion times [3–6]. Nevertheless, traditional EVM simultaneously fails to account for (i) the ongoing evolution of each project's risk profile and (ii) the correlation between cost and schedule deviations. It is not difficult to envision the later disadvantage, such as the rise in overhead costs, equipment rentals, and labor when delays happen [7–9]. Whereas, risk profile often changes continuously, for example, supply chain disruptions may intensify during certain periods while reducing in others [10]; high-risk events such as extreme weather or labor disputes may be intensive in some phases while diminished during other time in a project lifecycle [11]. Failing to consider these natural phenomena, traditional EVM with single-value extrapolations usually deviates its own forecasts from actual project outcomes [12, 13].

This research presents an augmented EVM measure that integrates two fundamental components: time-cost correlation and evolving risk profiles. The time-cost correlation component entails a correlation factor that modifies the influence of schedule delays on cost projections at each reporting

*Corresponding author. *E-mail address:* ducna@huce.edu.vn (Duc, N. A.)

period. The evolving risk profiles component monitors a numerical risk factor for each interval, facilitating the creation of probabilistic projections for final project costs and durations instead of depending on single-value estimations. This methodology generates distributions of potential outcomes for each monthly or milestone review, which effectively represent the interaction between cost and schedule uncertainty. Based on the fundamental principles of traditional EVM, the method is designed to be relatively straightforward to implement and to enhance risk management by utilizing a simulation-based inflation mechanism [14].

Sections 2 summarize the principles of EVM, advanced modeling efforts, and the current research gap concerning correlation and risk-based expansions. Section 3 delineates the mathematical framework that synthesizes correlation and interval risk, the augmented EVM algorithm, encompassing pseudo-code and partial proofs pertaining to its viability and convergence predictions. Section 4 examines the employed data structures, concluding in a partial demonstration, with comprehensive validation on two project case studies allocated for later sections. The proposed methodology seeks scalability for extensive, multi-year construction endeavors while concurrently producing traditional EVM indices to adhere to organizational protocols. The method addresses major shortcomings of traditional EVM in complex and unpredictable task settings by stressing correlation and dynamic risk. Section 5 provides an analysis of the results and discusses the construction management implications of the suggested methodology.

2. Literature review

2.1. EVM fundamentals

Traditional EVM tracks Planned Value (*PV*), Actual Cost (*AC*), and Earned Value (*EV*), which are essential for deriving performance metrics such as *CPI* and *SPI* [1]. The formulas for these indices are critical for project managers to assess performance: traditional EVM often assumes relative independence in the cost and time performance of tasks, which can lead to oversimplified forecasts. While some researchers have proposed range-based *EAC* estimates, these remain rudimentary approximations [15]. The following are the main indices that are used in traditional EVM:

$$\mathrm{CPI} = \frac{\mathrm{EV}}{\mathrm{AC}}; \quad \mathrm{SPI} = \frac{\mathrm{EV}}{\mathrm{PV}}; \quad \mathrm{EAC}\,(cost) \approx \mathrm{AC} + \frac{\mathrm{BAC} - \mathrm{EV}}{\mathrm{CPI}} \tag{1}$$

where *BAC* is the total Budget at Completion; *CPI* and *SPI* are cost/schedule performance index respectively; *EAC* is Estimate at Completion [16].

2.2. The Cost-Schedule correlation in construction projects

The interdependence of cost and schedule in construction is well-established, with delays frequently driving cost overruns and vice versa. Sambasivan and Soon [8] note that ensuring completion "within the budgeted time and cost" is a central role of project managers, reflecting how slippages in time almost inevitably translate to inflated budgets. Roumeissa [9] agrees with this, remarking that when delays occur, projects are either expedited—requiring additional funds—or extended—raising overhead expenses. Ramanathan et al. [17] emphasize how only "30% of construction projects" meet their scheduled completion dates, indicating the breadth of time-cost misalignment in practice. Larsen et al. [18] argue that a project's outcome hinges on proper owner engagement in timely procedures, while Koushki et al. [19] identify change orders and financial constraints as dual triggers for schedule delays and concurrent cost overruns.

This time-cost synergy similarly appears in the work of Jung and Woo [20], who advocate integrating cost and schedule controls to enhance monitoring; Afzal et al. [21] emphasize the nonlinear characteristics of project complexity that can intensify costs when timelines are delayed. EVM, an established method for monitoring project performance, is predicated on the integration of cost and schedule metrics [22]. Collectively, these studies highlight the essential significance of considering cost and time as interconnected variables, as neglecting to manage one aspect frequently compromises the other, hence increasing project risk.

2.3. Updating risk profiles in Earned Value Management

The necessity of integrating updated risk profiles into EVM is becoming more widely acknowledged as a critical component of effective project control in the construction industry. Anbari [16] emphasizes the ability of EVM to predict the cost and schedule at completion, suggesting that the integration of continuous risk updates can enhance its precision and encourage proactive corrective actions. This perspective is further supported by Hazır [23], who suggests that without changing risk assessments, EVM could not be able to identify significant uncertainty. In a similar vein, Babar et al. [24] show that adding risk variables to EVM improves the reliability of performance reviews. Acebes et al. [25] indicate that the combination of risk analysis with EVM yields more thorough insights by using Monte Carlo simulations to capture a more comprehensive spectrum of project behavior under uncertainty.

This risk-centered approach is also shared by Kim and Pinto [26], who stress the need for reliable and ongoing risk assessments to reduce overruns and enhance EVM's predictive ability. They observe that cost overruns are frequently observed as the norm. As they assess the updating of risk profiles, Tereso et al. [27] propose that the integration of EVM-risk automation is a research horizon for more efficient project monitoring. Ibrahim et al. [28] stress how important it is to include different risk factors in EVM estimates, especially when it comes to infrastructure. Highly fluctuating risks such as weather are considered by Muller et al. [29] in irrigation projects. Interestingly, Roghabadi and Moselhi [30] developed an "Earned Duration Management" - EDM (a derive of EVM) - especially for the project duration forecast. When looked at as a whole, these studies show that regular updates to the risk model are needed to keep it useful and accurate in the face of the inherent uncertainty of building projects.

3. Methodology

3.1. Proposed framework

a. Traditional EVM notation

Let $\mathrm{PV}(t)$ - planned value at month t; $\mathrm{EV}(t)$ - earned value at month t; $\mathrm{AC}(t)$ - actual cost at month t; BAC - budget at completion (total planned cost); $\mathrm{CPI}(t) = \dfrac{\mathrm{EV}(t)}{\mathrm{AC}(t)}$; $\mathrm{SPI}(t) = \dfrac{\mathrm{EV}(t)}{\mathrm{PV}(t)}$.

