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RESEARCH ARTICLE

Eliminating Sub-Optimality in Earned Value Management Scheduling

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ABSTRACT Strategic and operational project successes rely on optimal implementation, with time-to-execution being a key value driver and competitive advantage. Earned Value Management (EVM) is the most pervasive approach to scheduling and cost monitoring in large-scale projects. Earned Schedule (ES) is a derivation of EVM that specifically addresses scheduling metrics, aiming to enhance the accuracy and relevance of time-based project assessments. However, prior research has shown that both EVM and ES may produce sub-optimal scheduling results. In addressing these challenges, our research aims to significantly reduce sub-optimality in EVM and ES schedules, meaning to methodically minimize inefficiencies within EVM processes, though recognizing that absolute optimality may not be achievable due to inherent project complexities. Specifically, this research demonstrates the common conditions under which ''top-down'', ES metrics generate sub-optimal schedule assessments against the baseline. The purpose of our work is two-fold: First, we articulate why sub-optimality occurs. Second, utilizing our schedule variance path level metrics (SVP(t)), we address the ES limitation. The validity and practicality of our approach were demonstrated using three execution scenarios with simulation stress-tests. Our bottom-up approach considers schedule progress on critical and non-critical paths and utilizes total slack when necessary. Our results propose a tractable solution that improves schedule measurement accuracy, particularly in project environments with parallel activities and varying slacks. This enhancement is most significant in complex project topologies where traditional methods fall short, thereby underscoring the critical importance of detailed path-level analysis in scheduling across diverse tracking periods.

INDEX TERMS Earned schedule, earned value management, project monitoring and control, project schedule, schedule variance, total slack, critical path, path level variances, misleading project outcomes.

I. INTRODUCTION

Projects continue to fail, sometimes dramatically [1], often due to scheduling and cost overruns. In this study the authors focus on the scheduling component hence the cost component is considered beyond the scope of this study. Diamantas et al. [2] have previously highlighted that monitoring and controlling the project schedule is a challenge for the tools currently available to project managers. Scheduling sub-optimality is, therefore, a contributor to project failure and one for which we propose a methodological insight that rectifies this gap in the Earned Value Management (EVM) scheduling literature.

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It is estimated that approximately 30% of underperforming projects are terminated, while 10% of project investment costs are squandered [3]. Among the major causes of failure are poor project monitoring and control (PMC) systems which result in unreliable schedule and cost performance measurements and subsequent project estimate updates. Scheduling systems are intended to aid project managers in analyzing the schedule progress of their ongoing projects. Based on analytics, the duration and budget deviations from the project plan are calculated, and the estimates of the expected final duration and cost are forecasted [4], [5], [6]. It follows that if scheduling systems are faulty, the schedules, durations and costs are all materially affected, hence this is the focus of our contribution.

Among various PMC methods, EVM is the most used in practice [7]. It is widely applied in traditional, and to some extent, in agile and hybrid project environments. It is the recommended approach by the Project Management Institute [8], one of the leading organizations that advance project management education, research, and practice. EVM helps to measure the duration progress and cost performance in projects, and based on such to-date measurements, the estimates of the final expected duration and cost are computed. As a part of the EVM system, the Earned Schedule (ES) metric is explicitly used to monitor and measure the project schedule progress [9], [10], [11].

Recognizing the need for a refined approach in handling these challenges, this study brings the following contributions to project management scheduling:

- **Introduction of a new metric:** We propose the Schedule Variance at Path Level (SVP(t)), which enhances schedule measurement accuracy by focusing on individual path levels, significantly refining project monitoring.
- **Addressing sub-optimality:** Our method directly tackles the inherent limitations of traditional EVM and ES by providing a more granular and accurate assessment of project schedules.
- **Practical and theoretical advancement:** We provide empirical insights through simulations that validate our approach and offer practical guidelines for project managers to implement the approach in real-world scenarios.

ES is a top-down approach that is commonly used at the aggregate project level. However, for schedule analysis, it may produce contradictory results [12], [13], [14]. Used at the project level, the ES metric does not result in schedule progress discrepancies that may exist on the detailed project levels. The inherent limitation of the ES metric is that it treats all project paths as if they are critical, thereby assuming that each path equally influences the overall project duration. This overlooks the fact that some project paths contain total slacks, which means they can experience delays without necessarily impacting the final completion date of the project. The total slack is indeed defined as the amount of time one activity can be delayed without delaying the project's total duration [15]. As a result, the ES-based schedule analysis, conducted on the aggregate project level, may produce inaccurate values of schedule variances, which may result in false duration forecasts.

In this study, we aim to achieve two objectives. The first objective is to present how schedule progress analysis using traditional EVM techniques (including ES metrics) results in the above inaccuracy and discuss why this happens. We demonstrate that such inconsistencies emerge when comparing the schedule progress variances at the project level with those computed at the individual path level. To this end, the concepts of "false positives" and "false negatives" are presented in this study. By "false positive," we consider a project that is not late, but the traditional ES shows a delay. By "false negative," instead, we consider the traditional ES not showing a delay when the project is late or showing a delay with less than the actual project delay. The second objective is to propose a new approach to resolve the aforementioned limitations of EVM. Our approach considers the schedule progress variances at the individual path levels, both in critical and non-critical paths, and utilizes total slack times when necessary.

To explore the limitations of ES in project management, this study identifies the specific conditions under which ES may yield suboptimal results. These conditions include non-critical paths scheduled not at their latest start times, delays in non-critical paths that do not exceed the total slack and thus do not affect the project duration, and delays in non-critical paths that exceed the total slack, thereby directly affecting the project duration. These scenarios highlight inherent vulnerabilities in the ES approach, where the actual project status may be misinterpreted, either signaling a delay when the critical path is unaffected or failing to indicate a delay when non-critical path delays affect the project's timely completion. Our analysis asserts that these identified conditions are critical for evaluating the efficacy of ES and argues against the necessity for validation with a real project. By systematically simulating these conditions, we can adequately assess ES's reliability of the ES and propose improvements. This methodological choice is rooted in the premise that if ES limitations can be demonstrably proven under these conditions, the conclusions drawn can be extended to any project that exhibits similar characteristics. This approach thereby obviates the need for specific real-world project data to prove ES limitations, which may not always encapsulate suboptimal conditions of interest.

In the traditional application of ES and EVM, the distinction between scheduling activities at their early start versus late start times reveals a nuanced impact on the accuracy of the metrics for schedule performance assessment. Scheduling activities at their late start times by eliminating slack renders every activity critical to a project's timely completion. This approach eliminates suboptimal conditions in ES and EVM assessments, aligning them more closely with actual project delays and their direct impact on the project duration. Conversely, scheduling at early start times introduces slack, allowing noncritical activities to absorb delays without immediately affecting the project's overall timeline. However, this condition may lead ES and EVM to overstate schedule performance issues when delays in non-critical activities buffered by slack do not genuinely impact the project's completion date. This observation underscores a fundamental limitation of traditional ES and EVM methodologies, where the presence of slack can obscure the true state of project schedule performance. Our study contends that a nuanced understanding of these dynamics is crucial for accurate project management and monitoring, advocating for methodological refinement in the analysis and management of project schedules.

Therefore, the contributions of our study to the PMC body of knowledge are fundamental and three-fold. First, our proposed approach considers a delay in noncritical paths only when it should be considered (i.e., when it exceeds the total slack time) for the schedule variance at the aggregate project level. Second, non-critical path activities ahead of the schedule do not mitigate delays in the critical path. Consequently, effective in all project tracking periods, the proposed methodology produces more accurate and stable schedule variance results compared with those found by the traditional EVM-based ES metric. Third, our approach is simple and deterministic, and can be used in a spreadsheet. Field practitioners can use it to compare schedule variances found at the project level with those found at the path level. Consequently, they will be able to spot the tracking period in project life when a schedule progress anomaly emerges, thereby avoiding inaccurate or false final duration estimates.

