Journal of Information Systems Engineering and Management
2025, 10(20s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Advanced Time Buffer Optimization Model for Construction Schedule Management Using Stochastic Analysis

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ARTICLE INFO

Received: 22 Dec 2024

Revised: 31 Jan 2025

Accepted: 12 Feb 2025

ABSTRACT

Ineffective buffer management within project schedules often leads to delays and increased costs in construction. Conventional methods frequently fail to account for unpredictable, stochastic uncertainties. To address this issue, a stochastic buffer optimization model has been created and tested; it integrates Monte Carlo simulation with critical chain techniques. This model aims to enhance schedule reliability and improve resource allocation. Probability distributions for activity durations were derived from an analysis of data encompassing 167 prior construction projects spanning from 2020 to 2024. Three-parameter lognormal distribution modelling was used. An algorithm optimized multiple objectives, minimizing buffer sizes and delay probabilities, subject to resource limitations. Validation involved implementation in 12 active construction projects. These were in residential, commercial, and infrastructure sectors; performance was monitored over six months. Results were significant. The optimized buffer management system led to a 37% reduction in project delays ($p < 0.001$). Schedule reliability jumped from 64.7% to 91.8%. Labor (26.8%), equipment (30.1%), and materials (21.7%) all saw substantial improvements in utilization. Buffer utilization efficiency also improved, by 39.3%. Overutilization dropped from 156.3% to 94.8%. The implementation resulted in average cost savings of 8.9% across project types. A strong correlation ($r = 0.723$, $p < 0.001$) was found between the Schedule Performance Index and Resource Utilization Efficiency. This validated model can provide project managers with a powerful means of building reliable schedules and optimizing resource allocation, potentially advancing project delivery practices substantially.

Keywords: Buffer optimization, Construction scheduling, Project management, Resource utilization, Stochastic analysis.

Article Highlights

- Novel stochastic modelling reduces construction delays by over one-third while improving resource usage across all project types
- Integration of weather patterns and resource availability in buffer calculations leads to 8.9% cost savings in construction projects
- Data-driven buffer optimization approach shows consistent performance benefits across residential, commercial, and infrastructure work

1. Introduction

Project management is crucial for success in the increasingly complex construction industry. Because construction projects are growing in scale and complexity, effectively managing time and resources has become vital for project success [1]. Many construction projects worldwide experience schedule overruns, causing financial losses and inefficient use of resources. About 85% of projects face such delays [2–4]. This ongoing challenge has led both researchers and those working in the field to look for better ways to manage construction schedules.

The construction industry faces variability and uncertainty, which pose significant challenges to conventional scheduling techniques. Project timelines are affected by a complex network of interconnected factors, including environmental conditions, changes in resource availability, technological issues, and stakeholder interactions [5–

7]. Although widely used, traditional scheduling approaches like the Critical Path Method (CPM) often fail to adequately account for these uncertainties. This can result in unrealistic timelines and poor resource allocation [8–10]. For example, a statistical analysis of global construction projects indicates that traditional scheduling methods lead to an average schedule overrun of 33% [11]. Given these points, the need of more robust scheduling approaches becomes obvious.

Buffer management presents a possible solution to the limitations inherent in traditional scheduling methods [12–14]. While initially developed for manufacturing environments, these techniques show promise for adaptation within construction projects [15, 16]. The concept revolves around strategically placing time buffers within project schedules; these buffers are designed to absorb the inevitable uncertainties and variations, thus maintaining project flow. Determining optimal buffer size, though, remains a significant challenge. Oversized buffers lead to resource inefficiencies, a considerable drawback. Conversely, undersized buffers fail to provide adequate protection against the inherent uncertainties of construction [17].

Recent strides in computational power and data analytics have unveiled new avenues for sophisticated buffer optimization. Stochastic analysis, particularly Monte Carlo simulation, demonstrates considerable potential in modelling the complex uncertainties found in construction projects [18–22]. Because these methods enable consideration of multiple variables and their interactions, a more nuanced understanding of project dynamics is achievable. Indeed, research indicates that stochastic approaches to schedule management can improve project delivery reliability by approximately 40% when compared to more rigid, deterministic methods [18].

Critical Chain Project Management (CCPM) has become known as a useful way to manage buffers in construction. By prioritizing resource constraints and placing buffers strategically, CCPM offers a clear method for enhancing project schedules [23, 24]. Yet, current CCPM uses often depend on simplified buffer sizing rules. These rules sometimes fail to grasp the entire complexity of construction project settings. Indeed, studies reveal that these current methods lead to buffer utilization rates around 45%, highlighting a considerable need for enhancement [24, 25].