A deterministic forecast for final cost—EAC—at each t is [16]:

$$\mathrm{EAC}_{traditional}(t) = \mathrm{AC}(t) + \frac{\mathrm{BAC} - \mathrm{EV}(t)}{\mathrm{CPI}(t)} \tag{2}$$

b. Correlation and risk variables

The study introduces two additional inputs, updated at each month or milestone:

- RiskFactor$(t) \in [0, 1]$ reflects the magnitude of uncertainty for the upcoming interval(s). Higher values indicate broader cost/time deviations.

- CorrFactor$(t) \in [0, 1]$ expresses the time-cost synergy. When tasks slip, cost overruns are amplified more strongly for higher correlation.

c. Distribution-based forecast

Instead of returning a single EAC, a distribution for final cost is defined:

$$\hat{C}_n(t) = \text{EAC}_{traditional}(t) \times (1 + \text{CorrFactor}(t) \cdot \alpha) \times Z_n(t), n = 1, \ldots, N \tag{3}$$

where α is a user-chosen constant weighting correlation strength (e.g., $\alpha = 0.5$); $Z_n(t)$ is the n-th random draw from a distribution $\mathcal{D}(\text{RiskFactor}(t))$. For instance, if risk is high (RiskFactor(t) ≈ 0.8), *a* distribution might be assumed: $Z_n(t) \sim \mathcal{N}\left(1.0, (\beta \cdot 0.8)^2\right)$, with β as a base standard deviation (e.g., $\beta = 0.2$).

A similar equation is used for schedule forecast:

$$\hat{S}_n(t) = \text{DaysEAC}_{trad}(t) \times (1 + \text{CorrFactor}(t) \cdot \alpha_s) \times Y_n(t), n = 1, \ldots, N \tag{4}$$

where α_s can differ from α if time-cost correlation is asymmetric, and $Y_n(t)$ is drawn from a risk-based distribution for schedule.

d. Probability outputs

Once the set of $\hat{C}_1(t), \hat{C}_2(t), \ldots, \hat{C}_N(t)$ is calculated (and similarly for $\hat{S}_n(t)$), we can summarize: mean $\overline{C}(t) \approx \dfrac{1}{N}\sum_{n=1}^{N}\hat{C}_n(t)$; confidence intervals, e.g., $\left[\hat{C}_{5\%}, \hat{C}_{95\%}\right]$, which capture ranges of outputs based on levels of confidence.

Thus, each month yields a distribution-based final cost/time forecast, reflecting both the correlation factor and the evolving risk environment.

3.2. Theoretical formulations

a. Stochastic model setup

Let Ω denote the sample space of random outcomes for upcoming intervals. A *stochastic process* $\{R_t\}$ capturing risk multipliers over time is defined, where each *RiskFactor*(t) modifies the distribution of R_t. Then the final cost forecast is:

$$\hat{C}(t,\omega) = \text{EAC}_{traditional}(t) \times (1 + \text{CorrFactor}(t) \cdot \alpha) \times R_t(\omega), \omega \in \Omega \tag{5}$$

If $R_t(\omega) \sim \text{Lognormal}\left(\mu, \sigma^2\right)$ or $\text{Normal}\left(1, \sigma^2\right)$, heavier-tailed distributions can be incorporated if the project is prone to extreme events. The correlation factor enters multiplicatively so that an inflated duration leads to a proportionally inflated cost outcome.

b. Handling endogenous time-cost correlation

A joint distribution for $\hat{C}$ and $\hat{S}$ and via correlation matrices is integrated:

$$\begin{pmatrix} \hat{C}_n(t) \\ \hat{S}_n(t) \end{pmatrix} \sim \mathcal{N}\left(\overline{\mu}, \sum(\text{CorrFactor}(t), \text{RiskFactor}(t))\right) \tag{6}$$

where Σ encodes correlation, and $\overline{\mu}$ is derived from $\text{EAC}_{traditional}(t)$ and $\text{DaysEAC}_{trad}(t)$. Although more complex, this technique ensures cost/time expansions happen together in high-correlation intervals. For simplicity, the study adopts separate draws for cost and schedule in most references, but note that a full correlated approach is feasible.

c. Partial proof: convergence of forecast distributions

By standard law of large numbers, if each $\hat{C}_n(t)$ is an i.i.d. draw from the cost distribution, then:

$$\lim_{N\to\infty} \frac{1}{N} \sum_{n=1}^{N} \hat{C}_n(t) = \mathbb{E}\left[\hat{C}_n(t)\right] \text{ almost surely} \tag{7}$$

hence, the sample mean converges to the expected final cost under the current risk factor and correlation. Similarly, for large enough N, the sample distribution approximates the true underlying distribution, letting us estimate confidence intervals accurately.

3.3. Algorithmic Implementation

a. Preliminaries, definitions, and algorithmic procedure

- Traditional EVM

$$\text{CPI}(t) = \frac{\text{EV}(t)}{\text{AC}(t)} \text{ if AC}(t) > 0, \text{ else set CPI}(t) = 1 \text{ to avoid division by zero} \tag{8}$$

$$\text{EAC}_{CostTrad}(t) = \text{AC}(t) + \frac{\text{BAC} - \text{EV}(t)}{\text{CPI}(t)} \tag{9}$$

- Schedule

$$\text{SPI}(t) = \frac{\text{EVdays}(t)}{\text{AD}(t)} \tag{10}$$

where AD(t) is the actual days so far, and EVdays(t) is a schedule-based EV measure (e.g., $\min(\text{PlannedDays}(t), 0.9 \times \text{ActualDays}(t))$)

$$\text{EACDaysTrad}(t) = \text{AD}(t) + \frac{\text{PlanDaysTotal} - \text{EVdays}(t)}{\text{SPI}(t)} \tag{11}$$

- Risk and correlation

Let RiskFactor(t) be a scalar in [0, 1], representing how volatile or uncertain the project in month t. RiskFactor is derived from a structured review of incident logs, change-order records, and interviews with the project managers (for example, 0.0 - negligible uncertainty (routine work, no disruptions), 0.3–0.6 ≈ moderate uncertainty (weather delays, minor design clarifications, modest resource shifts), 0.7–1.0 ≈ high uncertainty (major scope changes, critical-path interference, supply shocks, labor unrest).

Let CorrFactor(t) be a scalar in [0, 1], indicating how strongly a slip in schedule drives a proportional cost overrun (and vice versa) at month t.

Sampling distribution: a multiplier $\mathcal{Z}_n(t)$ from a normal distribution $\mathcal{N}\left(1, (\beta \cdot RiskFactor(t))^2\right)$, or another suitable distribution - which corresponds to the project nature (for example, if certain delays can create large deviations in cost, then a heavy-tailed distribution might be used).

