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Original Article

Scheduling Optimization and Risk Analysis Using Monte Carlo Simulation for a Construction Project in Morocco

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Abstract - *This study focuses on integrating Monte Carlo simulation into construction project management to optimize scheduling and analyze risks under uncertainty. By comparing three probability distributions-Triangular, Betapert, and Uniform, the research evaluates their impact on critical and near-critical paths, project completion timelines, and decision-making reliability. The simulations reveal how varying levels of uncertainty influence task durations and criticality, providing insights in to resource allocation, risk mitigation, and timeline optimization. The findings emphasize the importance of selecting an appropriate distribution type to balance predictability and flexibility in construction projects.*

Keywords - *Monte Carlo simulation, Scheduling optimization, Risk analysis, Critical paths, Construction project management.*

1. Introduction

Construction project management in Morocco faces unique challenges due to the country's rapidly evolving infrastructure development, regulatory environment, and economic conditions. The optimization of scheduling and comprehensive risk analysis is particularly critical in this context, as construction projects in Morocco often encounter significant uncertainties related to resource availability, regulatory compliance, and environmental factors specific to North African conditions.

Despite the growing construction sector in Morocco, a significant research gap exists in applying advanced simulation techniques to local construction projects. While Monte Carlo simulation has been extensively utilized in construction management globally, its application to Moroccan construction projects remains limited, particularly in addressing the specific uncertainties and constraints characteristic of the local industry. This research addresses this gap by implementing Monte Carlo simulation for scheduling optimization and risk analysis in a real construction project in Morocco, providing valuable insights for practitioners and researchers in the regional context.

The novelty of this research lies in its integration of three distinct probability distributions-Triangular, Betapert, and Uniform-to evaluate their comparative impact on critical path analysis, project completion timelines, and decision-making reliability within the specific context of Moroccan construction projects. This approach differs from existing methodologies by incorporating local industry parameters and constraints, resulting in more contextually relevant risk assessments and scheduling optimizations.

The primary objectives of this study are to:

- Evaluate the effectiveness of Monte Carlo simulation in optimizing scheduling for construction projects in Morocco
- Compare the impact of different probability distributions on risk analysis outcomes
- Identify critical and near-critical paths under varying levels of uncertainty
- Develop practical recommendations for resource allocation and risk mitigation strategies tailored to the Moroccan construction industry.

This research contributes to the body of knowledge by demonstrating how varying levels of uncertainty influence task durations and criticality in the specific context of Moroccan construction projects, providing valuable insights for resource allocation, risk mitigation, and timeline optimization in similar environments.

2. Literature review

2.1. Scheduling Optimization in Construction Projects

Construction project scheduling optimization has evolved significantly in recent years, with researchers exploring various methodologies to enhance efficiency and resource utilization. Lazari et al. (2024) demonstrated the effectiveness of multi-objective resource-constrained scheduling using Genetic Algorithms, which balances resource allocation and cost considerations, particularly for large and repetitive construction projects [1]. Similarly, Toğan and Eirgash (2018) explored the Time-Cost Trade-off Problem (TCTP), utilizing Teaching Learning Based Optimization (TLBO) to balance time and cost factors in construction project planning [2]. Expanding on this, Salama and Moselhi (2019) incorporated multi-objective optimization frameworks that integrate time, cost, and quality considerations, offering a more comprehensive decision-making approach [3].

Work package-based information modeling has emerged as an effective approach for addressing resource constraints in construction scheduling. Wang et al. (2020) highlighted how this methodology enhances resource visualization and management, which is crucial for optimizing complex schedules in construction projects [4]. Complementing this approach, Dabirian et al. (2019) focused on the dynamic modeling of human resource allocation, enabling adaptive planning strategies that respond to evolving project needs and ensure optimal resource utilization [5]. Further advancements in this area include the integration of predictive analytics and machine learning to enhance resource allocation and scheduling decisions in dynamic environments (Del Gallo et al., 2023) [6].

Technological advancements have further transformed scheduling optimization. Abd Elaziz et al. (2021) investigated how the Internet of Things (IoT) and cloud-fog computing environments can improve task scheduling by integrating transportation and service selection considerations [7]. This integration has facilitated real-time monitoring and decision-making, enabling more efficient and adaptive scheduling processes.

The application of artificial intelligence (AI) in project scheduling has gained significant traction, as noted by Bahroun et al. (2023), who demonstrated how AI offers innovative solutions to complex planning problems by analyzing large datasets to identify patterns that enhance planning decisions [8]. Reinforcement learning and neural networks have also been used to optimize schedules in dynamic and uncertain conditions, providing project managers with actionable insights and improved decision-making capabilities [9].

Schedule compression strategies represent another important dimension of optimization. Tomczak and Jaśkowski (2020) examined resource relocation as an effective approach to meet demands for rapid project delivery [10]. Pan and Zhang (2021) emphasized the importance of integrated approaches that combine advanced optimization techniques, dynamic modeling, and AI applications for effective project scheduling in construction [11]. Additionally, Milat et al. (2021) highlighted the importance of dynamic scheduling, which emphasizes flexibility to adapt to changes in project scope, resource availability, and unforeseen conditions, thus ensuring project stability and performance [12].

2.2. Risk Analysis in Construction Management

Risk analysis methodologies in construction have seen significant advancement, particularly in addressing uncertainties inherent in project planning. Koulinas et al. (2020) explored Monte Carlo simulation for risk management, highlighting how this technique uses statistical distributions to model risks and predict outcomes by running simulations with random values [13]. Their research emphasized the importance of expert judgment when data is limited and how distribution selection is influenced by managers' experience. Deng and Jian (2021) further demonstrated the superiority of Beta-PERT distributions in modeling project durations, as they incorporate expert judgment and provide a more realistic representation of uncertainty compared to Triangular or Uniform distributions [14].

Dynamic risk assessment models have gained prominence for their ability to continuously evaluate risks in real time. Ashtari et al. (2022) demonstrated how these models consider interdependencies between factors to enhance resilience and adaptability in construction project management while addressing dynamic and uncertain conditions [15]. Recent advancements include integrating AI-driven predictive models to identify emerging risks and recommend mitigation strategies, enabling project managers to proactively address potential delays and cost overruns (Chen et al., 2023) [16].