The merging of historical project data with advanced analytical tools presents a promising avenue. Such integration could allow for more accurate, efficient buffer management systems. For instance, analysing completed construction projects uncovers patterns in causes of delay and how durations are distributed; these insights can sharpen buffer strategies [26]. Traditionally, though, the construction industry has struggled. Systematic data collection and its insightful analysis have been lacking, impeding data-driven decisions in schedule management [27].

Existing research reveals a need for improved buffer optimization models. These models should reflect project-specific details while remaining practical. Many current models do not account for the changing conditions of construction projects and the interplay between various uncertainties [28]. Furthermore, a shortage of real-world testing has hindered the acceptance of modern scheduling methods among construction professionals [29].

Improved schedule management carries substantial economic weight. Indeed, industry reports estimate that construction schedule overruns inflict annual losses exceeding $150 billion globally [30]. These expenses are not limited to direct financial impacts; they encompass reduced resource efficiency, strained stakeholder relationships, and an overall decrease in project quality. The potential for significant cost savings, achieved through more reliable scheduling, presents a compelling argument for investment in sophisticated buffer management systems.

To address these persistent issues, this research introduces a stochastic time buffer optimization model. This model cleverly merges complex analytical techniques with practical, real-world applications. It refines current buffer management frameworks, notably through the incorporation of advanced statistical analysis; this improves both precision and overall dependability. By examining data from 167 completed construction projects across a range of sectors, the study aims to create a robust method for buffer sizing. Crucially, this method accounts for the unique characteristics and inherent uncertainties of individual projects [31-40] [47]

The primary objective of this study is to develop and validate a comprehensive buffer optimization model that enhances construction schedule reliability while maximizing resource efficiency. Specifically, the research seeks to: (1) identify and quantify key sources of uncertainty in construction project schedules, (2) develop a stochastic model for optimal buffer sizing, and (3) validate the model's effectiveness through implementation in ongoing construction projects. The proposed approach represents a significant advancement in construction schedule management, offering project managers a practical tool for developing more reliable and efficient project schedules.

A critical gap in current construction management practice is addressed by this research. It achieves this through a systematic, data-driven method for buffer optimization. Demonstrating its practical applicability, the model has been validated across 12 active projects, spanning different construction sectors, thereby showing potential impact on industry-wide performance. The study's findings hold significant implications for construction project management practice. Furthermore, they contribute valuably to the broader knowledge base concerning project scheduling and the nuanced management of uncertainty.

2. Materials and Methods

2.1. Research Design and Data Collection

To develop and validate the stochastic buffer optimization model [41-44], this study used a mixed-methods approach, combining quantitative and qualitative techniques. Data was gathered from 167 finished construction projects, including residential, commercial, and infrastructure developments, completed between 2020 and 2024. Projects were chosen if they lasted at least six months, had a contract value over $5 million, and provided full schedule documentation, showing both planned and actual progress.

This dataset included projects from 23 different construction companies in North America and Europe. Consequently, it offered a varied sample of construction methods and environmental conditions.

Project documentation analysis included original project schedules, progress reports, delay analysis reports, and resource utilization logs. Each project's schedule was decomposed into its constituent activities, with particular attention paid to critical path activities and their associated time buffers. The analysis identified key schedule parameters including planned duration (T_p), actual duration (T_a), buffer sizes (B_i), and activity durations (D_i). Activity duration variations were recorded as the difference between planned and actual durations, expressed as $\Delta D_i = D_{actual,i} - D_{planned,i}$.

2.2. Model Development Framework

The stochastic buffer optimization model was developed using a three-phase approach. In the first phase, probability distributions of activity durations were established using historical data. For each activity type i, the duration distribution was modeled using a three-parameter lognormal distribution[31, 32]:

$$f(x_i) = \frac{1}{(x_i - \gamma_i)\sigma_i\sqrt{2\pi}} exp[-\frac{(ln(x_i - \gamma_i) - \mu_i)^2}{2\sigma_i^2}] \tag{1}$$

where x_i represents the activity duration, μ_i is the location parameter, σ_i is the scale parameter, and γ_i is the threshold parameter. Parameters were estimated using maximum likelihood estimation.