- Augmented cost/schedule

The final cost distribution for each drawn n at month t is

$$\hat{C}_n(t) = \text{CostTrad}(t) \times (1 + \text{CorrFactor}(t) \cdot \alpha) \times \mathcal{Z}_n(t) \tag{12}$$

Similarly, for schedule

$$\hat{S}_n(t) = DaysTrad(t) \times (1 + CorrFactor(t) \cdot \alpha_s) \times \mathcal{Y}_n(t) \tag{13}$$

where $\mathcal{Y}_n(t)$ is sampled from a similar or correlated distribution for days.

b. Integration into project controls

Augmented EVM is easily integrated into standard project management:

- EVM data input (PV, EV, AC) remains unchanged.

- Two extra indices "RiskFactor(t)" and "CorrFactor(t)" are updated monthly based on project conditions.

- The model implementing algorithm 1 yields final cost/time distributions, from which managers can interpret both *best guess* and *high/low risk* outcomes.

c. Data structures

For each interval t, the algorithm stores:

- PlannedCost(t), ActualCost(t): standard EVM cost data.

- PlannedDays(t), ActualDays(t): schedule aggregates in tracking EVM-like day counts.

- RiskFactor(t), CorrFactor(t): new indices to reflect environment.

Implementation can be in spreadsheets, by programming language, or commercial EVM tools that allow user-defined macros or scripts. In this study, the algorithm is implemented using Python 3.13.1 in macOS Sequoia 15.3 platform; the Monte Carlo simulation is performed by functions from the package SciPy v1.15.2 [31].

4. Results and analysis

4.1. Descriptive overview of projects and input data

The proposed methods are demonstrated and validated through the use of two completed construction projects, each of which possesses its own distinctive characteristics. A facility named project A is situated in an industrial zone in the province of Hung Yen, Vietnam. It is a practical example of the industrial sector, which is distinguished by its straightforward layouts and compressed timelines. Project B, by contrast, is a high-rise residential building in Hanoi city (Vietnam), illustrating the longer durations and more complex designs common in urban developments. Analyzing these two projects side by side enables the observation how EVM—both the traditional and augmented methods—handles varying risk profiles, sector-specific constraints, and evolving cost-time dynamics. Both projects' EVM data were carefully recorded and validated by project managers, who could also recall their changing risk conditions in monthly intervals. Although the owners permitted the use of these records for academic purposes, they required that cost figures remain confidential. As a result, all monetary values are scaled and expressed in currency units (c.u.) rather than explicit denominations.

Project A was planned for a 12-month horizon, with a final planned cost of 120,000 and a planned schedule of 300 days. Actual outcomes, however, show that the project ultimately reached a cost of 158,000 and 365 days—surpassing the original baseline in both dimensions. Table 1 shows a portion of data of the project. Early intervals (months 1–2) incurred relatively modest planned vs. actual differences (5,000 vs. 5,500 in cost, 30 vs. 34 days), but by mid-project (months 5-8), the gap widened substantially. For instance, at month 5, the planned cost of 55,000 compares to an actual of 65,000, and the schedule extends from the planned 150 days to 205. These discrepancies signal ongoing risk influences and schedule challenges.

Fig. 1 presents the evolution of planned and actual cost and schedule of project A. Within each month, the RiskFactor rises from 0.3-0.35 in the opening intervals to a peak around 0.72 in month 8 and then tapers back down to 0.45 by month 12. The CorrelationFactor generally follows a similar upward trend, moving from 0.3-0.4 in the first few months to 0.65 around mid-project before settling near 0.35. Such patterns suggest a highly volatile middle period (months 6-9), where both risk

Table 1. A portion of managerial data of project A

Month_Index	Planned_Cost (c.u.)	Actual_Cost (c.u.)	Planned_Days	Actual_Days	Risk_Factor	Correlation_Factor
1	5100	5500	30	34	0.3	0.3
2	10150	11500	60	70	0.35	0.35
...	...	...	...	...	...	...
11	120000	153000	300	355	0.5	0.4
12	120000	158000	300	365	0.45	0.35

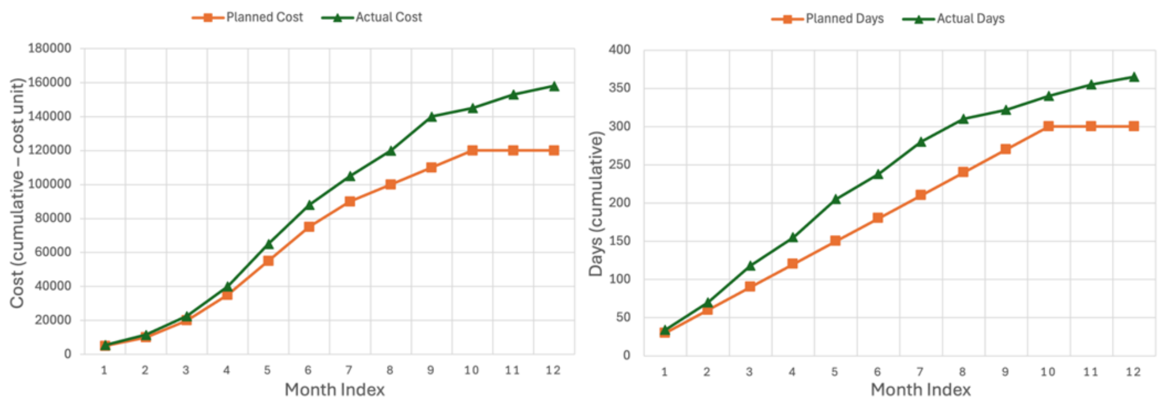

Figure 1. Planned and actual cost and schedule of project A

and time-cost coupling were more pronounced, contributing to higher actual cost and schedule than planned.

Project B is a larger effort spanning 22 months of recorded data, with a baseline that plateaus at c.u.450,000 in planned cost and 540 planned days—but the actual final cost reached c.u.591,000 and 660 days, clearly exceeding both targets. A portion of the project data is shown in Table 2. In the earliest stages (months 1–2), the gap between planned and actual was modest (e.g., c.u.5,000 vs. c.u.5,500 cost, 30 vs. 27 days in month 1), but from around month 5 onward, actual figures outpaced planning assumptions more drastically. By month 10, for example, the planned cost was c.u.300,000 while actual soared to c.u.350,000, and similarly for schedule (300 vs. 315 days).

Table 2. A portion of managerial data of project B

Month_Index	Planned_Cost (c.u.)	Actual_Cost (c.u.)	Planned_Days	Actual_Days	Risk_Factor	Correlation_Factor
1	5050	5500	30	27	0.3	0.3
2	15100	17000	60	61	0.35	0.35
...	...	...	...	...	...	...
21	450000	575000	540	640	0.3	0.25
22	450000	591000	540	660	0.3	0.2

The RiskFactor for project B starts at 0.3 and escalates to 0.85 by month 12, indicating a high-intensity risk environment in mid-project that persists through roughly month 14. Even after that point, risk remains non-trivial (0.7–0.8) until eventually declining to 0.3 by month 20–22. The CorrelationFactor similarly rises from 0.3 to as high as 0.85 in months 11–12, then decreases in the final intervals. This signals that, during the central to late phases, cost overruns and schedule slippages were strongly interlinked, and managers had to contend with both rising uncertainty and major cost-time synergy. Fig. 2 depicts planned and actual cost and schedule of the project.