Recent critiques have emphasized the importance of empirical validation in assessing the limitations of ES analysis. While we recognize the value of this perspective, our study suggests that the inherent aspects of project management render empirical validation less critical. We identify systemic vulnerabilities within the ES methodology, such as delays in non-critical paths that do or do not exceed total slack times, and issues that are not unique to any single project but are widespread across the methodology. In addition, gathering a statistically significant and comprehensive pool of real-world projects for empirical validation poses substantial challenges. Project data often contains proprietary or sensitive business information, which limits the availability and scope of academic research. Moreover, variability in project reporting and management across different industries can lead to inconsistencies that obscure clear analysis. These factors not only complicate the collection of data but can also lead to misleading generalizations from an inadequate sample of real projects. Given these constraints, our study opts for a theoretical and simulation-based framework that offers broad applicability across various contexts, without relying on empirical data. Previous studies have successfully employed theoretical and simulation-based validations in areas where real-world data are insufficient or unavailable. For example, Kim et al. [16] utilized a probabilistic forecasting model to enhance project duration predictions, acknowledging the complexities and uncertainties inherent in actual project data. Similarly, Barrientos-Orellana et al. [17] demonstrated the utility of simulation methods in EVM to assess the stability and accuracy under varying project conditions. These studies underscore the importance of employing theoretical models and simulations for developing and validating new methodologies, especially in project management where the intricacies of real-world data may not fully represent the diversity of potential project scenarios. Such models help in isolating and understanding theoretical nuances that might otherwise be overlooked.

Building on this foundation, the next subsection conducts a comparative analysis of project management and computational workflows. This analysis is crucial as it breaks down the workflow into distinct activities, allowing us to pinpoint where suboptimalities occur. By examining how both fields leverage directed structures to manage and optimize task dependencies, we gain insights into the structural and functional dynamics essential for enhancing project efficiency and addressing the challenges posed by traditional methods.

A. COMPARATIVE ANALYSIS OF PROJECT MANAGEMENT ACTIVITIES AND COMPUTATIONAL TASKS WITHIN DAG FRAMEWORKS

In project management, the terms "activity" and "activity dependencies" are foundational to scheduling and managing projects. These concepts are analogous to "tasks" and "task dependencies" in computational workflows, where both are often structured using Directed Acyclic Graphs (DAGs) referred to as "project networks" in project management. In this paper, we use project networks to represent project activities, like how computational workflows organize tasks.

A project network in project management illustrates the sequential and dependent nature of activities, emphasizing that some activities cannot commence until their preceding activities are complete. This is similar to computational workflows in systems like cloud computing or software development, where a task's readiness depends on the completion of prior tasks to avoid data inconsistencies or resource conflicts.

However, while the structural representation is similar, the application context differs significantly. In computational workflows, tasks are typically automated operations processed by computers, such as data processing jobs or software execution sequences. In contrast, project management activities often involve human resources, scheduling constraints, cost considerations, and physical resource allocations, which require a different analytical approach. The project networks used in our study are structured as DAGs, where each activity represents a node, and dependencies between these activities form directed edges with no cycles. This structure allows us to apply algorithms and techniques similar to those used in computational workflows, while also accommodating the unique characteristics and constraints of physical project environments.

The adaptation of workflow scheduling techniques to project management involves adjusting these methods to account for the more complex and varied nature of project activities. Methods like the Critical Path Method (CPM) are employed within project networks to determine the longest necessary path to project completion. This methodology is critical for identifying bottlenecks and optimizing schedules, similar to dependency resolution strategies in software development. To illustrate, the "critical path" in a project network is the sequence of activities that dictates the minimum project duration. This is akin to critical processing paths in computational systems where the longest path determines the execution time. Similarly, "slack time" in project management—the leeway for delaying an activity without affecting the project's end date—parallels the concept of buffer times in systems operations, which accommodate variations in task durations without impacting overall system performance.

In both fields, delays in critical tasks or activities can cascade and impact overall project timelines, necessitating robust management and mitigation strategies.

Similarly, the objectives of scheduling in project management—such as respecting deadlines, minimizing completion time (makespan), reducing costs, and enhancing reliability—are parallel to those in computational workflow scheduling.

II. RESEARCH BACKGROUND

A. THE PROJECT NETWORK FUNDAMENTALS

To apply EVM to a project, first, the performance measurement baseline (project baseline) is developed during the project planning phase. This development involves decomposing the total project scope to a manageable level, commonly through the Work Breakdown Structure (WBS), preparing the project schedule with activities and resources assigned, and creating a time-phase budget for each project activity [18], [19].

While EVM is effective in monitoring and controlling costs, as these are not directly tied to the project's critical path, schedule monitoring is more complex. Only critical activities significantly influenced the overall project duration, highlighting the challenges in managing schedules without focusing on these activities [2]. The conventional EVM methodology, which is robust in many respects, has limitations when addressing the dynamic nature of project scopes. Tariq et al. [20] explored these limitations by emphasizing the significant impacts of scope changes on project schedules and budgets. Their study underscores the necessity for EVM adaptations that can accommodate and accurately reflect these changes, suggesting enhancements to traditional EVM practices to ensure a more stable and reliable progress schedule. This aspect of their work highlights the critical need for flexibility in EVM applications to cope with the evolving project requirements and environments [20].

Furthermore, Jinhua et al. [21] addressed the adaptability of EVM in software project environments by introducing use case points as a complementary metric to refine the EVM's capability. This inclusion targets the often-criticized inflexibility of traditional EVM methods, enhancing their utility by integrating additional metrics that cater to the unique challenges of software development. Jinhua's approach promotes more stable and reliable schedule progress by evolving EVM beyond its conventional constraints, thereby accommodating the specific needs of different project types [21].

To address these identified issues, our methodology segments the project into multiple paths–critical and non-critical–and analyzes their alignment with the baseline. In our innovative approach, a delay in a non-critical path does not impact the overall project duration if it remains within the path's slack. This method captures data that are often overlooked in traditional EVM, where delays are treated equally, regardless of their nature or impact. This underscores a crucial limitation in standard EVM applications that necessitates careful consideration, reinforcing the need for our proposed modifications to enhance the precision and applicability of EVM for managing diverse project dynamics.