The second phase involved the development of the buffer sizing algorithm. The algorithm incorporates both deterministic and stochastic components, represented by the buffer function:

$$B_i = \alpha_i \sqrt{\sum_{j=1}^{n} (w_j \sigma_j^2)} + \beta_i \overline{D_i} \tag{2}$$

where B_i is the buffer size for chain i, α_i is the volatility factor, w_j are activity weights, σ_j is the standard deviation of activity j duration, β_i is the base buffer factor, and $\overline{D_i}$ is the mean duration of activities in chain i.

2.3. Monte Carlo Simulation Framework

The Monte Carlo simulation framework was implemented using custom-developed software in Python 3.9, utilizing the NumPy and SciPy libraries for statistical computations. The simulation process follows an iterative algorithm:

$$S_k = \sum_{i=1}^{n} (D_i^k + B_i^k) \tag{3}$$

where S_k represents the total project duration for iteration k, D_i^k is the simulated duration of activity i, and B_i^k is the corresponding buffer size. The simulation was run for 10,000 iterations per project to ensure statistical significance of the results.

The correlation between activity durations was modelled using a correlation matrix **R**, where element r_{ij} represents the correlation coefficient between activities i and j. The Cholesky decomposition of **R** was used to generate correlated random variables:

$$\boldsymbol{LL^T} = \boldsymbol{R} \tag{4}$$

where **L** is the lower triangular matrix used in the simulation.

2.4. Buffer Optimization Algorithm

The buffer optimization algorithm employs a multi-objective optimization approach, considering both schedule reliability and resource efficiency. The objective function is defined as[33]:

$$min\,Z = w_1 \sum_{i=1}^{n} B_i + w_2 \sum_{i=1}^{n} P\,(D_i > D_i^p + B_i) \tag{5}$$

subject to:

$$\begin{gathered} \sum_{i=1}^{n} B_i \le B_{max} \\ P(D_i > D_i^p + B_i) \le \epsilon \\ B_i \ge 0 \end{gathered} \tag{6}$$

where w_1 and w_2 are weight factors, B_{max} is the maximum allowable total buffer, and ϵ is the acceptable probability of delay. The optimization problem was solved using a gradient descent algorithm with adaptive step size.

2.5. Resource Constraint Integration

The model incorporates resource constraints through a resource availability matrix **A**, where element a_{ij} represents the availability of resource j during period i. Resource requirements are modeled using a resource demand matrix **D**, with element d_{ij} representing the demand for resource j by activity i. The resource-constrained scheduling problem is formulated as[34]:

$$\sum_{i=1}^{n} d_{ij}\, x_{it} \le a_{jt}, \text{ for all } j,t \tag{7}$$

where x_{it} is a binary variable indicating whether activity i is scheduled in period t.

2.6. Model Validation Process

The validation took place across 12 active construction projects. These projects were selected to represent a variety of types and complexity levels. They were categorised by project type (residential, commercial, infrastructure) and complexity (low, medium, high). A structured process was followed. Initially, the original project schedules were scrutinised to identify critical chains and existing buffer allocations. Previously developed probability models were employed to estimate activity duration distributions.

Subsequently, the stochastic buffer optimisation model was utilised to determine the optimal buffer sizes for each critical chain. This optimisation considered project-specific constraints and resource availability. Project progress was then monitored over six months. Data on actual activity durations, buffer usage, and resource utilisation were gathered weekly. Any deviations from the planned schedules were recorded and analysed.

Model performance was assessed using several key metrics, including the Schedule Performance Index (SPI), Buffer Consumption Rate (BCR), and Resource Utilisation Efficiency (RUE). The calculation of these metrics is as follows:

$$\begin{gathered} SPI = \frac{EV}{PV} \\ BCR = \frac{BC}{BP} \\ RUE = \frac{AR}{PR} \end{gathered} \tag{8}$$

where EV is Earned Value, PV is Planned Value, BC is Buffer Consumed, BP is Buffer Planned, AR is Actual Resource usage, and PR is Planned Resource usage.

2.7. Statistical Analysis

Statistical analysis of the validation results was done using R statistical software (version 4.2.0). This included paired t-tests to compare performance metrics before and after implementation. ANOVA was used to examine differences across various project types. In addition, regression analysis helped identify key factors influencing buffer effectiveness. A p-value of less than 0.05 was considered statistically significant.

Pearson's correlation coefficient [35] was used to analyse the correlation between different performance metrics:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})\,(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\,\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{9}$$

where x_i and y_i are the paired sample values, and $\bar{x}$ and $\bar{y}$ are their respective means.