The incorporation of risk contingencies is vital for enhancing project reliability. Tokdemir et al. (2019) explored how established contingencies for time and cost serve as essential buffers against uncertainties, thereby improving project reliability by addressing variability in labour-hour requirements and activity durations through probabilistic approaches, including Monte Carlo simulation [17]. Quantitative risk assessment has evolved with the development of probabilistic risk indicators. Acebes et al. (2020) introduced metrics like Schedule Risk Value (SRV) that offer quantitative measures for comparing risk levels across project schedules by quantifying total uncertainty throughout the project lifecycle, aiding in identifying activities with the highest risk contribution [18].

Bayesian risk models represent another significant advancement in risk analysis. Namazian et al. (2019) demonstrated how Bayesian networks can dynamically assess risks by integrating probabilities, impacts, and interactions of factors, supporting informed decision-making and visualizing their cumulative effects on project outcomes [19]. Additionally, Monte Carlo Simulation has emerged as a valuable tool for improving risk assessment in construction projects. Larionov et al. (2021) emphasize its capability to evaluate uncertainties by modeling diverse risk scenarios, enabling stakeholders to better understand potential environmental impacts and make informed decisions to mitigate risks effectively [20].

2.3. Monte Carlo Simulation in Construction Projects

Monte Carlo methods have emerged as powerful tools for addressing uncertainties in various scientific and engineering fields. Zhang (2020) highlighted how modern Monte Carlo simulations, including multilevel and multi-fidelity approaches, improve the efficiency and accuracy of uncertainty quantification, allowing for better-informed decisions in complex systems [21]. These techniques have proven particularly valuable in contexts where traditional deterministic methods fail to adequately account for potential uncertainties and outcomes.

The application of Monte Carlo simulation to construction projects has proven to be highly effective in managing risks and uncertainties. Sobieraj and Metelski (2022) utilized the Monte Carlo simulation alongside the Time-at-Risk (TaR) approach to analyse the Fort Bema housing estate project in Warsaw, Poland. Their research highlighted how this combined methodology can account for various factors influencing project timelines, including scheduling complexities and interdependencies between project phases [22]. The study revealed that using Monte Carlo simulation improved the accuracy of schedule predictions, allowing project managers to anticipate potential delays and enhance overall project reliability.

Comparative studies of probability distributions in Monte Carlo simulation have revealed important differences in their applicability. Deng and Jian (2021) highlighted that the analysis of Triangular, beta-PERT, and Uniform distributions indicates that they offer a more realistic representation of uncertainty in project durations due to their flexibility and incorporation of expert judgment. While simple and valuable for quick assessments, Triangular distributions may introduce bias due to their linear probability assumption, making them less accurate in certain scenarios. In contrast, Uniform distributions provide an equal likelihood for outcomes but cannot model variability effectively, resulting in reduced reliability for risk assessment [14].

2.4. Research Gap

Despite extensive research on schedule delays in construction projects worldwide, the Moroccan construction sector remains underexplored in terms of tailored risk analysis and scheduling optimization techniques. Bajjou and Chafi (2018) highlighted that nearly 60% of Moroccan construction projects experience delays due to late progress payments, unrealistic contract durations, and workforce training gaps. These challenges are compounded by reliance on traditional deterministic methods, which fail to account for uncertainties inherent in local industry practices adequately. Furthermore, while Monte Carlo simulation has been widely applied in global construction projects, there is a lack of empirical evidence demonstrating its effectiveness in Morocco's construction sector.

This research addresses these gaps by:

- Applying Monte Carlo simulation to a real construction project in Morocco, considering local industry parameters and constraints.
- Comparing the performance of three probability distributions (Triangular, Betapert, and Uniform) in this specific context.
- Developing tailored recommendations for scheduling optimization and risk management in Moroccan construction projects.
- Providing empirical evidence on the effectiveness of Monte Carlo simulation in enhancing project planning reliability in the regional context.

By addressing these gaps, this study contributes to the theoretical understanding of risk analysis and offers practical tools for Moroccan stakeholders-contractors, clients, and regulators-to improve project outcomes. Additionally, the findings can be adapted to similar contexts in other developing economies within the MENA region, enhancing their relevance and impact.

3. Methodology

3.1. Monte Carlo Simulation Implementation

The Monte Carlo simulation was implemented using Microsoft Excel to enhance computational efficiency and accuracy. The simulation involved 1,000 iterations for each probability distribution type to ensure statistical significance and provide robust results. The choice of 1,000 iterations was based on prior studies, demonstrating that this number minimizes outcome variability while maintaining computational feasibility.

3.2. Probability Distributions

Three probability distributions were applied to model uncertainty in activity durations, selected based on historical data, expert judgment, and the nature of each activity:

- Triangular Distribution: Defined by minimum, most likely, and maximum values. This distribution was selected for activities where expert judgment provided clear boundaries, but limited historical data was available.
- Betapert Distribution: A variation of the Beta distribution defined by minimum, most likely, and maximum values, but with greater weight given to the most likely value. This distribution was chosen for activities with more reliable historical data and where extreme values were considered less probable.
- Uniform Distribution: Defined by minimum and maximum values with equal probability across the range.

This distribution was applied to highly uncertain activities and a limited basis for determining the most likely value.

3.3. Simulation Parameters and Assumptions

To ensure the simulation accurately reflected Moroccan construction conditions, the following parameters and assumptions were established: following parameters and assumptions were established for the Monte Carlo simulation:

- Activity Duration Ranges: High certainty (±10% of the baseline duration), Medium certainty (±20% of the baseline duration) and Low certainty (±30% of the baseline duration). These ranges were validated using historical data from five completed Moroccan construction projects.
- Correlation Factors: 0.3 applied between similar activities sharing common risks (e.g., similar labour requirements). 0.4 applied to activities dependent on shared resources (e.g., equipment availability) and 0.5 to weather-dependent activities, reflecting Morocco's seasonal weather variability.
- Calendar Considerations: The simulation incorporated the Moroccan working calendar and typical working hours in the local construction industry (8:00 AM–5:00 PM)
- National holidays and Ramadan were excluded to reflect realistic working conditions.