The project schedule, along with the project budget, is part of the project baseline. The CPM is used to construct and manage such schedules. This method helps to understand project topology using a project network [22]. In this oriented graph, a project network path is defined as any possible sequence of activities from the start to the end of the project. Two main elements characterize the project topology: critical paths and total slack in noncritical paths. The critical paths are the longest in the project network and define the project in terms of its duration [23], [24], [25]. A project is delayed if any of the tasks on the critical path (i.e., critical tasks) are delayed. On the other hand, non-critical paths have total slack, and such paths can be delayed for a duration less than or equal to the total slack without causing a delay in the total project [24], [26]. Thus, to control the project duration effectively, monitoring the schedule variance on the critical path is crucial, as the length of the critical path dictates the project's completion time

B. THE SCHEDULE PROGRESS ANALYSIS USING ES AT THE PROJECT LEVEL

To assess project progress, EVM computes the amount of work completed in monetary units (Earned Value, EV) against the planned budget (Planned Value, PV) [4], [13]. A graphical representation of the EVM and ES metrics is shown in Figure 1. The EV is equal to the percentage of actual work completed multiplied by the planned value budgeted for this study. To measure the schedule progress at a particular tracking period (t), the Schedule Variance (SV) is used [6], [11], [27] as per (1):

$$SV_t = EV_t - PV_t \tag{1}$$

SV is expressed in monetary terms [4], [28], [29] and not in time units, making it difficult to interpret. The ES technique, an extension of EVM, has been proposed to overcome this unit of measure inconsistency. ES is a metric representing the time in which the PV corresponds to the EV (Figure 1) and is determined by (2) [9]. The ES is then compared with the Actual Time (AT) to determine the project progress (3). If SV(t) is greater than zero, the project is ahead of the schedule. However, if SV(t) is negative, as in the case shown in Figure 1, the project is behind schedule.

$$ES_t = PV_t^{-1}(EV_t) \tag{2}$$

$$SV_t\,(t) = ES_t - AT_t \tag{3}$$

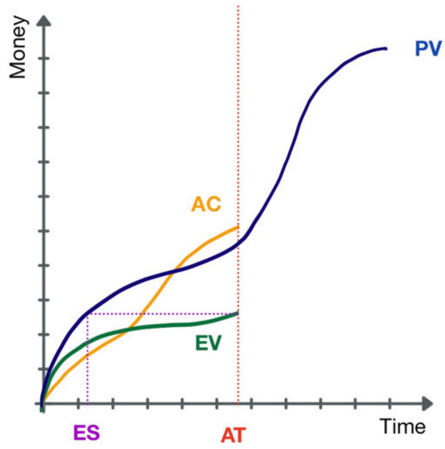

FIGURE 1. The EVM and ES metrics. ES is giving more reliable results compared to EVM on the schedule component.

C. THE ES(T) LIMITATIONS AT THE PROJECT LEVEL

Although (3) is logical to use compared to (1) because it reports the schedule progress in time units, SV(t) by (3) does not consider the project's network topology. This project-level metric does not account for how individual activities on multiple paths progress and their respective total slack times. SV(t) ignores the distribution of activities concerning its predecessors and successors. The error becomes more significant when the project network has more parallel activities than serial ones do [17]. Consequently, it is prone to providing false schedule variances [30], [31], [32], [33], [34], [35], [36], [37] and subsequent duration estimates.

We report two limitations of the SV(t) metric computed by using the traditional ES approach.

The first limitation is the inability to recognize the magnitude of the actual delay resulting from project paths. A total delay in the project schedule is generated only by a delay in critical activities or a delay in non-critical activities, which exceeds the total slack. Using equation (3) at the project level, a delay in a non-critical activity within its total slack influences the SV(t) calculation, while it should not.

The second limitation is that any delay in critical activities is mitigated by schedule performance in noncritical activities. To better understand this situation, consider a delay in the critical activity, and hence in the entire project. This delay was captured by (3) at the project level. However, if some noncritical activities are ahead of schedule, this desirable performance in the noncritical path should not offset the poor performance in the critical path. Instead, the ES metric at the project level is influenced by performance in noncritical activities, producing unreliable results. We might have a situation in which a delay in the critical activity is fully offset by the advancement (ahead of schedule) in non-critical activities.

D. A REVIEW OF PREVIOUS STUDIES

Numerous studies have addressed EVM's possible inaccuracies of EVM in schedule analysis at the project level. They recognized that this traditional approach does not consider the total slack time in non-critical activities.

Several studies have proposed probabilistic models to address this issue. Kim and Reinschmidt [16] recognized the importance of duration forecasting and how project managers seek reliable and simple indicators that accurately monitor the project status to enable appropriate control actions. They claimed that the limitations of EVM and CPM are deterministic analyses. They considered project uncertainties as an alternative by developing a probabilistic scheduling methodology using Bayesian Beta S-curves. However, powerful for use in scheduling analysis, the approach is cumbersome to implement in practice; being stochastic, it has a limited application in real case scenarios owing to computation complexities. Hammad et al. [23] proposed the prediction of changes in the critical path using a probability distribution. This methodology can be used in conjunction with CPM to enhance the accuracy of project monitoring. They proposed limiting the schedule analysis to critical and near-critical paths to obtain more accurate results. However, their approach was limited because it depended on the probability of the critical path change, which may not be sufficiently accurate. In addition, their method was complex because assigning probabilities to each project activity was necessary, limiting its application in real case scenarios.

Other studies have stated that ES inaccuracy can still be investigated at the project level, mainly because of little or unreliable schedule information at the path level. These are deterministic models but are still mainly used at the project level. Therefore, Hussein and Moselhi [34] used a different approach to overcome the EVM inaccuracy owing to the lack of path-level analysis. He introduced the Schedule Compression Index, which captures delayed progress in non-critical activities. The rationale is that a delay in non-critical activities does not necessarily reflect a delay in the project; it depends on the amount of total slack that the delayed activity has. The index considers project activities that are incomplete and, on average, provides more reliable results than the ES metric using the traditional EVM approach. We note that although powerful, this metric is still used at the project level and therefore does not assist project managers in differentiating between critical and non-critical activities. To overcome this issue, Ballesteros-Pérez et al. proposed two new metrics, Earned Schedule Max and Earned Schedule Min [11]. The authors measured the schedule progress in the project's most advanced and delayed paths to understand what may happen in critical and noncritical activities. A limitation of this study is that both indicators were still calculated at the project level. Therefore, project topology (potential schedule issues, including delays and total slack times) has not been fully considered. Andrade et al. [35] and Wood [32] also identified a possible reason for the inaccuracy of the traditional EVM and ES approaches when considering the schedule metrics in monetary units and not in time units. However, even if based on time units, the ES metric is derived from the EVM-based EV metric measured in monetary units.

Therefore, the authors tested a new approach, Earned Duration Management, that created new duration-based metrics. However, the schedule analysis with this approach works at the project level; therefore, project network specificities (activity criticality, delay, and total slack times) are not considered. For example, it is impossible to distinguish whether the source of a delay is a critical or noncritical activity.

The following authors investigated this issue by considering the project topology. Vanhoucke and Vandevoorde [33] noted the importance of project network topology as a crucial monitoring and forecasting parameter and indicated the activity total slack as a critical indicator. They also demonstrated that forecasting accuracy depends on project topology; the less the project is serial (i.e., the more parallel the project has activities), the less accurate the metrics at the project level. However, in this study, the criticality of ES inaccuracy was acknowledged and tested, but no mathematical model was proposed. Vanhoucke [31] addressed EVM and ES inaccuracy by proposing a sensitivity analysis at the activity level, identifying which non-critical activities are more likely to become critical and to influence the project duration. However, this approach is complex for use by practitioners; it is difficult to identify the subset of such activities, and the necessity to keep this subset to a number that allows a quick analysis is also a limitation. Later, Martens and Vanhoucke [36] project control considered one of the three most essential activities in project management, together with baseline scheduling and risk analysis. They introduced the concept of tolerance limits to detect when the project progress did not follow its schedule baseline. Additionally, to enhance EVM accuracy, they suggested calculating EVM metrics in terms of work content units instead of monetary units. However, as a powerful tool for schedule control, their approach cannot detect whether a delayed source is from critical or non-critical activities. Recently, Capone and Narbaev [38] conducted a comparative analysis to understand the likely differences in the schedule variances calculated at the project and path levels. They also confirmed that SV(t) produces inconsistent results in the schedule analysis because it does not consider the total slack times in non-critical activities when used at the project level.