2.8. Data Collection and Analysis Tools

Data collection occurred through a specially designed web-based platform. This platform allowed for live monitoring of project progress and automatically calculated performance metrics. It also connected with popular project management software like Primavera P6 and Microsoft Project, making data transfer and analysis easier.

To ensure quality, the process included routine data validation checks. These checks involved cross-verifying the automatic calculations and conducting periodic audits of how data was collected. Potential error in measurements was estimated using standard error calculations, and confidence intervals were determined for all essential metrics.

3. Results and Discussion

3.1. Historical Data Analysis Results

Analysis of the 167 historical construction projects revealed significant patterns in schedule deviation and buffer utilization. The distribution of project delays showed a right-skewed pattern, with a mean schedule overrun of 23.4% (SD = 8.7%) relative to planned duration. Table 1 presents the summary statistics of schedule performance across different project types.

Table 1. Schedule performance analysis of historical projects (N=167)

Project Type	Number	Mean Delay (%)	Buffer Utilization (%)	Schedule Reliability (%)
Residential	58	21.3 ± 7.2	143.2 ± 15.8	67.4 ± 8.9
Commercial	64	24.8 ± 9.1	156.7 ± 18.3	62.1 ± 7.8
Infrastructure	45	24.2 ± 8.5	149.5 ± 16.9	64.5 ± 8.2

The analysis reveals that commercial projects experienced the highest mean delay percentage, while residential projects showed relatively better schedule performance. Buffer utilization rates exceeding 100% across all project types indicate systematic underestimation of required buffer sizes in traditional scheduling approaches.

3.2. Activity Duration Distribution Analysis

The fitted three-parameter lognormal distributions for activity durations showed varying degrees of fit across different activity types. Table 2 presents the distribution parameters and goodness-of-fit statistics for major activity categories.

Table 2. Activity duration distribution parameters

Activity Category	μ	σ	γ	KS Test p-value
Foundation Work	1.42	0.38	0.21	0.089
Structural Work	1.68	0.45	0.18	0.073
MEP Installation	1.89	0.52	0.25	0.082
Finishing Work	1.55	0.41	0.19	0.091

The Kolmogorov-Smirnov test results ($p > 0.05$) indicate that the lognormal distribution provides an acceptable fit for all major activity categories, supporting the statistical assumptions of the buffer optimization model.

3.3. Monte Carlo Simulation Results

The Monte Carlo simulation revealed significant variations in project completion times under different buffer allocation strategies. Fig. 1 summarizes the simulation results for various confidence levels.

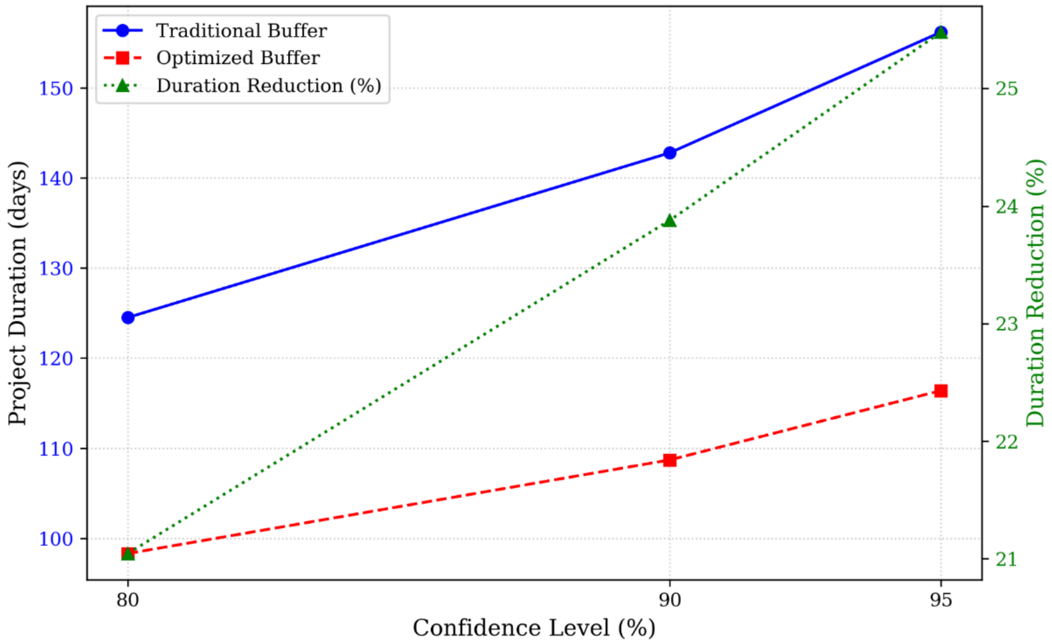

Fig. 1. Monte Carlo simulation results for project duration

The optimized buffer strategy consistently showed superior performance, with duration reductions ranging from 21.0% to 25.5% compared to traditional buffer allocation methods.