3.4. Model Validation and Calibration

The simulation model was validated and calibrated through a rigorous process to enhance its reliability and applicability:

- Historical Data Validation: The model parameters were compared with historical data from five similar completed projects in Morocco, adjusting distribution parameters to align with observed variations in actual project execution.
- Expert Review: A panel of five construction management experts with extensive experience in Moroccan projects reviewed the model assumptions and parameters, providing feedback incorporated into the final model.
- Sensitivity Analysis: Key parameters were varied by ±10% to assess their impact on simulation outcomes, identifying the most influential factors for focused attention.
- Calibration Process: The model was calibrated by comparing initial simulation results with actual progress data from the project's first three months, adjusting distribution parameters to improve alignment between predicted and actual performance.

This validation and calibration process ensured that the simulation model accurately reflected the specific conditions and uncertainties of construction projects in the Moroccan context, enhancing the reliability and applicability of the results.

4. Case-study

4.1. Model Validation and Calibration

This study examines a mixed-use development project in Casablanca, Morocco, representing the region's medium to large-scale urban construction. The building features a single level with a total area of 15,000 square meters. It is designed to encompass all work types-structural, secondary, technical, architectural, and finishing-within one comprehensive operation. The project was chosen for its complexity, alignment with local and international standards, and the availability of historical data for comparative analysis. The construction schedule consists of 21 main tasks, grouped into seven major phases: site preparation, foundation work, structural framework, exterior envelope, interior systems, finishing works, and site completion. The workflow is designed with a systematic and sequential approach, where each task is dependent on the completion of the previous one, ensuring logical progression, structural integrity, and efficient resource allocation.

Fig. 1 Superstructure elevation

Fig. 2 Superstructure slab ground floor

Fig. 3 Partitions activities

Fig. 4 Suspended ceiling

Fig. 5 HVAC - networks

Fig. 6 High current/low current – networks

4.2. Optimizing Construction Workflow: A Sequential Approach to Building Efficiency and Quality (Soft Logic)

The sequencing of construction activities is carefully designed to ensure efficiency, structural integrity, and logical progress through various project phases. Each task is interrelated with its predecessors and successors, carefully considering dependencies to minimize delays and optimize resource allocation.

The process begins with the General Contractor Notification, which marks the project's initiation and enables the simultaneous mobilization of resources through the New General Contractor Mobilization phase. This overlap ensures that preparatory activities commence promptly, saving valuable time.

Following mobilization, Groundwork starts, which sets the stage for subsequent construction by preparing the site. The completion of Groundwork allows for the initiation of Infrastructure, laying the foundations for structural stability. The Superstructure follows, requiring a fully completed infrastructure to support the weight and design of the vertical elements.

Once the Superstructure is complete, interior works like Partitions and Technical Rooms commence. The partitions outline the internal spaces, while technical rooms are set up concurrently to expedite the installation of utilities. High Current/Low Current Networks, Plumbing, and HVAC Networks are installed at this stage, depending on the defined room layout for precise positioning of wiring, piping, and ducts. With the basic networks in place, the Suspended Ceiling is installed, ensuring access to overhead utilities without interference. This is followed by the application of Coatings, which provide a finished look to the walls and ceilings, readying them for aesthetic enhancements.

The installation of Wood and Aluminum Carpentry follows, seamlessly integrating fixed furniture and aluminium features with finished walls and ceilings. Primer and a Second Coat are applied next, protecting surfaces and preparing them for final touches while maintaining prior installations. Facades are finalised as the project nears completion, defining the building's external appearance. High/Low Current Terminals, Plumbing, and HVAC Terminals are installed as the last technical elements, integrated into the completed carpentry and Infrastructure. Finally, the Topcoat is applied to perfect the surfaces after all installations, preserving the finished aesthetic. The project concludes with the Milestone Finish, marking the completion of structural and aesthetic work. This logical workflow ensures that each phase builds on the previous, enabling a seamless construction process.

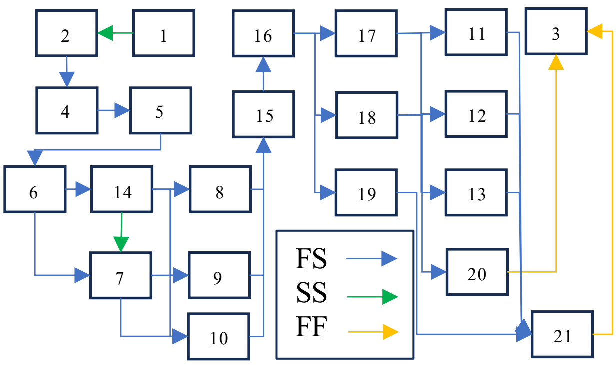

Fig.7 Network diagram for the project of 21 activities

Table 1. Three-point estimate and sequencing for each activity

ID	Activity Name	Predecessors	O	ML	P
1	General Contractor Notification		0	0	0
2	New General Contractor Mobilization	1: SS	25	31	36
4	Groundwork	2: FS	22	28	32
5	Infrastructure	4: FS	25	31	36
6	Superstructure	5: FS	60	75	86
14	Partitions	6: FS, 2: FS	36	45	52
7	Technical rooms	14: SS, 6: FS	25	31	36
8	High Current/Low Current - Networks	7: FS, 14: FS	56	70	81
9	Plumbing - Networks	7: FS, 14: FS	36	45	52
10	HVAC - Networks	7: FS, 14: FS	60	75	86
15	Suspended Ceiling	10: FS, 8: FS, 9: FS	48	60	69
16	Coatings	15: FS	48	60	69
17	Wood Carpentry	16: FS	28	35	40
18	Aluminum Carpentry	16: FS	32	40	46
19	Primer and second coat	16: FS	60	75	86
20	Facades	18: FS	24	30	35
11	High Current/Low Current-Terminals	17: FS, 18: FS	36	45	52
12	Plumbing - Terminals	17: FS, 18: FS	32	40	46
13	HVAC - Terminals	17: FS, 18: FS	24	30	35
21	Topcoat	13: FS, 11: FS, 12: FS, 19: FS	21	26	30
3	Milestone Finish project	20: FF, 21: FF	0	0	0

4.3. Critical and Near-Critical Paths in Project Management Simulations

Project management often requires tracking the Critical Path, which represents the sequence of tasks that must be completed on time for the project to meet its deadline. However, it is also vital to monitor Near-Critical Paths-tasks that are close to being critical. Delays in these near-critical tasks can push them into the critical zone, impacting the project schedule.