Lipke [9] introduced an ES-based SV(t) measured in time units as an alternative to the EVM-based SV measured in monetary units. However, SV(t) fails to detect a delay's origin; it does not consider that a delay from non-critical activities impacts the project's total duration differently than a delay from critical activities. Later, Lipke [39] suggested utilizing (1) and (3) only on the critical path in case the project contains parallel activities (i.e., multiple paths), because this may lead to more accurate results. This case assumes that the critical path is constant. However, the critical path may change during project execution, particularly when the total slack times are relatively small. Our proposed methodology considers possible changes in the critical path when progressing from one tracking period to another.

In summary, while previous studies have explored EVM-based SV limitations and introduced deterministic or probabilistic models, they often overlook the project's topology. Although SV(t) addresses the issue of measuring schedules in monetary units, it, like other metrics, typically focuses only on the project or activity level without considering path-level dynamics. The deficiency of SV(t) in analyzing path-level schedule progress is recognized, but has not yet been effectively addressed in existing solutions.

Our study addresses recent calls to bridge the gap between academic research and industry practice in Earned Value Management Systems (EVMS), as highlighted by Adlakha and Kulkarni [40]. They noted significant gaps in the understanding and application of EVMS across sectors, emphasizing the need for methods that blend theoretical depth with practical use. Our research develops a mathematical approach to address SV(t) limitations by calculating it for each project path and comparing it with the total slack of the path. Unlike traditional ES, our model can identify delays that affect the overall project duration, ensuring that performance in non-critical paths does not obscure delays in critical paths, thereby enhancing reliability and accuracy throughout the lifecycle of the project.

As detailed in Table 1, the synthesis of previous research illustrates the evolution of EVM adaptations and their impact on project management practices. This comprehensive review establishes a solid foundation for our study, which builds upon these insights to propose further refinements to EVM methodologies, aiming to enhance the accuracy and applicability of project scheduling.

III. METHODOLOGY

A. THE PROPOSED APPROACH TO OVERCOME THE ES LIMITATIONS AT THE PROJECT LEVEL

To address the limitations of SV(t) discussed in Section II-C, we expand upon traditional ES analysis by scrutinizing its conventional aggregation at the project level and discuss the limitations this poses, such as obscured insights into individual path performances and the potential for misleading project health indicators. Our approach uniquely disaggregates ES metrics to the path level, a refinement that differentiates the performance of critical from non-critical activities, allowing for precise monitoring and adjustment of specific project segments. This methodological innovation not only provides detailed insights into the dynamics of the critical path but also reveals how the performance of non-critical activities can influence the critical path, particularly when delays in non-critical paths exceed the total slack. Such granularity in analysis enables project managers to identify and rectify schedule deviations in real-time, enhancing responsiveness to project dynamics and preventing potential impacts on overall project timelines. It is important to note,

TABLE 1. The related studies in the literature.

Author(s) and Year	Key Findings	Relevance to Current Study
Tariq et al. (2020)	Explored limitations of EVM due to scope changes.	Highlights the need for flexibility in EVM applications
Jinhua et al. (2008)	Introduced use case points in software projects to enhance EVM's flexibility.	Demonstrates adaptation of EVM to software projects
Kim et al. (2009)	Developed probabilistic scheduling using Bayesian Beta S-curves.	Supports use of probabilistic models for accurate scheduling.
Hammad et al. (2020)	Proposed forecasting critical path changes using probability distribution.	Suggests focusing on critical and near-critical paths for better accuracy.
Hussein et al. (2013)	Introduced Schedule Compression Index for delayed progress in non-critical activities.	Challenges the traditional project-level focus of EVM.
Ballesteros-Pérez et al. (2019)	Measured schedule progress in most advanced and delayed paths.	Emphasizes importance of considering path-level dynamics.
Vanhoucke et al. (2015)	Noted importance of project network topology as a crucial monitoring parameter.	Acknowledged the criticality of project topology in forecasting accuracy.
Martens et al. (2014)	Introduced tolerance limits and suggested calculating EVM metrics in work content units.	Suggested improvements for schedule control in EVM.
Andrade et al. (2018)	Proposed a sensitivity analysis at the activity level	Highlights the complexity of predicting critical path changes, suggesting a detailed activity-level analysis.
Wood (2018)	Discussed inaccuracies of traditional EVM and ES when using monetary units for scheduling metrics.	Supports the need for metrics based on time units to improve schedule tracking accuracy.
Lipke (2019)	Introduced ES-based SV(t) measured in time units and suggested focusing metrics only on the critical path for projects with parallel activities.	Advocates for the use of time-based metrics to enhance accuracy and suggests a focused approach for complex projects.

however, that the effectiveness of this approach can vary depending on specific project characteristics, such as the complexity of the project network and the distribution of tasks. In environments with predominantly sequential tasks or minimal slack, the benefits of our path-level analysis may be less pronounced. This variability underscores the need for project managers to consider the specific context of their projects when applying our metrics, thereby ensuring that the methodology is adapted to suit distinct project conditions and challenges.

To address these considerations, the current study proposes a new metric, Schedule Variance at Path Level (SVP(t)), which is specifically designed to offer a more nuanced understanding of schedule variances across different project paths. The SVP(t) was calculated as per (4):

$$SVP_t\ (t) = MIN\ (SV_t\ (t)_i + Slack_i) \tag{4}$$

where $SV_t(t)_i$ represents (3) but is calculated at the path level for the i^{th} path in the tracking period t. $Slack_i$ is the total slack of the i^{th} path, which is equal to zero in the case of critical paths. MIN is a function that returns the minimum sum of SV(t) and the total slack across all paths.

Our refined SVP(t) metric accounts for delays in non-critical paths only when they exceed the total slack, ensuring that advanced schedule performance in non-critical paths does not offset delays in critical ones. This distinction allows for more accurate reflection of actual project delays, producing realistic schedule variance results compared to traditional EVM-based ES metrics. Additionally, the computational overhead of our proposed method is minimal, primarily involving basic arithmetic operations to compute the SVP(t) for each project path.

B. DEMONSTRATION USING PROJECT NETWORK DATA

To address ES vulnerabilities, we employed a simulation-based validation strategy, allowing controlled examination of ES under specific, theoretically derived conditions that illustrate its limitations. By simulating projects with non-critical paths scheduled variably, we provide a detailed critique of ES effectiveness in realistic project management scenarios.

We validate our approach using the fictional project network detailed in Table 2, featuring an assembly line construction with three paths— one critical and two non-critical–each with different total slack times. To illustrate the practical application of our approach, we present case studies where path-level ES metrics identified critical delays that were not apparent at the project level. These examples highlight how our approach can prevent schedule slippage by enabling targeted interventions. This demonstration not only showcases our methodology, and the mathematical model represented by (4) but also validates its effectiveness in handling more complex project network scenarios and various path slack configurations.

Figure 2 shows the project network with seven activities on nodes, their codes, and their duration values in weeks. The project had three paths. The first noncritical path (NCP1) through noncritical activities A, B, C, F, and G had a duration of 12 weeks. The critical path (CP1) through critical activities A, E, F, and G has a duration of 14 weeks, which constitutes the project's total duration. The second non-critical path (NCP2) through non-critical activities A, D, and G had a duration of 9 weeks. Critical activities concern the installation of conveyor belts. In NCP1, we have noncritical activities B and C related to the installation and testing of the power line of the conveyor belt. In NCP2, there is only one non-critical

TABLE 2. Project schedule for assembly line construction with task dependencies.