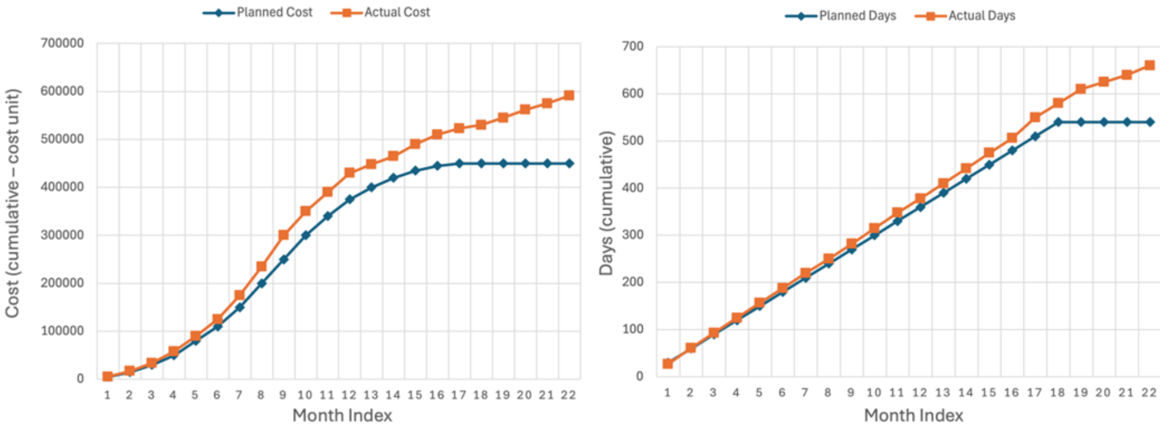

Figure 2. Planned and actual cost and schedule of project B

Both projects therefore provide complementary test cases for the assessment of the augmented EVM that incorporate interval-based risk monitoring and time-cost correlation and whose results will be compared with those from the traditional EVM.

4.2. Analysis of the two projects' actual data

a. Project A

As shown in Fig. 3, the actual cost progresses from a modest figure in month 1 to a final value of c.u.158,000 by month 12, exceeding the original baseline of c.u.120,000. Traditional EVM initially projects a considerably higher cost (around c.u.133,000 in the earliest stage), then gradually locks in on the actual final, ending at c.u.158,000. In contrast, the augmented cost forecast provides a range of outcomes each month. Early intervals see moderately wide intervals, while mid-project months (e.g., 5–8) yield significantly broader bounds, reflecting the rising RiskFactor and CorrelationFactor. By month 12, the augmented method still anticipates possible overruns above c.u.180,000, overshooting reality but ensuring those scenarios are not ignored.

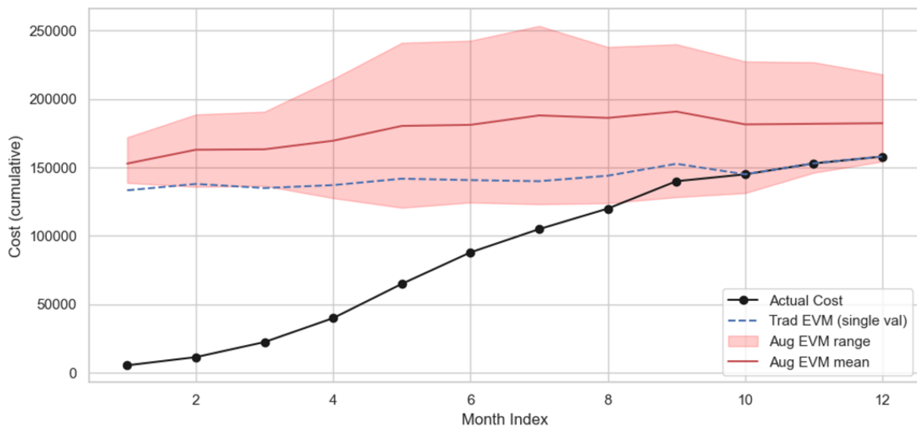

Figure 3. Project A final cost forecasts updated by months of two EVM methods

A similar pattern appears for Project A's schedule (Fig. 4). The traditional approach quickly settles near 300–365 days but ends up exactly at the final 365 in month 12. The augmented approach, however, produces distributions that sometimes stretch dozens of days above actual figures, particularly in intervals with a heightened correlation. While these higher estimates do not materialize, they reflect the possibility that extended labor or overheads could have pushed the final duration beyond 365. Managers thus see a buffer for worst-case schedule slippages—helpful for contingency decisions, even if events ultimately prove less severe.

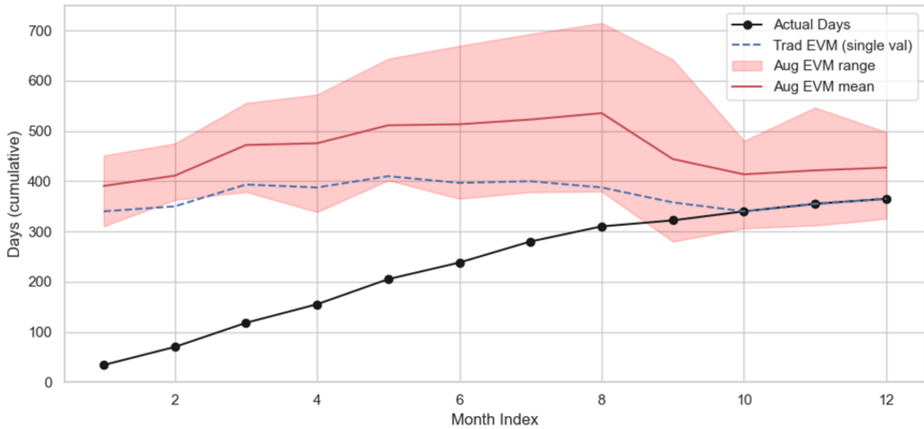

Figure 4. Project A final schedule forecasts updated by months of two EVM methods

Fig. 5 shows a violin plot of the monthly cost distributions, underscoring how often the range surpasses the real actual cost. Each violin/box illustrates the full Monte-Carlo cost distribution generated by the Augmented EVM for that month—its width shows the relative probability density, the box marks the inter-quartile range, and the central line indicates the simulated mean forecast at completion. It is observed that in the middle intervals (Months 5–8), the range surpassing the real actual cost widely. Specifically, the upper tails can approach or exceed c.u.200,000, while actual cost lingers around c.u.65,000–120,000 in the same window. This “over-coverage” may appear conservative, yet it accurately mirrors the synergy between cost inflation and schedule delays if certain risks had compounded. Meanwhile, the traditional EVM single-line forecast does not illustrate that risk exposure—sometimes appearing close to actual cost, other times drifting above or below in a narrower band.