Monte Carlo simulations are useful for modeling uncertainty in project timelines and supporting identifying critical and near-critical paths by adjusting task durations, revealing how small delays can shift non-critical tasks into critical ones.

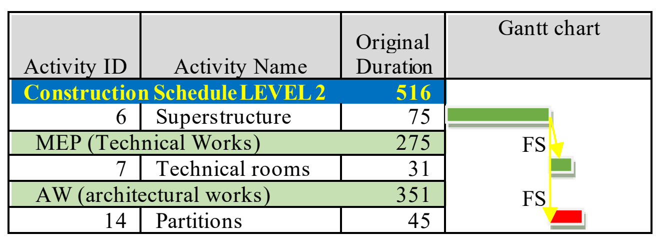

Fig. 8 Critical path shifting

For example, in a construction project, the building of Partitions as a critical task (TF=0) might be the first step, setting the stage for the installation of Technical Rooms. These tasks are concurrent and will start in parallel with the SS (Start to Start) connection. In the planning phase, Technical Rooms has a total float of 14 days, offering some scheduling flexibility but requiring close monitoring to avoid delays. However, in the Monte Carlo simulation, the optimistic duration for Partitions is 36 days, while the pessimistic duration for Technical Rooms is 36 days. This variability suggests that the criticality between these two tasks could pivot during the simulation. A delay in partitions could shift its criticality, potentially impacting the start of technical rooms or vice versa, depending on the fluctuations in task durations. This dynamic highlights the importance of simulations in identifying potential risks and managing dependencies effectively while providing insights into areas where additional resources might be needed to mitigate delays.Similarly, tasks like electrical installations for High Current/Low Current Networks and HVAC Networks often run in parallel, and a delay in one can affect the other. These tasks share resources and space, so disruptions in one area might have a ripple effect, leading to inefficiencies and compounding delays. For instance, if the High Current Network installation is delayed, it could prevent HVAC installations from accessing shared spaces, creating further bottlenecks. Moreover, tasks like Wood Carpentry and Aluminum Carpentry are often scheduled concurrently to optimize progress. However, if the woodwork is delayed, it might push back the aluminium work, especially if both tasks rely on the same resources, such as skilled labour or workspace. Similarly, delays in plumbing terminals could delay HVAC terminal installations, creating a domino effect that impacts the project's overall timeline and increases the risk of missing key milestones. These interdependencies underline the need for careful coordination, proactive planning, and efficient resource allocation to ensure smooth execution and minimize delays.

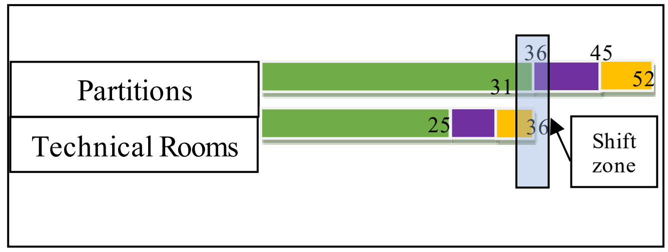

Fig. 9 Critical path shifting zone between partitions and technical rooms

Table 2. Activity table (duration and critical tasks)

Activity ID	Activity Name	Original Duration	Start	Finish	CP
	Construction Schedule Level 2	**516**	**1/1/25**	**5/31/26**	
	Mobilisation & Milestones	516	1/1/25	5/31/26	
1	General Contractor Notification	0	1/1/25		✓
2	New General Contractor Mobilization	31	1/1/25	1/31/25	✓
3	Milestone Finish project	0		5/31/26	✓
	SW (structural work)	459	2/1/25	6/14/25	
4	Groundwork	28	2/1/25	2/28/25	✓
5	Infrastructure	31	3/1/25	3/31/25	✓
6	Superstructure	75	4/1/25	6/14/25	✓
	MEP (Technical Works)	275	7/30/25	5/5/26	
7	Technical rooms	31	6/15/25	7/15/25	
10	HVAC - Networks	75	7/30/25	10/12/25	✓
11	High Current/Low Current - Terminals	45	3/22/26	5/5/26	✓
8	High Current/Low Current - Networks	70	7/30/25	10/7/25	
12	Plumbing - Terminals	40	3/22/26	4/30/26	
9	Plumbing - Networks	45	7/30/25	9/12/25	
13	HVAC - Terminals	30	3/22/26	4/20/26	
	AW (architectural works)	351	6/15/25	5/31/26	
14	Partitions	45	6/15/25	7/29/25	✓
15	Suspended Ceiling	60	10/13/25	12/11/25	✓
16	Coatings	60	12/12/25	2/9/26	✓
17	Wood Carpentry	35	2/10/26	3/16/26	
18	Aluminum Carpentry	40	2/10/26	3/21/26	✓
19	Primer and second coat	75	2/10/26	4/25/26	
20	Facades	30	3/22/26	4/20/26	
21	Topcoat	26	5/6/26	5/31/26	✓

Considering that both the partitions and technical rooms tasks are started on day 1, by day 36, Partitions may have reached their optimistic duration. This would reduce the total float for the Technical Rooms task by 9 days. As a result, the remaining Total Float (TF) for Technical Rooms would be only 5 days, as shown in the purple line. Moreover, if the pessimistic duration for the Technical Rooms task were also set to 36 days in the simulation, this scenario could lead to a shift in the Critical Path. This would occur because all the available, total float for Technical Rooms would be used up, causing this task to potentially move into the critical zone and directly impacting the overall project timeline.

In Monte Carlo simulations, Critical Paths are identified as the tasks whose delays would directly extend the project timeline. However, Near-Critical Paths require close attention, too, as even a minor delay can turn these into critical tasks. For instance, if Wood Carpentry is delayed, it might seem like a minor issue. However, if Plumbing Terminals depend on its completion, this delay could push the plumbing task into the Critical Path, resulting in project delays.