Activity Code	Activity Description	Duration (weeks)	Predecessors
A	Hardware specification and design	4	-
B	Installation of the conveyor belt's power line	2	A
C	Testing of the conveyor belt's power line	1	B
D	Plant's legal authorities' signatures	2	A
E	Prototype implementation	5	A
F	Assemble pre-production model	2	C, E
G	Assemble production model	3	D, F

activity, D, related to the signatures of the production plant's legal authority. These activities in NCP1 have a total slack of two weeks, whereas the activity in NCP2 has a total slack of five weeks.

While Figure 2 clearly illustrates a workflow structured as a DAG, akin to those found in computational workflows, it is essential to highlight the significant operational differences between the two. The depicted project network encompasses tasks that are fundamentally non-computational, involving elements such as human resources, scheduling constraints, and physical implementations, which diverge markedly from the purely computational tasks managed in IT environments. These distinctions critically influence the scheduling techniques applicable; for example, methods optimized for computational efficiency are often unsuitable directly for managing human-centric activities without adaptation. Thus, while the structural approach may resemble that used in computational workflows, the execution and optimization strategies must be distinctly tailored to address the specific challenges and dynamics of project management.

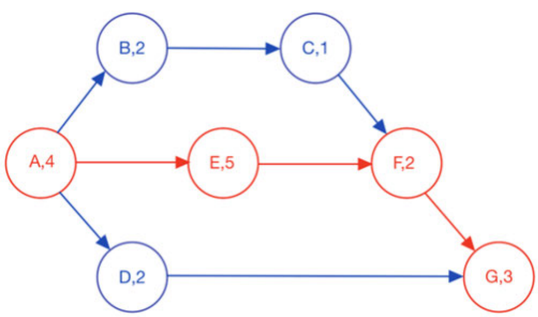

FIGURE 2. A hypothetical project network with one critical path and two non-critical paths.

Figure 3 shows the project baseline in the case of the schedule based on the early start of activities, that is, all the activities start as soon as possible. The power line installation and testing (activities B and C) cannot start before week five because activity A should be completed by that week, and activity B ends before week ten because, in that week, activity F starts. Activities B and C require only three weeks of work; therefore, they have two weeks of total slack before Activity F starts. Activity D requires two weeks of work and starts no earlier than week five, as activity A is completed before it starts. Activity D ends before week 12 because activity G starts that week; therefore, activity D has a total slack of five weeks.

Level	Activity	1	2	3	4	5	6	7	8	9	10	11	12	13	14
CP1	A	20	10	5	30										
NCP1	B					20	10								
NCP1	C							40							
NCP2	D					40	30								
CP1	E					30	30	20	20	30					
CP1	F										10	10			
CP1	G												20	30	20
Project	PV	20	10	5	30	90	70	60	20	30	10	10	20	30	20
Project	CumPV	20	30	35	65	155	225	285	305	335	345	355	375	405	425
CP1	PV	20	10	5	30	30	30	20	20	30	10	10	20	30	20
CP1	CumPV	20	30	35	65	95	125	145	165	195	205	215	235	265	285
NCP1	PV	0	0	0	0	20	10	40	0	0	0	0	0	0	0
NCP1	CumPV	0	0	0	0	20	30	70	70	70	70	70	70	70	70
NCP2	PV	0	0	0	0	40	30	0	0	0	0	0	0	0	0
NCP2	CumPV	0	0	0	0	40	70	70	70	70	70	70	70	70	70

FIGURE 3. The EVM and network data on the early start baseline.

Figure 4 shows the project baseline in the case of a schedule based on activities that start late, that is, all the activities start as late as possible, but maintain a project duration of 14 weeks. The power line installation starts in week seven and ends in week nine with no total slack. Activity D requires two weeks of work, starting on week ten and ending on week 11, with no total slack. In the case of a late start, all activities are critical because any delay in any activity impacts the project duration. Figure 3 and 4 also show the critical paths in red, which resemble CP1, the weekly project planned budget (PV) and cumulative (CumPV) planned values for the total project (column level with the value of the project), and all paths (column level with the values of CP1, NCP1, and NCP2). The PV values for each activity for each week are provided in the green background.

Level	Activity	1	2	3	4	5	6	7	8	9	10	11	12	13	14
CP1	A	20	10	5	30										
NCP1	B							20	10						
NCP1	C									40					
NCP2	D										40	30			
CP1	E					30	30	20	20	30					
CP1	F										10	10			
CP1	G												20	30	20
Project	PV	20	10	5	30	30	30	40	30	70	50	40	20	30	20
Project	CumPV	20	30	35	65	95	125	165	195	265	315	355	375	405	425
CP1	PV	20	10	5	30	30	30	20	20	30	10	10	20	30	20
CP1	CumPV	20	30	35	65	95	125	145	165	195	205	215	235	265	285
NCP1	PV	0	0	0	0	0	0	20	10	40	0	0	0	0	0
NCP1	CumPV	0	0	0	0	0	0	20	30	70	70	70	70	70	70
NCP2	PV	0	0	0	0	0	0	0	0	0	40	30	0	0	0
NCP2	CumPV	0	0	0	0	0	0	0	0	0	40	70	70	70	70

FIGURE 4. The EVM and network data on the late start baseline.

In the next section, we discuss the results of the SVP(t) applications on three project execution scenarios: two scenarios in the early start baseline and one in the late-start baseline. Total slack plays a fundamental role in determining whether an activity is critical. Moreover, critical activities play a fundamental role in determining the duration of a project. By selecting the three different project executions, the authors analyzed the schedule progress under two opposite conditions: the activities' maximum total slack possible (early start) and zero total slack for all the activities (late start). The ES metrics were calculated using both the classical EVM approach (at the project level) and our proposed approach (at the path level).

C. VALIDATION USING PROJECT NETWORK SIMULATIONS

In addition, we validated our approach by simulating different possible executions of the sample project network presented in Figure 2. The simulator uses a probability distribution of the path duration, following the Program Evaluation Review Technique (PERT) approach. PERT assumes that the duration of a project activity follows a beta probability distribution: [40] PERT was initially designed by the US Navy in 1958 to better control project scheduling of weapon development systems. For each activity, PERT considers a three-point estimate, namely the most likely duration, pessimistic duration, and optimistic duration, to define the beta distribution [41]. A beta probability distribution was constructed from these three values [42]. According to the bottom-up project estimation approach [19], the estimation accuracy is typically between -10% and $+30\%$ of the most likely duration. Based on this assumption, $+30\%$ of the duration value was used as the pessimistic duration, and -10% of the duration value was used as the optimistic duration. The authors used the Python language to design a software to simulate 100 different project executions following the PERT probability distribution and compared (4) with (3) on each of the 100 simulated executions.

Overall, in each project execution scenario, we demonstrate that our proposed approach using SVP(t) (4) generates more realistic and accurate schedule variances than those computed using the traditional SV(t) model (3). In the simulations, for each project execution scenario taken randomly following the beta distribution, new metric values were calculated and compared with the values obtained by the traditional metric.

IV. RESULTS AND DISCUSSION

Figures 5, 7, and 9 present the results of the three different execution scenarios for the sample project schedule. The SV(t) values obtained by the traditional ES approach using (3) and the SVP(t) values obtained by the proposed approach using (4) were calculated for each scenario. For the presented scenarios, the study analyzes the circumstances in which the traditional SV(t) detects the project delay when it progresses as scheduled ("false positive") or suggests the project delay which is less than the actual delay ("false negative").

A. SCENARIO 1: THE EARLY START CASE – THE DELAY IN NCP IS MORE THAN ITS TOTAL SLACK

Figure 5 shows the project and path levels EV, ES, and SV(t) when CP1 was delayed (the project's actual duration did not coincide with the planned duration). There is also a delay in non-critical activities (activities B and C) on NCP1 for more than the path total slack (the total slack is two weeks, and the delay in NCP1 is three weeks). The baseline is shown in Figure 3 (early start schedule).