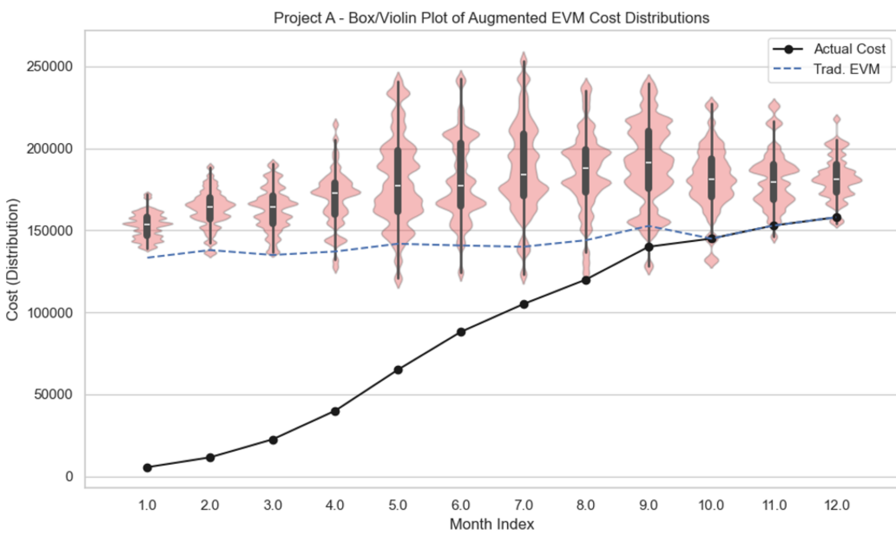

Figure 5. Project A’s cost distributions by augmented EVM

Fig. 6 depicts the errors of forecast of both methods. From an error viewpoint, traditional EVM starts with a large gap relative to final cost in early months but narrows to near zero as the project closes. The augmented method typically yields a smaller early error—since the actual cost is extremely low at month 1—but preserves a positive offset throughout the project, sometimes by tens of thousands. By month 12, the traditional approach is perfectly aligned with the actual, whereas the robust approach remains above it. From a construction management stance, this *overestimation* is essentially the price of ensuring that potential adverse outcomes (amplified by moderate-high correlation factors) remain within the forecast domain, giving managers a richerbasis for proactive control decisions.

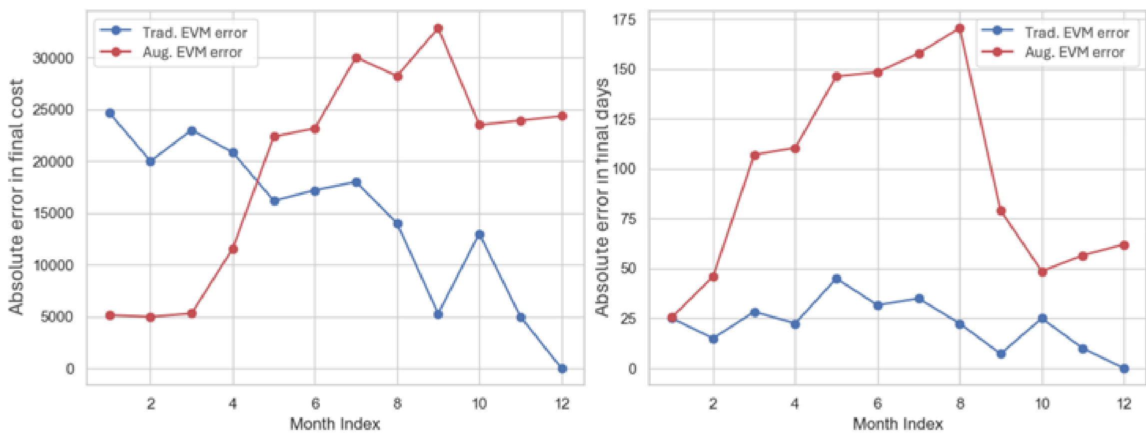

Figure 6. Final forecast error of cost and schedule of project A

b. Project B

Fig. 7 shows the cost forecasts of project B. The actual cost grows slowly in the early intervals but ultimately reaches c.u.591,000 by month 22, well above its original budgeted plan of c.u.450,000. The traditional EVM line quickly settles around the c.u.500,000-600,000 range, then glides up to c.u.591,000 near the project's close. Meanwhile, the augmented forecast produces a broad cost distribution in many intervals, particularly from around month 8 onward, where mid- to upper-range estimates may soar above c.u.800,000 or even approach a million. Although these upper bounds never become reality - in this project, they demonstrate how the robust method accounts for worse-case risks, including the high correlation factor (up to 0.85) that can amplify cost if schedule slips intensify.

Schedule forecasts of project B are depicted in Fig. 8. A similar trend emerges for the schedule dimension. Throughout the majority of the project, the traditional EVM's single line hovers around 600 days, eventually converging to the actual outcome of 660 at month 22. The Augmented approach, however, yields intervals spanning several hundred days—some distributions going as high as 1,000+ days at peak risk points. While such extremes do not materialize, their presence underscores that if correlated disruptions had escalated, the schedule might have extended far beyond 660 days.

In a violin plot of Project B's cost distributions (Fig. 9), managers see how each month's augmented forecast typically overshoots the actual cost—often significantly—yet remains valuable for risk coverage. By mid-project (months 10–14), the distributions' upper tails can approach or surpass one million, reflecting a heightened synergy of high RiskFactor (≥ 0.7) and strong CorrelationFactor (≥ 0.75). Meanwhile, the traditional EVM line does not communicate such a wide uncertainty; it merely tracks a steady upward trajectory, converging with actual only in the final intervals.