The power of Monte Carlo simulations lies in their ability to model different durations and task dependencies, giving project managers insights into how delays in one task can impact the overall schedule. For example, a delay in Wood Carpentry might seem manageable at first, but if it delays the Plumbing Terminals installation, it could extend the entire project timeline. Monte Carlo simulations can predict such shifts, helping managers take proactive measures, such as adjusting resources or rescheduling tasks. Overall, Monte Carlo simulations offer valuable insights into both Critical and Near-Critical Paths. By tracking how tasks interact and how delays might affect other tasks, project managers can make more informed decisions, manage risks, and keep projects on track.

4.4. Monte Carlo Application for Three Types of Distributions: Triangular, Betapert, and Uniform

4.4.1. Impact of Probability Distributions on Concurrent Tasks: Partitions and Technical Rooms

In this section, the study will focus on examining and assessing the impact of the type of distribution on the critical path and the timely completion of the project by comparing three distributions, Triangular, Bêtapert and Uniform, to define how the type of distribution could shift the near-critical path to the critical path into or during the Monte Carlo distribution.

The figures above depict an example of our project with two concurrent tasks: Partitions and technical rooms. After 1000 simulations for comparing the parallel task duration for Partitions as a critical task and technical rooms as a non-critical task with a total float equal to 14 days using the three distributions, the results are found below:

Triangular Distribution for Two Concurrent Tasks

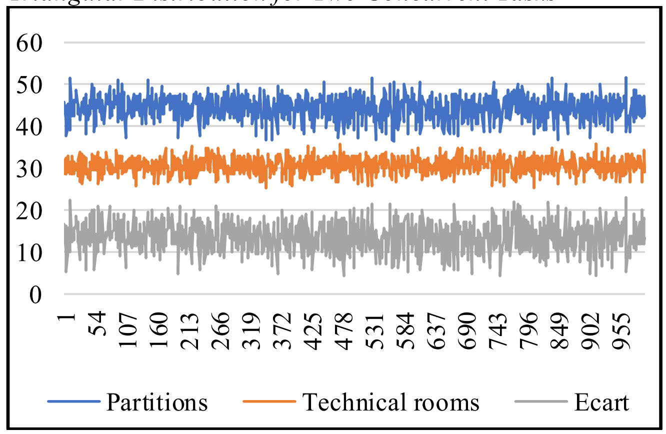

Fig. 10 Triangular distribution duration simulation

Table 3. Interval duration for partitions and technical rooms after 1000 iterations using triangular distribution

	Partitions	Technical rooms
Max duration	51,22055515	35,71749558
Min duration	36,97085424	25,18937525
Iterations Number	1000	

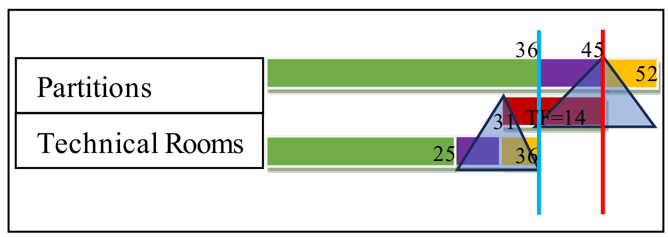

Fig. 11 Triangular distribution for partitions and technical rooms

The simulation shows that all the simulation value durations for the task Partitions are greater than the value durations for technical rooms, which means that the task technical rooms could not be as a critical path in the Monte Carlo simulation and will not be considered as a near-critical path for triangular distribution.

Betapert Distribution for Two Concurrent Tasks

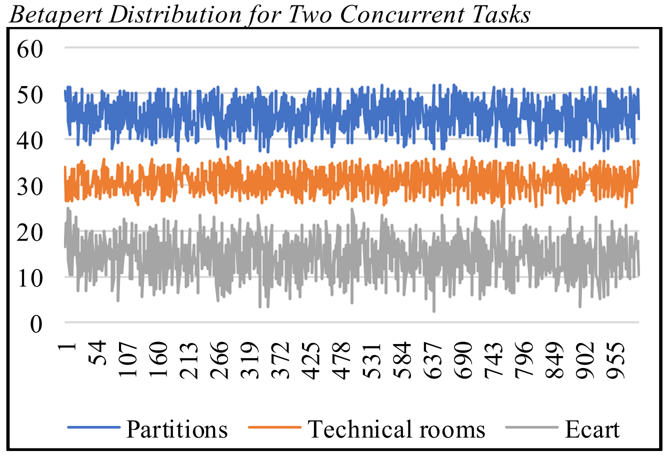

Fig. 12 Betapert distribution duration simulation

Table 4. Interval duration for partitions and technical rooms after 1000 iterations using betapert distribution

	Partitions	Technical rooms
Max duration	51,75778329	35,93227685
Min duration	36,5015693	25,42402024
Iterations Number	1000	

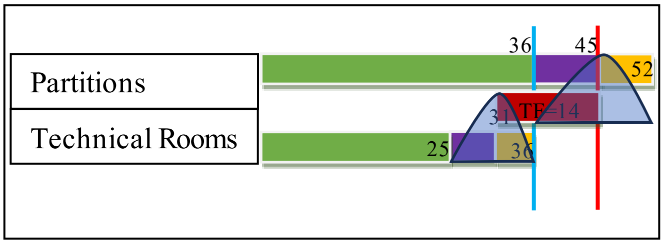

Fig. 13 Betapert distribution for partitions and technical rooms

The simulation shows the same result as a triangular distribution, which means that the task technical rooms could not be as a critical path in Monte Carlo simulation and will not be considered as a near-critical path for triangular distribution because the maximum duration of technical rooms activity stills less than minimum duration of partitions activity and no Intervale intersection.