Level	Activity	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
CP1	A	20	10	5	30													
NCP1	B					10	10	10										
NCP1	C								20	10	10							
NCP2	D					40	30											
CP1	E					30	30	20	20	30								
CP1	F											10	10					
CP1	G													20	30	20		
Project	PV	20	10	5	30	90	70	60	20	30	10	10	20	30	20	0	0	0
Project	CumPV	20	30	35	65	155	225	285	305	335	345	355	375	405	425	425		
Project	EV	20	30	35	65	145	215	245	285	325	335	345	355	375	405	425		
Project	ES	1,00	2,00	3,00	4,00	4,89	5,86	6,33	7,00	8,67	9,00	10,00	11,00	12,00	13,00	14,00		
Project	SV(t)	0,00	0,00	0,00	0,00	-0,11	-0,14	-0,67	-1,00	-0,33	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00		
CP1	PV	20	10	5	30	30	30	20	20	30	10	10	20	30	20	0	0	0
CP1	CumPV	20	30	35	65	95	125	145	165	195	205	215	235	265	285			
CP1	EV	20	30	35	65	95	125	145	165	195	195	205	215	235	265			
CP1	ES	1,00	2,00	3,00	4,00	5,00	6,00	7,00	8,00	9,00	9,00	10,00	11,00	12,00	13,00			
CP1	SV(t)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-1,00	-1,00	-1,00	-1,00	-1,00			
NCP1	PV	0	0	0	0	20	10	40	0	0	0	0	0	0	0	0	0	0
NCP1	CumPV	0	0	0	0	20	30	70	70	70	70	70	70	70	70			
NCP1	EV	0	0	0	0	10	20	30	50	60	70	70	70	70	70			
NCP1	Slack					2	2	2	2	2								
NCP1	ES					4,50	5,00	6,00	6,50	6,75								
NCP1	SV(t)					-0,50	-1,00	-1,00	-1,50	-2,25								
NCP2	PV	0	0	0	0	40	30	0	0	0	0	0	0	0	0	0	0	0
NCP2	CumPV	0	0	0	0	40	70	70	70	70	70	70	70	70	70			
NCP2	EV	0	0	0	0	40	70	70	70	70	70	70	70	70	70			
NCP2	Slack					5	5											
NCP2	ES					5,00	6,00											
NCP2	SV(t)					0,00	0,00											
TOTAL	SVP(t)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-0,25	-1,00	-1,00	-1,00	-1,00	-1,00			

FIGURE 5. The results of Scenario 1: The delay in NCP is more than its total slack, thus impacting the project duration.

The project-level SV(t) values show that the project has a delay starting from week five, SV(t)$= -0.11$. However, the project level results are misled since the project is not late until week 8, that is, when the delay in NCP1 impacts CP1. Thus, we have a false-positive result suggested by SV(t) at the project level.

By contrast, the SVP(t) values, calculated as per (4), capture the correct project schedule status (no delay until week eight and delay from week 9). Hence, in this case, project managers should not take corrective measures until week 8, even though (3) falsely suggests this at the project level. The execution of activities B and C in NCP1 is behind the schedule by more than the total path slack. Thus, there was an impact on the CP1. The progression behavior of SV(t) at the project level and SVP(t) at the path level are graphically shown in Figure 6. We note that SVP(t) has a more regular behavior than SV(t), granting a more stable project schedule assessment, which is realistic.

B. SCENARIO 2: THE EARLY START CASE – THE DELAY IN NCP1 IS LESS THAN ITS TOTAL SLACK

Figure 7 shows the project's EV, ES, and SV(t) when it experiences a delay in non-critical activities B and C on

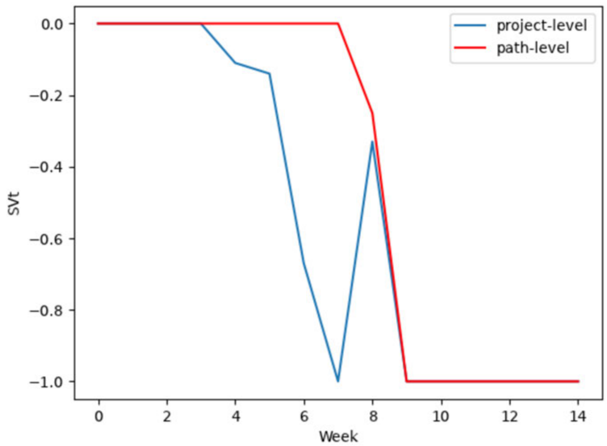

FIGURE 6. Scenario 1: The SV(t) progression at the path level is more stable than the progression at project level.

NCP1, for an amount equal to path total slack (the total path slack is two weeks, and the delay of activities B and C is two weeks). The baseline is shown in Figure 3 (early start schedule).

The project-level ES values show that the project had a delay in weeks 7 and 8, with corresponding negative values of SV(t), −0.33, and −0.50. However, in this case, the project-level results are misleading and generate a "false positive." The project does not experience any delay in weeks 7 and 8 because the delay is only due to NCP1 and it does not impact CP1. Therefore, project managers are suggested by SV(t) at the project level to activate countermeasures to bring the project back on track from week seven while it is not needed. In contrast, the SVP(t) values capture the correct project schedule status.

Level	Activity	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
CP1	A	20	10	5	30													
NCP1	B					20	10											
NCP1	C							20	10	10								
NCP2	D					40	30											
CP1	E					30	30	20	20	30								
CP1	F										10	10						
CP1	G												20	30	20			
Project	PV	20	10	5	30	90	70	60	20	30	10	10	20	30	20	0	0	0
Project	CumPV	20	30	35	65	155	225	285	305	335	345	355	375	405	425			
Project	EV	20	30	35	65	155	225	265	295	335	345	355	375	405	425			
Project	ES	1,00	2,00	3,00	4,00	5,00	6,00	6,67	7,50	9,00	10,00	11,00	12,00	13,00	14,00			
Project	SV(t)	0,00	0,00	0,00	0,00	0,00	0,00	-0,33	-0,50	0,00	0,00	0,00	0,00	0,00	0,00			
CP1	PV	20	10	5	30	30	30	20	20	30	10	10	20	30	20	0	0	0
CP1	CumPV	20	30	35	65	95	125	145	165	195	205	215	235	265	285			
CP1	EV	20	30	35	65	95	125	145	165	195	205	215	235	265	285			
CP1	ES	1,00	2,00	3,00	4,00	5,00	6,00	7,00	8,00	9,00	10,00	11,00	12,00	13,00	14,00			
CP1	SV(t)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00			
NCP1	PV	0	0	0	0	20	10	40	0	0	0	0	0	0	0	0	0	0
NCP1	CumPV	0	0	0	0	20	30	70	70	70	70	70	70	70	70			
NCP1	EV	0	0	0	0	20	30	50	60	70	70	70	70	70	70			
NCP1	Slack					2	2	2	2	2								
NCP1	ES					5,00	6,00	6,50	6,75	7,00								
NCP1	SV(t)					0,00	0,00	-0,50	-1,25	-2,00								
NCP2	PV	0	0	0	0	40	30	0	0	0	0	0	0	0	0	0	0	0
NCP2	CumPV	0	0	0	0	40	70	70	70	70	70	70	70	70	70			
NCP2	EV	0	0	0	0	40	70	70	70	70	70	70	70	70	70			
NCP2	Slack					5	5											
NCP2	ES					5,00	6,00											
NCP2	SV(t)					0,00	0,00											
TOTAL	SVP(t)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00			

FIGURE 7. The results of Scenario 2: The delay in non-critical activity within its total slack is not impacting the project duration.