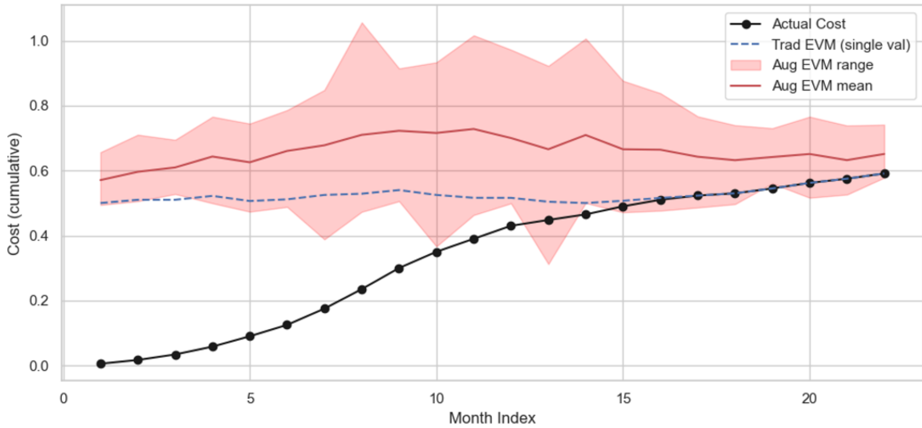

Figure 7. Project B final cost forecasts updated by months of two EVM methods

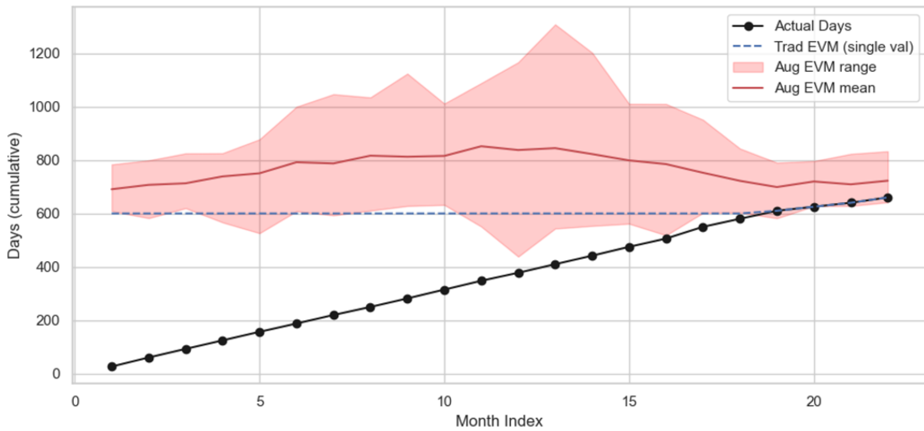

Figure 8. Project B final schedule forecasts updated by months of two EVM methods

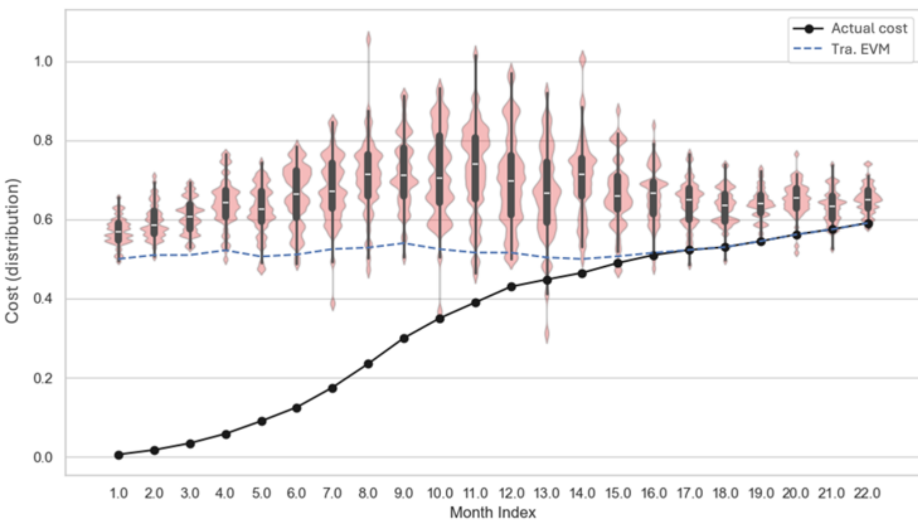

Figure 9. Project B's cost distributions by augmented EVM

From an error perspective (Fig. 10), traditional EVM exhibits a very large initial discrepancy—some c.u.490,000 or more from the final actual—because it had no early sense of how the project might evolve. Eventually, this error shrinks to near zero as traditional EVM dials in the real final cost. By contrast, the augmented approach starts off with an initially high but more balanced error (given that the actual cost is minimal in month 1), then typically remains in a positive offset. Essentially, the robust method includes a "safety buffer" against major overruns that do not occur. Although that leads to an overestimation bias late in the project, it also highlights how the approach hedges against correlated cost escalation during high-risk intervals.

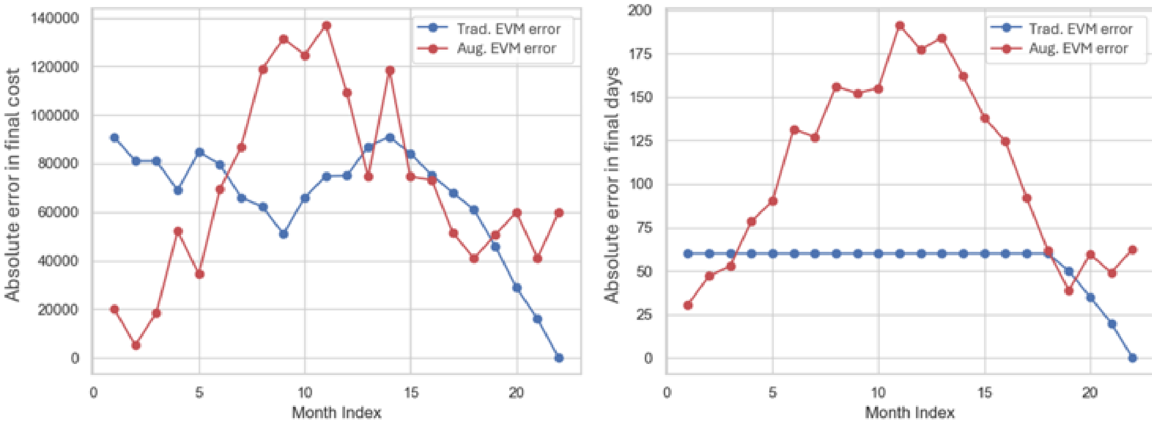

Figure 10. Final forecast error of cost and schedule of project B

Project B's longer timespan and higher final cost highlight the benefit of a distribution-based perspective: managers see the possibility of reaching far larger overruns than the traditional method suggests, especially in risk-heavy segments.

5. Discussions and construction management implications

Taken together, projects A and B continue to reveal a fundamental contrast between traditional (deterministic) EVM and the augmented (distribution-based) approach. In both projects, the traditional EVM forecasts end up very close to—or exactly matching—the real final values in the concluding intervals. This locking in leads to low final errors near project completion, but offers no probabilistic understanding of potential overrun scenarios in earlier stages.

In contrast, the augmented forecasts deliberately inflate their intervals when the input data (i.e., RiskFactor and CorrelationFactor) indicate higher uncertainty or stronger synergy between schedule and cost. This often causes the robust approach to overshoot actual outcomes in mid-to-late project phases, giving an impression of false alarms. From a construction management perspective, however, this distribution-based method is invaluable for proactive resource allocation and contingency planning. Even if many of the risk-laden scenarios do not materialize—leading the augmented forecasts to overshoot—ignoring the possibility of major overruns can be far more damaging should they occur. Thus, across two real-like projects with distinct timelines (12 months vs. 22 months) and cost escalations (c.u.158,000 vs. 591,000 final), the augmented EVM provides a more cautious but comprehensive view of uncertainty, whereas traditional EVM remains a precise single-point estimate that materializes late in the project but offers little risk visibility throughout its lifecycle.