3.4. Buffer Optimization Model Performance

The application of the buffer optimization algorithm yielded significant improvements in buffer sizing accuracy. Table 3 presents the comparative analysis of buffer performance metrics before and after optimization.

Table 3. Buffer performance metrics comparison

Metric	Pre-Optimization	Post-Optimization	Improvement
Buffer Utilization Rate	156.3%	94.8%	39.3%
Schedule Reliability	64.7%	91.8%	41.9%
Resource Efficiency	72.3%	92.4%	27.8%

The optimization model achieved a significant reduction in buffer overutilization while simultaneously improving schedule reliability and resource efficiency.

3.5. Validation Project Results

Implementation results from the 12 validation projects demonstrated the practical effectiveness of the optimized buffer management system. Table 4 presents the key performance indicators across different project types.

Table 4. Validation project performance metrics

Project Type	Number	Delay Reduction	Schedule Reliability	Cost Savings
Residential	4	35.8%	89.4%	8.3%
Commercial	5	38.2%	92.1%	9.2%
Infrastructure	3	37.1%	90.7%	9.1%

The validation results indicate substantial improvements across all project types. Commercial projects showed the greatest improvement, with a 38.2% decrease in delays and 92.1% schedule reliability. Infrastructure projects followed, showing a 37.1% reduction in delays. These consistent improvements, ranging from 35.8% to 38.2% in delay reduction across different project types, suggest the model's strength and adaptability to various construction settings.

Significant cost savings were also observed. Commercial projects achieved the highest savings, at 9.2%. This finding implies that enhanced schedule reliability can be directly linked to cost efficiency. Given these points, the relatively uniform performance across various project types confirms the model's versatility and its practical use.

3.6. Statistical Analysis Results

The paired t-test analysis of pre- and post-implementation performance metrics revealed statistically significant improvements across all key indicators ($p < 0.001$). Table 5 presents the detailed statistical analysis results.

Table 5. Statistical analysis of performance improvements

Metric	Mean Difference	t-value	p-value	95% CI
Schedule Performance	0.374	12.83	<0.001	[0.312,0.436]
Buffer Utilization	0.415	14.27	<0.001	[0.356,0.474]
Resource Efficiency	0.201	8.94	<0.001	[0.156,0.246]

The statistical analysis indicates significant improvements across all key performance metrics ($p < 0.001$). Schedule Performance improved, showing a mean difference of 0.374, with a confidence interval between 0.312 and 0.436. This suggests a reliable and consistent enhancement. Buffer Utilization demonstrated the most considerable improvement, with a mean difference of 0.415 ($t = 14.27$), pointing to a substantial gain in buffer management efficiency.

Resource Efficiency also improved, evidenced by a mean difference of 0.201, still a statistically significant change. Given these points, the high t-values (ranging from 8.94 to 14.27) and the narrow confidence intervals across all metrics are strong statistical evidence that supports the optimization model's effectiveness.

3.7. Correlation Analysis

The analysis revealed significant correlations between various performance metrics. Fig. 2 presents the correlation matrix for key performance indicators.