The execution of activities B and C lags behind the schedule within the total slack path. In this case, there is no impact on CP1, and therefore, has no impact on the project schedule. The different progressions of SV(t) and SVP(t) are shown in Figure 8. In addition, in this case, we note a misleading behavior in SV(t), while SVP(t) is aligned with the actual project schedule status (no delay in all weeks).

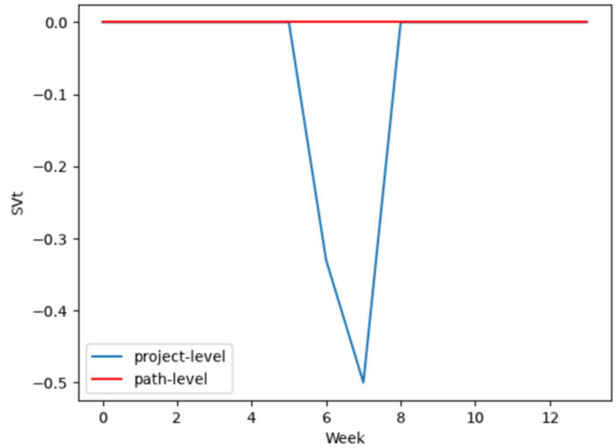

FIGURE 8. Scenario 2: The SV(t) progression at the path level is more stable than the progression at project level.

C. SCENARIO 3: THE LATE START CASE – THE DELAY IN THE NON-CRITICAL PATH

Figure 9 shows the project and path levels EV, ES, and SV(t) when there is a delay in NCP1 but under the condition of a late start and with no total slack. The baseline is shown in Figure 4 (late start schedule).

The project level SV(t) = −0.13 shows that the project starts late on week 7, but with the corresponding SV(t) values being negative with the wrong magnitude. Indeed, the delay observed is greater than the delay calculated with SV(t), because this metric is mitigated by the total slack of other paths that are not late. Again, the project-level results mislead and generate false negatives." Therefore, project managers are suggested by SV(t) at the project level to activate countermeasures to bring the project back on track from week 7 but with an incorrect magnitude. The correct schedule variance is detected by an SVP(t) value of −0.25 from week 7. The different progressions of SV(t) and SVP(t) are shown in Figure 10. In addition, in this case, we note a misleading behavior of SV(t), whereas SVP(t) is aligned with the actual project schedule delay magnitude.

D. SIMULATOR DESIGN AND FUNCTIONALITY

To robustly evaluate our proposed method, we developed a Python-based simulator that applies ES metrics at the path level within a simulated project network environment. This simulator allows for a detailed assessment of project performance by simulating various project execution scenarios based on probabilistic time estimates using PERT.

Level	Activity	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
CP1	A	20	10	5	30													
NCP1	B							15	7	8								
NCP1	C										40							
NCP2	D										40	30						
CP1	E					30	30	20	20	30								
CP1	F											10	10					
CP1	G													20	30	20		
Project	PV	20	10	5	30	30	30	40	30	70	50	40	20	30	20	0	0	0
Project	CumPV	20	30	35	65	95	125	165	195	265	315	355	375	405	425	425		
Project	EV	20	30	35	65	95	125	160	187	225	305	345	355	375	405	425		
Project	ES	1,00	2,00	3,00	4,00	5,00	6,00	6,88	7,73	8,43	9,80	10,75	11,00	12,00	13,00	14,00		
Project	SV(t)	0,00	0,00	0,00	0,00	0,00	0,00	-0,13	-0,27	-0,57	-0,20	-0,25	-1,00	-1,00	-1,00	-1,00		
CP1	PV	20	10	5	30	30	30	20	20	30	10	10	20	30	20	0	0	0
CP1	CumPV	20	30	35	65	95	125	145	165	195	205	215	235	265	285			
CP1	EV	20	30	35	65	95	125	145	165	195	195	205	215	235	265			
CP1	ES	1,00	2,00	3,00	4,00	5,00	6,00	7,00	8,00	9,00	9,00	10,00	11,00	12,00	13,00			
CP1	SV(t)	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-1,00	-1,00	-1,00	-1,00	-1,00			
NCP1	PV	0	0	0	0	0	0	20	10	40	0	0	0	0	0	0	0	0
NCP1	CumPV	0	0	0	0	0	0	20	30	70	70	70	70	70	70			
NCP1	EV	0	0	0	0	0	0	15	22	30	70	70	70	70	70			
NCP1	Slack							0	0	0	0							
NCP1	ES							6,75	7,20	8,00	9,00							
NCP1	SV(t)							-0,25	-0,80	-1,00	-1,00							
NCP2	PV	0	0	0	0	0	0	0	0	0	40	30	0	0	0	0	0	0
NCP2	CumPV	0	0	0	0	0	0	0	0	0	40	70	70	70	70			
NCP2	EV	0	0	0	0	0	0	0	0	0	40	70	70	70	70			
NCP2	Slack										0	0						
NCP2	ES										10,00	11,00						
NCP2	SV(t)										0,00	0,00						
TOTAL	SVP(t)	0,00	0,00	0,00	0,00	0,00	0,00	-0,25	-0,80	-1,00	-1,00	-1,00	-1,00	-1,00	-1,00			

FIGURE 9. The results of Scenario 3: Non-critical activities B and C, which belong to NCP1, are behind the schedule and impact CP1. EVM is not detecting the correct magnitude of the delay.

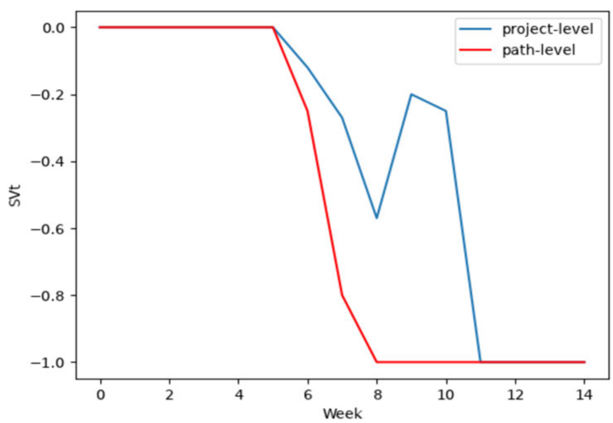

FIGURE 10. Scenario 3: The SV(t) progression at path level more stable than the progression at project level.

E. THE SIMULATION PROCESS

We generate task durations using a beta distribution, reflecting the optimistic, pessimistic, and most likely scenarios for each task, ensuring that our simulation captures a realistic range of potential project outcomes.

Subsequently, for each simulated period, ES schedule variance (SV(t)) is calculated cumulatively across the project's timeline to determine the schedule performance at each point. The simulator then computes schedule variance for each path (SVP(t)), allowing us to identify which paths are ahead or behind schedule. This step is crucial for testing the effectiveness of applying ES metrics at a detailed level. Results are plotted to visually compare the traditional project-level schedule variance against our novel path-level variance, highlighting the enhanced detection capabilities of our approach.

F. THE SIMULATION RESULTS

Figure 11 displays the SV(t) and SVP(t) progressions across 100 project simulations, randomly generated using the PERT distribution based on three-point estimates (most likely, pessimistic, and optimistic durations). The network remained constant across the simulations to maintain simplicity without losing generality. Figure 11 illustrates that SVP(t) shows a more stable and robust progression than SV(t), which appears more sensitive to variations in any part of the project, even in non-critical activities that might have minor or no impact on the overall project duration. Variations in any project part at any time can cause fluctuations in SV(t) (3), labeled "project-level" in Figure 11, where the curve slope frequently changes. Conversely, SVP(t) (4), labeled "path-level," features more stable curves in bold green, unlike the project-level's dashed red curves.