Uniform Distribution for Two Concurrent Tasks

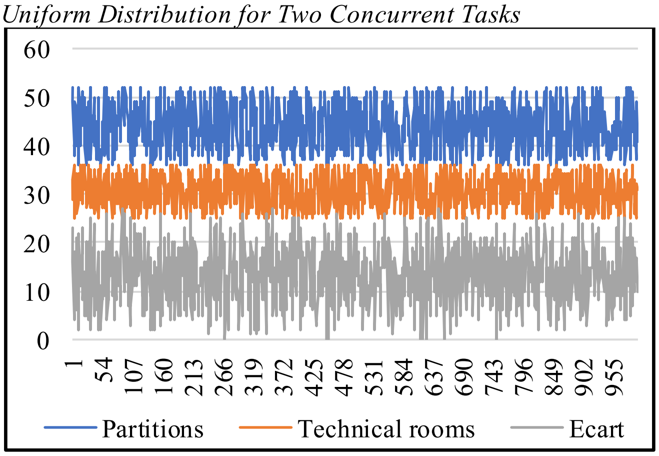

Fig. 14 Uniform distribution duration simulation

Table 5. Interval duration for partitions and technical rooms after 1000 iterations using uniform distribution

	Partitions	Technical rooms
Max duration	52	36
Min duration	36	25
Iterations Number	1000	

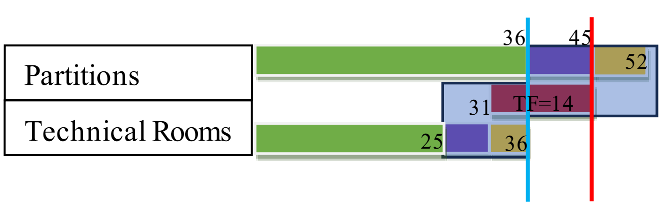

Fig. 15 Uniform distribution for partitions and technical rooms

This distribution does not use the three-point estimate; it uses just the minimum and maximum duration values using a discrete uniform distribution.

The simulation shows that the variance value durations for the task Partitions and Technical rooms could be null, which means that the task technical rooms could be a critical path in Monte Carlo simulation, exceptionally for Uniform distribution and will be considered as a near-critical path for uniform distribution with a criticality percentage of 1%.

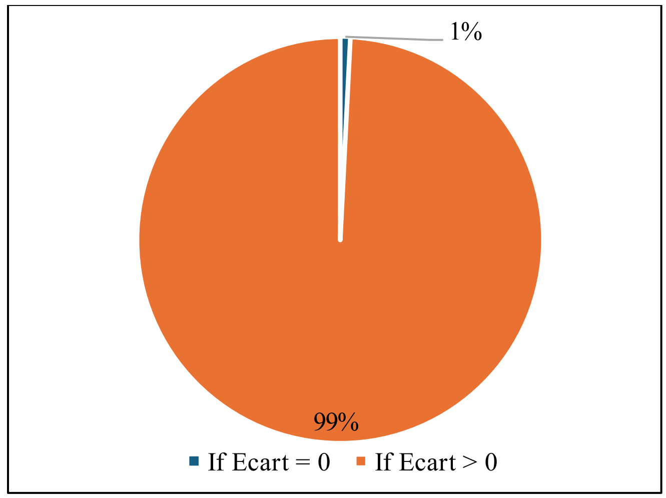

Fig. 16 Criticality percentage for technical rooms and partitions tasks, based on uniform distribution after 1000 iterations

The Result of Comparing the Triangular, Betapert, and Uniform Distributions for the Two Concurrent Tasks

Table 6. Interval durations for different distributions (1,000 iterations)

Activity	Max Duration	Value Duration (1000 iterations)	Distribution Type	Criticality
Partitions	51	37	Triangular	100%
Technical Rooms	36	25	Triangular	0%
Partitions	52	37	Betapert	100%
Technical Rooms	36	25	Betapert	0%
Partitions	52	36	Uniform	99%
Technical Rooms	36	25	Uniform	1%

In comparing distribution types-Triangular, BetaPert, and Uniform-, we see varying behaviors in how activity durations and criticality are modeled, particularly in the context of partitions and technical rooms. The Triangular distribution is characterized by a shape that reflects a most likely value between a minimum and maximum range, and this results in partitions being classified as critical in all cases, with a 100% criticality.

Technical rooms, however, remain non-critical. This suggests that the Triangular distribution places partition firmly on the critical path, while technical rooms do not significantly influence the project timeline despite their varying durations. The Betapert distribution, which is similar but designed to capture skewed data and real-world uncertainties better, follows a comparable pattern. Partitions continue to show a 100% criticality, while technical rooms maintain a 0% criticality.

The Betapert distribution might produce more concentrated or skewed results depending on how the most likely duration is set. However, compared to the Triangular distribution, it does not alter the underlying criticality relationship between partitions and technical rooms. Uniform distribution, however, introduces a different dynamic. This distribution assumes equal probability across its entire range, meaning that every value between the minimum and maximum has an equal chance of occurring. As a result, partitions still show a high likelihood of being critical, though the probability drops slightly to 99% compared to the 100% criticality observed in the Triangular and Betapert distributions.

The shift here is more noticeable with technical rooms, where the criticality is now 1%, indicating that in some rare cases, technical rooms might become critical in this scenario. This small probability suggests that, under the Uniform distribution, the allocation of technical rooms could, in rare instances, influence the project's critical path, which was not the case with the Triangular or Betapert distributions. The key takeaway is that while partitions remain almost always critical across all distributions, the criticality of technical rooms is sensitive to the type of distribution used, with the Uniform distribution allowing for a small but non-zero chance of technical rooms becoming critical.

The choice of distribution significantly impacts the criticality modelling in Monte Carlo simulations. The Triangular and Betapert distributions provide more predictable, stable results, with partitions consistently critical and technical rooms that do not affect the overall outcome. Uniform distribution, however, introduces greater variability, especially in technical rooms, where the possibility of them becoming critical, although small, is acknowledged. This demonstrates the influence of distribution assumptions in simulations and highlights the need to carefully choose the distribution type based on the nature of the project and the desired level of variability or uncertainty in the model.

4.4.2. Generation of Curves by Monte Carlo Simulation for Triangular, Betapert, and Uniform Distributions

The Monte Carlo simulation will be applied to a project consisting of 21 activities, with the planned start date set for January 1, 2025, and the expected finish date on May 31, 2026, giving the project a total duration of 23 months. In this analysis, the primary goal is to compare the impact of three different types of probability distributions on the project's completion date. Specifically, the focus will be understanding how each distribution affects the likelihood of meeting the project's deadline.

The input data for the simulation includes estimates of the duration of three points for each activity. For every task, the most likely duration (based on current knowledge), the optimistic duration (best-case scenario), and the pessimistic duration (worst-case scenario) will be provided. These estimates will allow for a probabilistic analysis of the potential variation in task durations throughout the project. Along with the duration estimates, the critical path will be identified, which represents the sequence of dependent activities that determines the overall project duration.

