

PROBABILISTIC SCHEDULING OF RESIDENTIAL CONSTRUCTION USING MONTE CARLO SIMULATION

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Abstract

The Precedence Diagram Method (PDM) relies on deterministic activity times to calculate the Total Project Duration (TPD), a characteristic that inherently limits its predictive accuracy. To address this limitation, the present study integrates Monte Carlo Simulation (MCS) with conventional PDM calculation to predict the TPD of a luxury housing project. Initially, the critical path was identified through the conventional PDM approach. Subsequently, MCS was applied, running 10,000 iterations under the assumption of a normal distribution for all activity durations. The choice of normal distribution is grounded in Central Limit Theorem (CLT), which is efficient for aggregate project level. The TPD for each iteration was recorded, thus generating a probability distribution for project completion time. The deterministic PDM analysis initially yielded a TPD of 420 days. In contrast, the MCS approach produced a mean TPD of 397 days (a 23-day reduction) and revealed only a 45.6% probability of meeting the original deterministic completion date. By incorporating the inherent variability of activity durations, the MCS-derived TPD provides significantly more realistic timeline projections and probabilistic insights. This study demonstrates the potential of MCS in residential construction projects, which remains underutilized in Thailand. Consequently, this research demonstrates a tangible advancement over conventional, deterministic network planning methodologies.

Keywords: Construction Project Scheduling; Construction Uncertainty; Monte Carlo Simulation; Precedence Diagram Method; Residential Building Project; Risk Management

Introduction

Growth was notably projected for Thailand's construction sector during 2024-2025, covering new residential and commercial properties like offices and retail spaces, in addition to renovations of existing hotels and retail areas (SCB Economic Intelligence Center, 2024). Accordingly, Thailand's construction sector has significant growth opportunities in two main segments:

(1) government-led, public-sector construction initiatives such as key infrastructure projects including the expansion of mass transit, double-tracked railway, and motorway networks. The Eastern Economic Corridor (EEC) development is a key attention. (2) the private construction sector includes both residential and commercial developments. Specifically, residential projects are

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recognized as a crucial segment (SCB Economic Intelligence Center, 2024). Comprehensive construction planning, particularly in the foundational scheduling stage, is vital for construction project success.

Conventional PDM's fundamental flaw—its omission of inherent uncertainties—systematically leads to schedule delays that escalate into critical financial overruns. This systemic failure necessitates the application and validation of the PDM-MCS integration to mitigate these risks. Moreover, conventional scheduling methods like CPM and PERT rely on single-point estimates, failing to account for the inherent uncertainty and risk in activity durations, particularly in complex residential construction. Addressing this gap, this study integrates the Precedence Diagramming Method (PDM) with Monte Carlo Simulation (MCS) to systematically assess the probability of meeting project time objectives by incorporating risk probability distributions, thus providing a more robust scheduling model than traditional approaches, which is in line with Karabulut (2017), Fadjar *et al.* (2022), and Nuntiya *et al.* (2023).

This study selected residential projects for this project management planning study because these construction projects are numerous and widely dispersed across Thailand, directly impacting the fundamental household economic level. Furthermore, residential projects often face high time and cost risks during initial planning, which, combined with the availability of required data, led to the application and validation of the PDM-MCS integration to mitigate these risks.

This research investigates the implementation schedule of a completed luxury residential project. The objective was set to evaluate the effectiveness of the PDM-MCS integration, to improve scheduling accuracy, and to manage uncertainty in the aforementioned residential construction. The two-story, reinforced concrete structure had a usable area of 2,166 m², a total construction area of 4,450 m², and a contract value of 53.5 million baht (including VAT). Data from the original construction plan, a conventional bar chart, was used to develop a Precedence Diagram Method (PDM) plan detailing all activity levels and their implementation periods. Monte Carlo Simulation (MCS) techniques were employed to refine schedule calculations, enhancing both conciseness and accuracy. This research focuses on project implementation timelines and the interrelationships between construction activities. Fundamentally, deadlines emerge as a critical factor, significantly influencing both quality and cost. This aligns with the principles of the project management triangle, which illustrates the interconnected relationship

between a project's time, cost, and scope (El-Far *et al.*, 2023; Rosalinda *et al.*, 2023). Consequently, this study offers a detailed analysis of the construction schedule for the aforementioned luxury housing project, which will be discussed further.