The latest results reinforce a fundamental tension between traditional EVM and the more robust, augmented EVM approach. Traditional methods typically lock onto the real final cost and duration in the later stages, ultimately minimizing final error—especially in projects A and B, which both saw deterministic forecasts match their realized outcomes near project close. However, throughout the bulk of each lifecycle, those single-point EVM lines offered limited visibility into possible budget or schedule escalations, providing no probabilistic range for risk-laden months. In practice, managers relying solely on traditional EVM might not realize how high costs could climb under adverse correlations until performance indices drastically shifted.

By contrast, the augmented approach deliberately inflates its monthly cost and schedule intervals whenever RiskFactor and CorrelationFactor signal compounding hazards. As evident in the mid-project phases of both case studies, these forecasts often overshoot actual outcomes, yielding higher absolute errors near completion. Yet this over-coverage is precisely the mechanism by which the robust method accommodates worst-case scenarios. From a construction management perspective, having that broader distribution allows earlier contingency planning: if correlated tasks slipped further, or if risk-laden conditions intensified (as at times in project B), managers could have proactively addressed those potential overruns and schedule extensions before they threatened the critical path.

Looking across projects A and B, it is clear that false alarms—where augmented EVM overshoots—are generally less damaging than ignoring potential cost-time synergies altogether. A single deterministic projection may offer a neat final convergence, but it fails to highlight the range of possible project "drift" in mid-to-late intervals. Consequently, construction managers seeking to minimize surprises benefit from the distribution-based perspective, despite its occasional biases. In essence, the additional risk intelligence better aligns project controls with real-world volatility, enabling more proactive resource allocations and schedule buffers that reduce the likelihood of crisis if multiple risk factors compound.

6. Conclusions

This study addresses two critical gaps of traditional earned value management in construction projects: (i) the lack of the consideration of the correlation between schedule slippage and cost overrun, and (ii) the static treatment of risk, which ignores temporal variations and mid-project uncertainties. By integrating a monthly (or interval-based) RiskFactor and CorrFactor, the study introduces augmented EVM, a framework that:

- Retains traditional EVM inputs and metrics (planned value, earned value, actual cost) and the usual derived indices (CPI, SPI).

- Generates a distribution-based forecast of final cost and final schedule—rather than a single-point EAC—by combining Monte Carlo sampling with the time-cost correlation logic.

- Adapts each monthly update to reflect evolving risk profiles, allowing managers to see not only a best-guess outcome but a full range of possible overruns.

Validation on two real-like construction projects demonstrated that, although the traditional EVM approach can converge well in the late stages of a project (once most uncertainties are resolved), it often yields large misestimates in early or mid-phases. In contrast, the augmented EVM method systematically covered a broad spectrum of potential outcomes when RiskFactor and CorrFactor were high—thereby enabling more proactive resource and contingency planning.

From a construction management perspective, these findings underscore the importance of tracking schedule-cost interactions—especially when tasks slip, resource usage expands, or market fluctuations increase overhead. The risk-based distributions produced each month can help stakeholders appreciate the degree of uncertainty more concretely, strengthening communication and contingency budgeting. Although the approach sometimes leans conservative (overestimating final cost or schedule when extreme conditions do not materialize), this false alarm is often preferable to the opposite scenario in which an unanticipated overrun far exceeds traditional EVM forecasts.

The methodological contributions open up new areas for further study, such as incorporating dynamic risk management into project controls to build robust data-driven strategies that can keep up with complicated volatile modern projects.

References

[1] Raz, T., Shenhar, A. J., Dvir, D. (2002). Risk Management, Project Success, and Technological Uncertainty. *R and D Management*, 32(2):101–109.

[2] Didraga, O. (2013). The Role and the Effects of Risk Management in IT Projects Success. *Informatica Economica*, 17(1/2013):86–98.

[3] Mayo-Alvarez, L., Alvarez-Risco, A., Del-Aguila-Arcentales, S., Sekar, M. C., Yañez, J. A. (2022). A Systematic Review of Earned Value Management Methods for Monitoring and Control of Project Schedule Performance: An AHP Approach. *Sustainability*, 14(22):15259.

[4] Teller, J., Kock, A., Gemünden, H. G. (2014). Risk Management in Project Portfolios is More than Managing Project Risks: A Contingency Perspective on Risk Management. *Project Management Journal*, 45(4):67–80.

[5] Xu, W. (2021). Application of Earned Value Method in Project Cost Management and Schedule Management. *Proceedings of Business and Economic Studies*, 4(4):146–152.

[6] Ouelhadj, D., Petrovic, S. (2008). A Survey of Dynamic Scheduling in Manufacturing Systems. *Journal of Scheduling*, 12(4):417–431.

[7] Shishodia, A., Dixit, V., Verma, P. (2018). Project Risk Analysis Based on Project Characteristics. *Benchmarking: An International Journal*, 25(3):893–918.

[8] Sambasivan, M., Soon, Y. W. (2007). Causes and Effects of Delays in Malaysian Construction Industry. *International Journal of Project Management*, 25(5):517–526.

[9] Roumeissa, S. (2019). Impact of Delay on Cost Overrun in Construction Projects in Algeria. *European Journal of Interdisciplinary Studies*, 5(2):25.

[10] Chernenko, Y., Haidaienko, O., Tkachenko, V. (2022). Development of a risk management method for development projects of providers of housing and utility services. *Technology Audit and Production Reserves*, 6(2(68)):22–28.

[11] González, G. E. G., Casas, G. H. P., Coronado, C. A. L. (2013). Project Manager Profile Characterization in the Construction Sector in Bogotá, Colombia. *Project Management Journal*, 44(6):68–93.

[12] Chang, H. (2014). Matrix Method Application on the Civil Engineering Project Management. *Advanced Materials Research*, 919–921:1462–1465.

[13] Nizam, A., Elshannaway, A. (2019). Review of earned value management (EVM) methodology, its limitations, and applicable extensions. *Journal of Management and Engineering Integration*, 12(1):59–70.

[14] Cervone, H. F. (2006). Project risk management. *OCLC Systems & Services: International digital library perspectives*, 22(4):256–262.

[15] Feylizadeh, M. R., Hendalianpour, A., Bagherpour, M. (2012). A fuzzy neural network to estimate at completion costs of construction projects. *International Journal of Industrial Engineering Computations*, 3(3):477–484.

[16] Anbari, F. (2004). Earned value project management method and extensions. *IEEE Engineering Management Review*, 32(3):97–97.

[17] Ramanathan, C., Narayanan, S. P., Idrus, A. B. (2012). Construction delays causing risks on time and cost - a critical review. *Construction Economics and Building*, 12(1):37–57.