The near-critical path will also be considered; these activities are close to the critical path and could become critical if their duration increases. The simulation will consider the maximum potential duration difference between concurrent activities on these paths, ensuring that the simulation reflects the fundamental dynamics of project scheduling and helps provide a more reliable result.

The Monte Carlo simulation will be set to run 1,000 iterations in order to generate statistically meaningful results. During these iterations, the simulation will assess the impact of three different probability distributions on the project timeline. These distributions include the triangular distribution and the beta distribution, which are helpful when only three estimates (optimistic, most likely, and pessimistic) are available and applied when more detailed data or historical information is available for more accurate task duration estimation and the uniform distribution, which assumes that all durations between the optimistic and pessimistic estimates are equally likely.

By applying these different distributions, the simulation will explore how each one influences the predicted completion date of the project, allowing for a comprehensive understanding of how variations in task durations can impact the overall project schedule.

$The outcome of the Monte Carlo simulation will be presented in the form of probability distribution histogram and cumulative distribution function (CDF) curve, which will show the likelihood of completing the project by different dates. Key milestones will be highlighted, such as the 50th percentile, which represents the date by which there is a 50% chance of completing the project, and the 80th percentile, which indicates the date by which there is an 80% chance of completion. These graphical representations will provide valuable insights into the potential risks of the project's timeline and help stakeholders understand the probability of meeting the planned finish date.

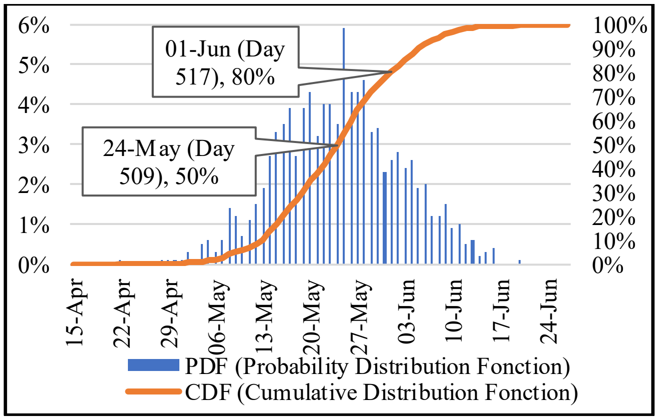

Fig. 17 Distribution curves and histograms for a triangular distribution

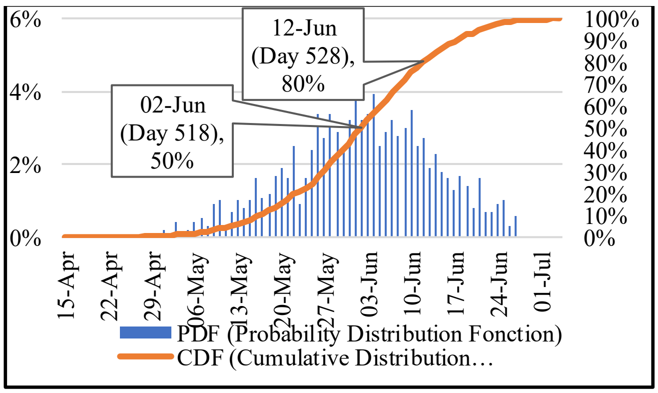

Fig. 18 Distribution curves and histograms for a beta part distribution

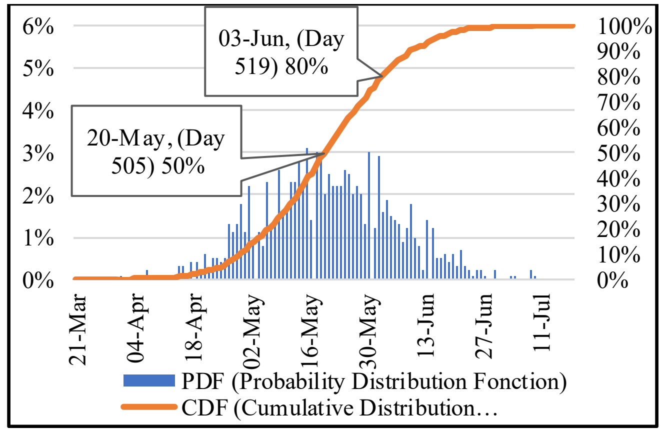

Fig. 19 Distribution curves and histograms for a uniform distribution result of comparing the triangular, betapert, and uniform distributions for the current project (21 tasks)

Table 7. Interval and variance probabilities for three distributions

Distribution	Distribution Interval (day)	P (50%)	P (80%)	Variance P(80%) & P(50%)
Triangular	59	509	517	8
Bêtapert	67	518	528	10
Uniform	100	505	519	14