Literature Review

Effective scheduling is vital for managing delays in residential building projects, especially as globalization increases their scale and complexity in Thailand. Project management software helps mitigate these challenges by reducing paperwork and saving time (Harshavardhan *et al.*, 2023). Along with cost and performance, timeliness constitutes a crucial metric for evaluating project success (Kamandang, 2021). Consequently, adherence to project deadlines is crucial for project success (Kamandang, 2021; Naguib *et al.*, 2022). Specifically, project delays significantly hinder overall performance (Mejía *et al.*, 2023). To achieve effective project scheduling, project managers must carefully consider resource allocation, activity duration estimation, and robust strategies for handling project uncertainty (Zhou *et al.*, 2013). Perminova *et al.* (2008) highlight uncertainty in project scheduling, particularly regarding resource availability, which results from insufficient data on eventualities. A study in Indonesia investigated this, identifying key factors at both the planning and implementation stages that contribute to overall project success (Zhou *et al.*, 2013). The frequent omission of comprehensive scheduling clauses in construction contracts makes time management critical. Failure to meet deadlines leads to significant financial penalties and indirect damages, and despite extensive research, practitioners still grapple with proper scheduling and delay mitigation (Hansen *et al.*, 2023). Construction projects are characterized by highly variable, site-specific conditions, labor-intensive operations, the involvement of diverse stakeholders, fragmented supply chains, significant dependence on a wide range of suppliers of materials and equipment, and the dominance of SMEs (Hosseini *et al.*, 2012). Project schedule planning depends on various key factors: (1) Project Scope and Design: The clarity and detail of the project design. (2) Resource Availability: Consistent access to labor, materials, and equipment. (3) External Factors: Unpredictable elements like weather, site constraints, and regulatory permits. (4) Project Management: The effectiveness of communication, risk management, and scheduler expertise. (5) Other Factors: Considerations such as project cash flow and safety regulations (Durdyev and Hosseini, 2020). Critical

delays impact activities on the project's critical path and therefore push back the final completion date. In contrast, non-critical delays affect individual tasks but do not impact the overall project deadline. Concurrent delays occur when two or more separate, independent delays happen at the same time. Delays are also categorized by responsibility: excusable or compensable delays are typically unforeseeable and outside the contractor's control, while non-excusable delays are the contractor's responsibility (Lepage, 2017). External delays are caused by third parties outside the project, such as government agencies or utility providers. Conversely, internal delays originate from the project's own stakeholders (Durdjev and Hosseini, 2020). For successful project management in residential construction, defining and scheduling clear timelines, deliverables, and milestones is critical to track progress and prevent costly delays (Rathod and Patil, 2016). This research analyzes a residential building project schedule to examine its relationship with scheduling techniques and network diagram types. The methodology for this analysis is detailed in the following section.

Project Schedule Network Diagrams with CPM/PDM

Network scheduling is one of the most significant project management techniques (Hajdu and Isaac, 2016). The logic of network techniques is graphically understandable and visible because they are represented in a graphical form that illustrates the order of activities by linking vertices and arrows. This approach is demonstrated by the three initial techniques that were created: the Program Evaluation and Review Technique (PERT), the Critical Path Method (CPM), and the Precedence Diagram Method (PDM) (Hajdu and Isaac, 2016; Asyrofi and Arumsari, 2023). In this research, the researchers will specifically focus on CPM and PDM, respectively. CPM is a fundamental project scheduling technique that optimizes completion time by identifying the critical path (the longest sequence of activities). This process facilitates efficient scheduling and resource management to ensure timely project delivery (Asyrofi and Arumsari, 2023; Danfulani *et al.*, 2023). CPM is an essential tool for construction project managers, providing a systematic framework for planning, scheduling, and monitoring projects. The technique functions by analyzing the network of activities to predict the total project duration. This process involves calculating the earliest and latest start and finish times for each task, which determines the float (or slack) available for every activity. Consequently, this approach helps ensure projects are completed on time, within budget, and to the desired quality

standards (Danfulani *et al.*, 2023). PDM evolved to offer enhanced flexibility in project planning by enabling the clear visualization of task dependencies and relationships. In contrast to CPM, which prioritizes timeline optimization, this technique refines project plans by emphasizing task relationships and sequences. This approach improves overall project coordination, establishing a more dynamic and communicative framework for project scheduling and execution.