[18] Larsen, J. K., Shen, G. Q., Lindhard, S. M., Brunoe, T. D. (2016). Factors Affecting Schedule Delay, Cost Overrun, and Quality Level in Public Construction Projects. *Journal of Management in Engineering*, 32 (1).

[19] Koushki, P. A., Al-Rashid, K., Kartam, N. (2005). Delays and cost increases in the construction of private residential projects in Kuwait. *Construction Management and Economics*, 23(3):285–294.

[20] Jung, Y., Woo, S. (2004). Flexible Work Breakdown Structure for Integrated Cost and Schedule Control. *Journal of Construction Engineering and Management*, 130(5):616–625.

[21] Afzal, F., Yunfei, S., Sajid, M., Afzal, F. (2019). Integrated priority decision index for risk assessment in chaos: cost overruns in transport projects. *Engineering, Construction and Architectural Management*, 27 (4):825–849.

[22] Hasan, R., Chowdhury, S. A., Akter, J. (2021). Construction Project Monitoring: The Cost and Schedule Control by Earned Value Method (EVM). *Journal of Technology Management and Business*, 8(1).

[23] Hazır, O. (2015). A review of analytical models, approaches and decision support tools in project monitoring and control. *International Journal of Project Management*, 33(4):808–815.

[24] Babar, S., Thaheem, M. J., Ayub, B. (2017). Estimated Cost at Completion: Integrating Risk into Earned Value Management. *Journal of Construction Engineering and Management*, 143(3).

[25] Acebes, F., Pereda, M., Poza, D., Pajares, J., Galán, J. M. (2015). Stochastic earned value analysis using Monte Carlo simulation and statistical learning techniques. *International Journal of Project Management*, 33(7):1597–1609.

[26] Kim, B.-C., Pinto, J. K. (2019). What CPI = 0.85 Really Means: A Probabilistic Extension of the Estimate at Completion. *Journal of Management in Engineering*, 35(2).

[27] Tereso, A., Ribeiro, P., Cardoso, M. (2018). An Automated Framework for the Integration between EVM and Risk Management. *Journal of Information Systems Engineering & Management*, 3(1).

[28] Ibrahim, M. N., Thorpe, D., Mahmood, M. N. (2019). Risk factors affecting the ability for earned value management to accurately assess the performance of infrastructure projects in Australia. *Construction Innovation*, 19(4):550–569.

[29] Muller, C. F., Neal, M. B., Carey-Smith, T. K., Luttrell, J., Srinivasan, M. (2021). Incorporating weather forecasts into risk-based irrigation decision-making. *Australasian Journal of Water Resources*, 25(2): 159–172.

[30] Roghabadi, M. A., Moselhi, O. (2020). Forecasting project duration using risk-based earned duration management. *International Journal of Construction Management*, 22(16):3077–3087.

[31] Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., Carey, C. J., Polat, I., Feng, Y., Moore, E. W., VanderPlas, J., Laxalde, D., Perktold, J., Cimrman, R., Henriksen, I., Quintero, E. A., Harris, C. R., Archibald, A. M., Ribeiro, A. H., Pedregosa, F., van Mulbregt, P., Vijaykumar, A., Bardelli, A. P., Rothberg, A., Hilboll, A., Kloeckner, A., Scopatz, A., Lee, A., Rokem, A., Woods, C. N., Fulton, C., Masson, C., Häggström, C., Fitzgerald, C., Nicholson, D. A., Hagen, D. R., Pasechnik, D. V., Olivetti, E., Martin, E., Wieser, E., Silva, F., Lenders, F., Wilhelm, F., Young, G., Price, G. A., Ingold, G.-L., Allen, G. E., Lee, G. R., Audren, H., Probst, I., Dietrich, J. P., Silterra, J., Webber, J. T., Slavič, J., Nothman, J., Buchner, J., Kulick, J., Schönberger, J. L., de Miranda Cardoso, J. V., Reimer, J., Harrington, J., Rodríguez, J. L. C., Nunez-Iglesias, J., Kuczynski, J., Tritz, K., Thoma, M., Newville, M., Kümmerer, M., Bolingbroke, M., Tartre, M., Pak, M., Smith, N. J., Nowaczyk, N., Shebanov, N., Pavlyk, O., Brodtkorb, P. A., Lee, P., McGibbon, R. T., Feldbauer, R., Lewis, S., Tygier, S., Sievert, S., Vigna, S., Peterson, S., More, S., Pudlik, T., Oshima, T., Pingel, T. J., Robitaille, T. P., Spura, T., Jones, T. R., Cera, T., Leslie, T., Zito, T., Krauss, T., Upadhyay, U., Halchenko, Y. O., Vázquez-Baeza, Y. (2020). SciPy 1.0: fundamental algorithms for scientific computing in Python. *Nature Methods*, 17(3):261–272.

Appendix A. Algorithm

```
Algorithm AugmentedEVM(T, {PV, EV, AC, RiskFactor, CorrFactor}, BAC, PlanDaysTotal,
alpha, beta, N):

Initialize a data structure Results to store forecast info for each t in [1..T]
for t in 1..T do:
   # 2.1 Compute traditional EVM single-value (Cost)
   if AC(t) > 0 then:
      CPI(t) = EV(t) / AC(t)
   else:
      CPI(t) = 1.0
   end if
   CostTrad(t) = AC(t) + (BAC - EV(t)) / CPI(t)

```

```
        # 2.2 Compute traditional EVM single-value (Schedule)
        # e.g. SPI(t) = EVdays(t) / AD(t), if AD(t) != 0
        # DaysTrad(t) = AD(t) + (PlanDaysTotal - EVdays(t)) / SPI(t)

        # 2.3 Generate distribution for Cost (Augmented)
        # RiskFactor(t) in [0..1], CorrFactor(t) in [0..1]
        sigma_t = beta * RiskFactor(t)
        costDist = empty list
        for n in 1..N do:
            Z_n = sample Normal(1.0, sigma_t^2)
            costAug_n = CostTrad(t) * (1 + CorrFactor(t)*alpha) * Z_n
            costDist.append(costAug_n)
        end for

        costAugMin(t)  = min(costDist)
        costAugMax(t)  = max(costDist)
        costAugMean(t) = average(costDist)

        # 2.4 Generate distribution for Schedule
        # similar pattern, call them alpha_s, a separate correlation weight)
        # daysDist, daysAugMin(t), daysAugMax(t), daysAugMean(t)
        # 2.5 Store results for this month t
        Results[t].CostTrad       = CostTrad(t)
        Results[t].CostAugMin     = costAugMin(t)
        Results[t].CostAugMax     = costAugMax(t)
        Results[t].CostAugMean    = costAugMean(t)
        Results[t].CostDistArray  = costDist
        # similarly for schedule
  end for
return Results
```