The simulation results reveal that SVP(t) identifies only six different progress scenarios across the hundred simulations, indicating that changes in the critical path and overall project duration occur in only a few instances. This suggests that variability in activity duration typically affects the non-critical paths NCP1 and NCP2 within their total slack, thus not altering the total project duration. This is accurately captured by SVP(t), which evaluates the schedule variance at the path level considering the total slack times. By contrast, SV(t) suggests a new schedule for each of the hundred simulations, implying unrealistic impacts on the project's total duration, thus highlighting the inaccuracy of using SV(t) at the project level.

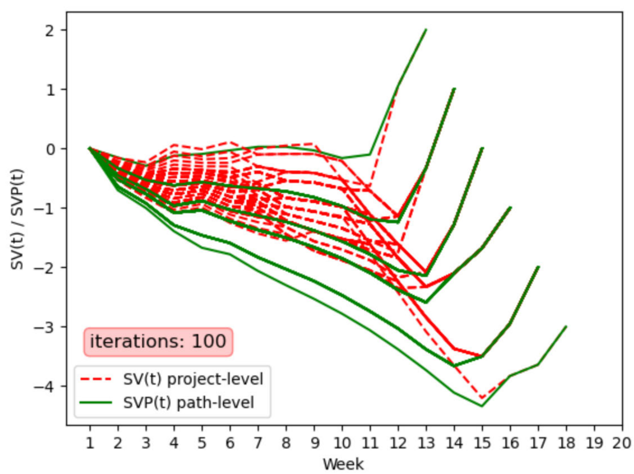

FIGURE 11. The comparison of the traditional SV(t) project-level and proposed SVP(t) path-level values. SVP(t) is having a more stable and robust progression compared to SV(t).

G. DISCUSSION

The findings from applying our approach to the project network show that the traditional ES-based SV(t) metric provides less accurate schedule progress variance. This approach generates false (contradictory) results compared with the proposed approach using the SVP(t) metric. The main difference between the two approaches is that the SV(t) metric is used at the project level, whereas the SVP(t) metric is used at the path level. Our study demonstrated this on three project network executions (on both early start and late start cases), and this finding was confirmed by a simulation test on 100 project networks.

We report the main reason for the schedule inaccuracy with SV(t). This metric considers the progress in the critical path but does not consider the progress in the non-critical paths with their total slack and aggregates the path progress to the project level. As a result, the conventional ES technique provides schedule progress values that are unreliable in many scenarios. This occurred in two directions. First, when the project is not late, it is detected as late (false positive) (the scenarios in Sections IV-A and IV-B, with their results in Figure 5 and 7, respectively). Second, when the project is late, it is not detected (false negative) or detected with an incorrect magnitude (the scenarios in Section IV-C, with the results in Figure 9). The consequences in both cases have potential negative impacts on project performance. In the first case, expensive and unnecessary corrective actions can be taken, risking the project budget or profitability. In the second case, no sufficient corrective actions can be taken by the project manager when needed, compromising the project's success. Moreover, an unrealistic schedule variance may lead to poor project monitoring and, consequently, poor project control, thereby increasing the risk of project failure.

Our approach significantly improved the accuracy of the traditional approach used at the project level. As an expected result of our methodology, we noticed that our SVP(t) metric at the path level is more reliable than the traditional SV(t) metric at the project level because it generates more accurate or true schedule variance results.

While the computational demands of our methodology increase with the number of activities and paths within a project, it is essential to recognize that these are human-driven activities, typically manageable by project managers without exceeding the computational capabilities of modern systems. Our approach is designed to operate efficiently within these realistic bounds, ensuring practical applicability even as project complexity grows. This scalability ensures our methodology is not only suitable but also robust for real-world project management settings, where the number of activities and paths aligns with human oversight capabilities. Evaluations through simulations demonstrate robustness across a variety of project configurations, reinforcing the method's capability to efficiently handle multiple project paths and varying levels of complexity. This makes it particularly valuable for complex projects where multiple tasks and dependencies must be managed simultaneously, ensuring that project managers can maintain accuracy in schedule assessments even as project scope expands.

A potential critique of our research is related to the validation of our model through real-world projects, which merits careful consideration. However, it is our contention that the essence of this research—identifying and addressing the suboptimal conditions of Earned Schedule analysis—transcends the need for empirical validation with a real project. The conditions under which ES demonstrates sub-optimal performance are not merely hypothetical but are grounded in the practical realities of project management, where non-critical path scheduling and delays play a pivotal role in overall project assessment. By constructing a simulated environment in which these conditions are systematically explored, our study provides a controlled lens through which to examine the nuances of the ES performance. This approach enables a focused critique of ES, isolating variables that a real-world project, with its myriad complexities and external influences, may be obscure. Hence, our validation strategy, centered on a theoretical exploration of ES vulnerabilities, offers a targeted contribution to the discourse on project management methodologies, challenging the prevailing reliance on ES without dismissing its value in contexts where its limitations are less pronounced. Our findings reveal systemic issues within the ES framework in that empirical validation with a single real-world project may not be fully captured. The conditions under which ES exhibits suboptimal performance, highlighted through our simulations, underscore the necessity for a theoretical reevaluation of its metrics. Therefore, our study's reliance on simulated scenarios is not a limitation, but a deliberate strategy to isolate and examine ES's inherent vulnerabilities of ES.

Project managers can use the proposed approach to improve schedule monitoring and duration forecasting accuracy. An improvement in this area directly reflects project risk reduction and therefore increases the chances of project success. The major strength of our suggested approach is that we do not introduce a new set of formulas but only calculate SV(t) metric at the path level (namely, by a new SVP(t) metric) and then aggregate its values from multiple paths to the project level.

V. CONCLUSION

Projects pose unique challenges for project managers in monitoring and controlling schedules and duration forecasting. The ES approach, which is used as a standard methodology, is top-down and does not consider schedule progress discrepancies at individual path levels. This results in inaccurate or false schedule variances, leading to poor duration forecasts and poor project decision-making. We identified an inability to provide realistic schedule results in the project topology. To address this issue, the authors propose two approaches: introducing a path-level study and constructing a new metric, SVP(t), which considers schedule progress variances on individual path levels, both in critical and noncritical paths. This approach is more stable across all tracking periods and is more stable across all tracking periods. To further substantiate the findings of this study, future research is encouraged to apply path-level schedule analysis using the Schedule Variance Path Level (SVP(t)) metrics across a more extensive empirical dataset, drawing from a wide array of real-life projects. Leveraging simulations has unveiled specific vulnerabilities within the Earned Schedule framework; however, empirical validation stands to deepen these insights by juxtaposing theoretical predictions with tangible project outcomes. While our approach significantly enhances the scheduling process, it is important to recognize the inherent limitations. Specifically, our method, like all project management tools, cannot achieve universal optimality due to varying project complexities and dynamic conditions. There are constraints related to data availability, the subjective interpretation of project statuses, and the adaptability of the method across different industries and project scales that may affect its applicability and effectiveness. Such collaborative efforts between scholars and practitioners promise not only to refine the set of management metrics but also to strike an optimal balance between analytical rigor and computational efficiency, ultimately enhancing project schedule performance assessment in diverse project management landscapes.

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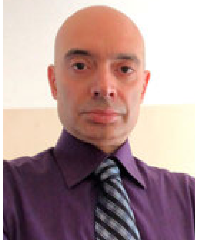

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