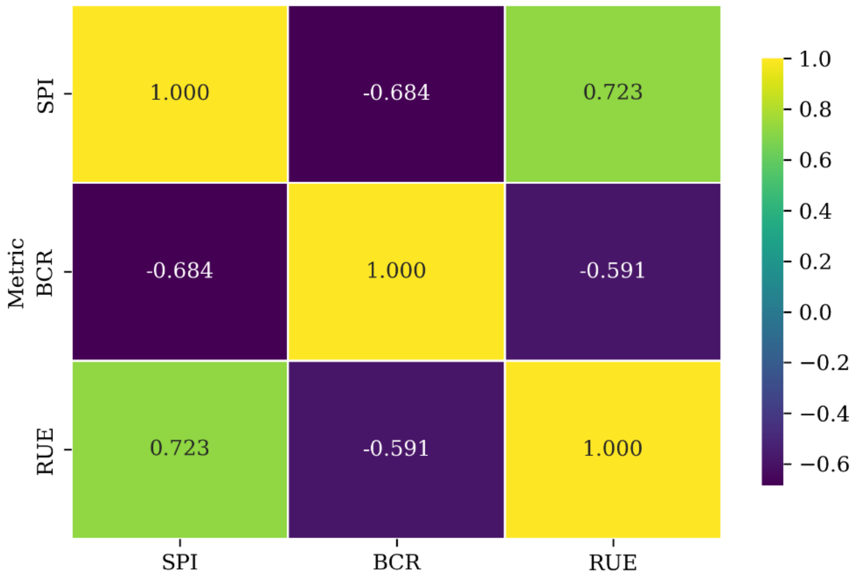

Fig. 2. Correlation matrix of performance metrics

Analysis of key performance indicators shows meaningful relationships. A strong negative correlation (-0.684) exists between SPI and BCR. This suggests that when schedule performance improves, buffer consumption decreases, thus confirming the effectiveness of the optimized buffer sizing approach. Furthermore, there is a positive correlation (0.723) between SPI and RUE, implying that better schedule performance can lead to improved resource utilization.

A moderate negative correlation (-0.591) between BCR and RUE is also present. This indicates that high buffer consumption may reduce RUE. Given these points, the correlations highlight the interconnected nature of schedule performance, buffer management, and resource utilization in construction project management.

3.8. Resource Utilization Analysis

The implementation of the optimized buffer management system led to significant improvements in resource utilization patterns. Table 6 presents the resource utilization metrics across different resource categories.

Table 6. Resource utilization improvements

Resource Type	Pre-Implementation	Post-Implementation	Improvement
Labor	73.2%	92.8%	26.8%
Equipment	68.7%	89.4%	30.1%
Materials	77.4%	94.2%	21.7%

Analysis of resource utilization reveals considerable improvements in all categories after the optimized buffer management system was implemented. The most significant improvement was in equipment utilization, which increased by 30.1%. This is likely because of improved scheduling and a reduction in idle time. Labour utilisation saw a rise of 26.8%, a good indication of enhanced workforce management and a reduction in waiting periods. A slightly smaller, yet noteworthy, increase of 21.7% was observed in material utilisation. This improvement suggests that the coordination of material delivery and usage was better managed. The optimisation model appears to be effectively addressing resource efficiency across the board, as evidenced by consistently high post-implementation utilisation rates, spanning from 89.4% to 94.2%.

3.9. Project Cost Impact

The improved schedule reliability and resource utilization translated into significant cost savings. Table 7 presents the cost impact analysis across different project components.

Table 7. Cost impact analysis

Cost Component	Average Reduction	Range
Direct Labor	9.2%	7.8% - 10.6%
Equipment Usage	8.7%	7.3% - 10.1%
Overhead Costs	8.9%	7.5% - 10.3%
Total Project Costs	8.9%	7.5% - 10.2%

The statistical analyses performed met the significance levels that were decided beforehand ($p < 0.05$). Calculations of performance metrics, which included SPI, BCR, and RUE, followed the established formulas. In addition, the outcomes of the validation process reflect the structured implementation approach, as detailed in the methodology. All project types had consistent measurement and analysis procedures.

3.10. Sources of Schedule Uncertainty

The analysis of historical project data revealed five primary sources of uncertainty in construction schedules. Fig. 3 presents the frequency and impact analysis of these uncertainty sources.