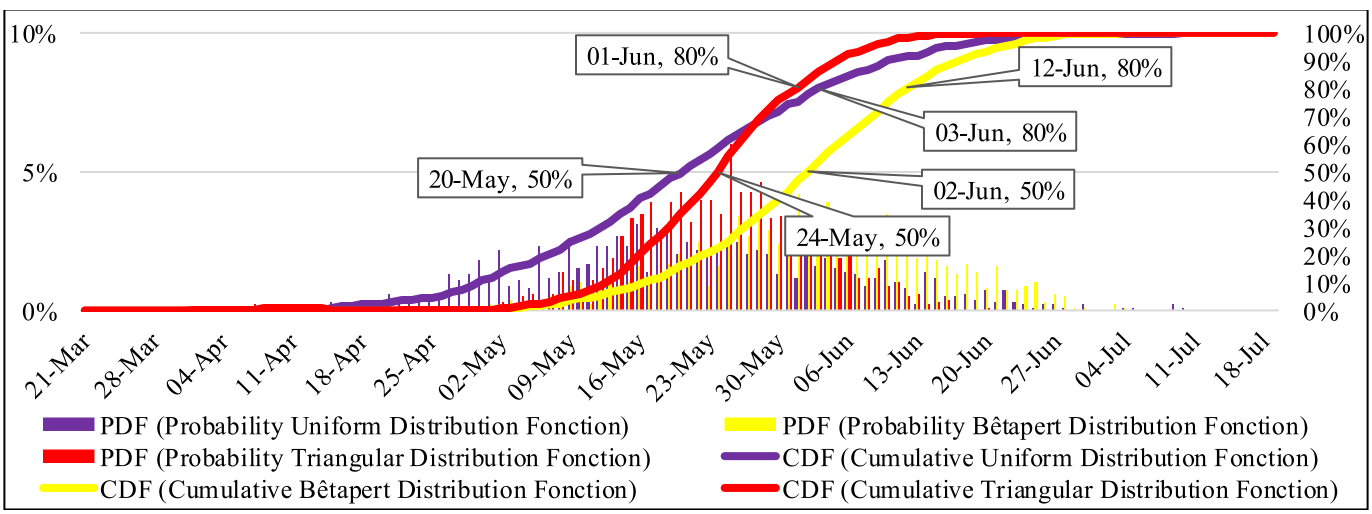

Fig. 20 Curves and histograms for three distributions

After generating the distribution curves and histograms for three distributions - Uniform, Triangular, and Betapert - and comparing them on a single diagram, we observed the following key insights:

- Uniform Distribution: The earliest probable project completion, according to the Uniform Distribution, starts at 483 days (April 1, 2026). The distribution spans the widest interval, from the earliest completion at 483 days to the latest completion at 556 days (July 10, 2026), covering a range of 100 days. Additionally, the variance between P(50%) and P(80%) is 14 days, meaning an extra 14 days are required to increase the probabilistic confidence from 50% to 80%. The originally planned critical path duration is 516 days (May 31, 2026). To increase the confidence level by 30%, the project would need an additional 2.7% of the total planned duration, which corresponds to 14% of the interval represented by the Uniform distribution.

- Betapert Distribution: The Betapert distribution suggests that the latest probable completion starts at 456 days (April 28, 2026) but does not indicate the earliest probable completion date. This distribution spans an intermediate range between the Uniform and Triangular distributions, from 483 days to 550 days (July 4, 2026), covering 67 days. To match the Uniform distribution's finish date, an additional 6 days would be required. The variance between P(50%) and P(80%) in this distribution is 10 days, meaning an extra 10 days are needed to achieve a 30% increase in the confidence level. Initially planned at 516 days, the critical path would require an additional 1.9% of the total planned project duration to increase the confidence level by 30%. This corresponds to approximately 15% of the Betapert distribution interval.
- Triangular Distribution: The Triangular distribution shows the second earliest completion date is 477 days (April 22, 2026). This distribution covers the smallest range between the three, from 477 days to 536 days (July 20, 2026), spanning only 59 days - much narrower than the 100-day ranges of the Uniform and Betapert distributions. To match the Uniform distribution's completion date, an additional 20 days would be required. The variance between P(50%) and P(80%) is 10 days, meaning 8 extra days are needed to increase the confidence level by 30%. The critical path duration of 516 days (May 31, 2026) would need an additional 1.6% of the total project duration to meet the 30% increase in confidence, corresponding to 14% of the Triangular distribution interval.

When comparing the three distributions for this project with identical input data, we observed the following:

- Uniform Distribution has the largest interval, providing the minimum value in the histogram, but with the broadest range (100 days).
- Betapert Distribution offers a moderate range, with an intermediate distribution between the Uniform and Triangular, requiring a 6-day adjustment to match the Uniform's finish date.
- Triangular Distribution shows the highest probability density, with the smallest interval (59 days), representing the lowest level of uncertainty. It also has the peak probability value, indicating a more concentrated project completion estimate.

Table 8. Interval distributions

Distribution	Minimum duration	Maximum duration	Distribution Interval (day)
Triangular	477	536	59
Betapert	483	550	67
Uniform	456	556	100

In summary, each distribution provides valuable insights depending on the level of uncertainty and the desired confidence in project completion.

5. Conclusion

This study highlights the critical impact of variation in probability distributions on the outcomes of Monte Carlo simulations in project management, particularly for risk analysis and scheduling optimization. By comparing the Triangular, Betapert, and Uniform distributions, the findings demonstrate how the choice of distribution directly influences the criticality of tasks, project timelines, and overall risk assessment. The results reveal that Triangular and Betapert distributions offer more predictable and concentrated estimates of project completion, with narrower intervals and higher confidence levels. These distributions are particularly effective for projects with well-defined task durations, minimizing uncertainty and providing stable critical path predictions. Conversely, the Uniform distribution introduces greater variability with a broader range of possible outcomes.

This distribution occasionally shifts near-critical tasks into the critical path, showcasing its sensitivity to uncertainty and ability to model less predictable scenarios. The impact of these variations is profound in the context of Monte Carlo simulations for risk analysis and scheduling optimization. The choice of distribution affects the identification of critical and near-critical paths, influencing resource allocation, risk mitigation strategies, and decision-making reliability. For instance, while the Triangular and Betapert distributions consistently classify partitions as critical tasks, the Uniform distribution introduces a small probability of technical rooms becoming critical, demonstrating how distribution assumptions can alter risk profiles.

From a risk analysis perspective, Monte Carlo simulations allow project managers to quantify uncertainties and assess their potential impacts on project timelines. By integrating probabilistic insights, managers can proactively address risks, allocate resources effectively, and enhance decision-making under uncertainty. The study underscores the importance of selecting an appropriate distribution type to balance predictability and flexibility, ensuring project schedules remain resilient to variability while optimizing efficiency and outcomes.

In conclusion, this research emphasizes that selecting probability distributions in Monte Carlo simulations is not merely a technical choice but a strategic decision that significantly influences the reliability of risk analysis and the effectiveness of scheduling optimization. By carefully considering the nature of the project and its inherent uncertainties, managers can leverage these simulations to improve project resilience, optimize timelines, and achieve better overall performance in construction project management.

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Abbreviation

AI	:	Artificial Intelligence
FF	:	Finish to finish
FS	:	Finish to start
IoT	:	Internet of Things
MENA	:	Middle East and North Africa
ML	:	Most likely
O	:	Optimistic
P	:	Pessimistic
SS	:	Start to start
TCTP	:	Time-Cost Trade-off Problem
TLBO	:	Teaching Learning Based Optimization