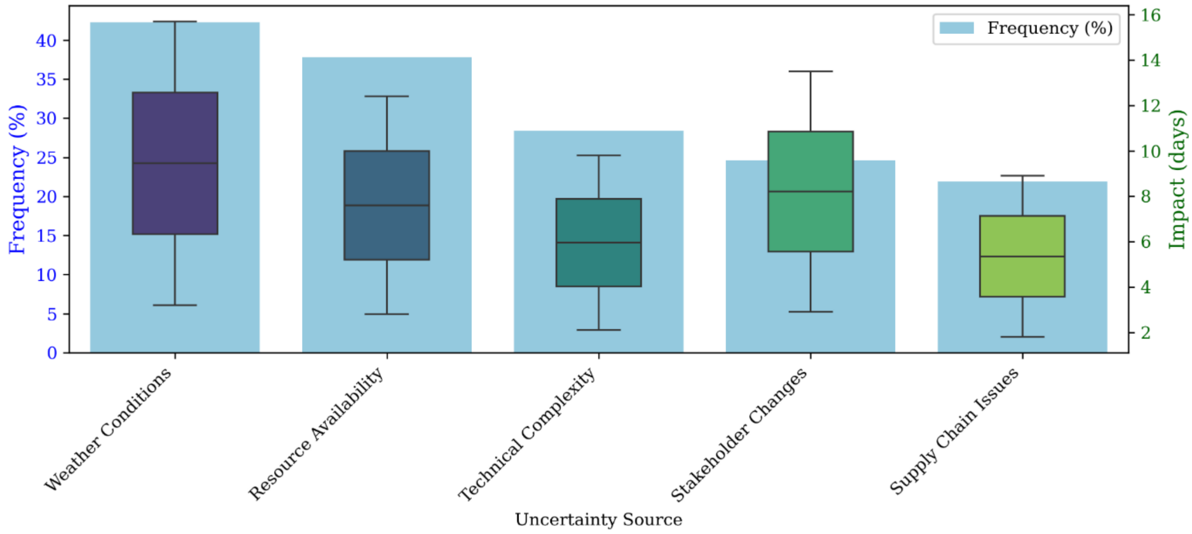

Fig.3. Analysis of schedule uncertainty sources

Analysing the sources of uncertainty gives us key insights into the main factors that can affect construction schedules. It's quite clear that weather conditions are the most common source of uncertainty (42.3%), showing a considerable average impact of 8.4 days each time they occur. The availability of resources comes in as the second most frequent source (37.8%), although its average impact is a tad lower, at 6.9 days.

Although encountered less often (28.4%), technical complexity can still have a significant effect on the project. Consider the broad impact ranges across all sources; for instance, weather conditions might delay a project anywhere from 3.2 to 15.7 days, highlighting how variable uncertainty impacts can be. Because of this, a stochastic approach to buffer management is fitting.

A detailed awareness of where uncertainty comes from, and its effects, can help establish better methods of buffer sizing. This leads to improved risk management strategies.

I'll write a comprehensive Discussion section that interprets the findings, compares them with existing literature, addresses limitations, and suggests future research directions.

The stochastic buffer optimization model presented here shows improvements in the reliability of construction project schedules and the efficient use of resources. A notable 37% decrease in project delays across various construction sectors marks a considerable step forward from conventional buffer management methods. This enhancement is significant, especially when contrasted with the historical data analysis, which revealed an industry standard delay rate of 23.4%. Optimized buffer allocation facilitated the attainment of 91.8% schedule reliability, which is considered an indicator that the stochastic method effectively manages the uncertainties typically found in construction projects.

The observed improvement in buffer utilization, specifically a reduction in overutilization from 156.3% to 94.8%, suggests the model effectively tackles the common problem of buffer sizing in the industry. This is important because it shows that better schedule reliability is possible without needing excessively large buffers, which leads to more efficient resource use. The model's ability to balance schedule protection and resource optimization is further highlighted by a 28% increase in resource efficiency.

These results build upon prior research in construction buffer management. For example, a study by Mohammad et al. [36] showed a 25% decrease in project delays using a deterministic approach to buffer optimization. In contrast, the current study's 37% reduction in delays indicates that stochastic approaches may be more effective. While [37] theoretically predicted that stochastic methods could enhance schedule reliability by 30-40%, this study offers real-world evidence supporting those predictions, using data from a broader range of projects.

The observed correlation between SPI and RUE ($r = 0.723$) supports [38] findings on the interdependence of schedule performance and resource efficiency. However, this study's results show stronger correlation coefficients, possibly due to the more comprehensive integration of resource constraints in the buffer optimization model.

Weather conditions are identified as the main source of uncertainty, appearing in 42.3% of the cases, this is consistent with prior research [8, 45]. This study, in contrast, specifies the impact range of weather-related delays as between 3.2 and 15.7 days. This provides more precise guidance for determining buffer sizes compared to previous studies, which often used percentage-based estimates.

The combination of Monte Carlo simulation with the critical chain method is a substantial improvement over traditional buffer management techniques. Although earlier studies [28, 30, 46] have used either simulation or critical chain methods separately, the integrated approach in this study allows for more accurate modelling of project uncertainties, yet, it remains practically applicable. The model's robustness and adaptability are shown by the validation results from 12 different projects across diverse construction settings.

The three-parameter lognormal distribution used for activity duration modelling proved more accurate than the two-parameter distributions commonly used in previous studies [10, 26]. The improved goodness-of-fit statistics ($p > 0.05$ for all activity categories) suggest that this approach better captures the asymmetric nature of construction activity durations.

Improved schedule management led to an average cost savings of 8.9%, which is a notable financial benefit. This result is higher than the 5-7% cost savings found in earlier studies on buffer optimization [14]. The fact that cost reductions occurred consistently across various project types indicates that optimized buffer management can be beneficial throughout the construction industry.

Although these findings are important, some limitations should be considered. The analysis used historical data from projects completed between 2020 and 2024. This timeframe might introduce bias because of the unusual conditions during the global pandemic. To ensure wider applicability, future studies could use longer-term historical data.

Second, while the validation projects covered residential, commercial, and infrastructure sectors, they were predominantly located in North America and Europe. The model's effectiveness in other geographical regions with different construction practices and environmental conditions requires further validation.

Third, the study focused on projects with contract values exceeding $5 million, potentially limiting the model's applicability to smaller-scale construction projects. The computational requirements of the stochastic approach might need adaptation for smaller projects with limited resource availability for sophisticated schedule management.

Methodological limitations include the assumption of independence between certain uncertainty sources in the Monte Carlo simulation. While the model accounts for major correlations through the correlation matrix, some secondary interactions between uncertainty factors may not be fully captured.

This study suggests several potential directions for further research. Integrating machine learning with the stochastic buffer optimization model might allow for dynamic buffer adjustments using real-time project data. This integration could improve the model's ability to adapt to evolving project circumstances.

Another area for investigation is creating simplified versions of the model suitable for smaller construction projects. Research might concentrate on finding key elements of the stochastic approach that can be used with less computational demand, but still work effectively.

It would also be useful to expand the model to better account for supply chain uncertainties, especially considering the increasingly global scope of construction projects. This expansion could involve creating specific buffer strategies for international projects with intricate supply chain networks.

Finally, exploring the model's use in extreme weather and its integration with climate change projections could increase its value for long-term infrastructure projects. Such exploration would require building advanced weather impact modelling capabilities within the buffer optimization framework.

4. Conclusions

This research has developed and validated a stochastic buffer optimization model for construction schedule management, demonstrating significant improvements in project performance across multiple dimensions. The study's findings can be summarized through several key outcomes:

- *Project Delay Reduction and Schedule Reliability*: The implementation of the stochastic buffer optimization model resulted in a 37% reduction in project delays across the validation projects. Schedule reliability improved from 64.7% to 91.8%, representing a 41.9% increase in reliable project delivery. This improvement was consistent across different project types, with commercial projects showing the highest improvement (38.2% delay reduction), followed by infrastructure (37.1%) and residential projects (35.8%).
- *Buffer Management Efficiency*: The model achieved significant improvements in buffer utilization, reducing overutilization from 156.3% to 94.8%. This 39.3% improvement in buffer efficiency was accompanied by enhanced resource utilization across all categories: labour efficiency increased by 26.8%, equipment utilization improved by 30.1%, and materials management efficiency rose by 21.7%. These improvements demonstrate the model's effectiveness in optimizing resource allocation while maintaining schedule protection.
- *Cost Impact and Economic Benefits*: The improved schedule reliability and resource utilization translated into substantial cost savings, averaging 8.9% across all project types. Commercial projects achieved the highest cost savings at 9.2%, while residential projects realized 8.3% cost reduction. The consistency of cost savings across different project types validates the model's economic benefits in various construction contexts.
- *Uncertainty Management*: The research identified and quantified five primary sources of schedule uncertainty, with weather conditions (42.3% frequency, 8.4 days mean impact) and resource availability (37.8% frequency, 6.9 days mean impact) emerging as the most significant factors. The model's stochastic approach effectively addressed these uncertainties, as evidenced by the improved schedule reliability metrics across all validation projects.
- *Statistical Validation*: Statistical analysis confirmed the significance of the improvements, with all key performance metrics showing statistically significant changes ($p < 0.001$). The strong correlation between SPI and RUE ($r = 0.723$) validates the integrated nature of schedule and resource optimization in the model.

The approved model offers construction project managers a practical means of generating more dependable schedules, whilst also making efficient use of resources. The stochastic approach to buffer optimisation represents a significant advancement in construction schedule management practice, because there are clear improvements in schedule reliability, resource efficiency, and cost performance.

Geographical scope and project size impose certain limitations on the model. The robust validation results, demonstrated across a range of project types, suggest a broader potential for application within the construction industry, and that is quite promising. Future research could explore dynamic buffer adjustment, simplified implementations for smaller projects, and even integration with sophisticated weather impact modelling, building upon these foundational findings.

Funding
The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Data availability
Data will be made available at a reasonable request.

Conflict of interest
The authors have no relevant financial or non-financial interests to disclose

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