PDM is a networking method within the AON (Activity on Node) classification. In this method, the activity is represented by a generally rectangular node, with arrows indicating the relationship between related activities. Thus, the dummy logical dependencies are not required in PDM. The precedence method diagram describes logical activity relationships; each node represents an activity with a start (S) and a finish (F) point (Tang *et al.*, 2015). Table 1 compares the CPM and PDM methods. Based on these distinctions, the researchers applied PDM to schedule the residential building case study, as detailed in the Methodology.

Table 1. Differences between CPM and PDM (Modified from Asyrofi and Arumsari, 2023)

Attributes	CPM	PDM
Diagram Representation	Activities on arrows	Activities on nodes (boxes)
Dummy Activities	Uses dummy activities to show dependencies	No dummy activities
Activity ID	Two separate numbers (i & j) for each activity	Single unique number for each activity
Project Duration Calculation	Uses forward and backward pass	Uses the same calculation as CPM
Strengths	Well-established method, widely used in project management software	More flexible for complex dependencies, easier to visualize logic
Weaknesses	Cluttered with dummy activities, less intuitive for complex projects	Limited to scheduling, doesn't consider resources
Typical Use Cases	Construction, engineering, and manufacturing projects	Research & development, software development projects Increasingly used in the construction industry.

Monte Carlo Simulation

Avlijaš (2019) stated that Monte Carlo Simulation (MCS) is valued for project time management, supporting risk analysis and schedule prediction despite underutilization by practitioners.

This evaluation of MCS for project time and schedule management combines traditional foundations with this modern technique for analysis. MCS has evolved into a key tool for software project schedule management. It enhances the reliability of schedule predictions, assists in plan execution, and helps control project duration by using probability distributions to model potential outcomes.

Applying the MCS Technique to suspension bridge construction scheduling yielded a predictive accuracy of 93.99% to 98.77%. This result confirms that MCS is a highly effective method for estimating project timelines (Santony, 2020). The limitations of project scheduling using PDM are related to estimating duration and potential inaccuracies in project schedules. Additionally, several academic papers discuss the challenges associated with accurate project scheduling and emphasize the need for combining multiple techniques with regular updates to improve accuracy. Specifically, the Project Management Institute (PMI) does not explicitly state that PDM's accuracy is under 50%; it does discuss the limitations and challenges associated with project scheduling and the importance of using multiple techniques with regular updates to ensure accuracy (Project Management Institute [PMI], 2017). This study analyzes the weaknesses of network scheduling methods like PDM by applying MCS to construction project risks. Project complexity and investment value directly impact duration, and unforeseen risks often cause delays and cost overruns. MCS provides a robust method for assessing these scheduling risks (Hendradewa, 2019). Nevertheless, the residential building project from the original study was selected as the case study. By applying mathematical approaches used in CPM-PERT and MCS, Hendradewa (2019) suggested that project managers can mitigate risks and evaluate the feasibility of completing a project on schedule. Specifically, simulation techniques like CPM-PERT and MCS can forecast potential outcomes. The simulation results showed a 62.04% possibility of completing the project in 197 days and a 95% possibility of completing it in 203.1 or approximately 204 days. This provides a tangible, quantifiable assessment of accuracy. Karabulut (2017) studied a project execution tracking system in a medium-sized construction company, proposing two different approaches for project scheduling and monitoring. The study compared traditional methods like CPM and PERT with MCS to estimate the completion time for a luxury villa. The CPM method yielded an optimistic estimate of 186 working days. In contrast, MCS suggested a 50% probability of completion in 205 days, but with a 50% risk of delay. The studies by both Karabulut

(2017) and Hendradewa (2019) shared a similar approach. Chilmi and Wulandari (2020) acknowledged an analysis of the probability and sensitivity of activities affecting project duration. After using of Monte Carlo crystal ball simulation to optimize project duration, the existing schedule of Laves Mall Project proved to be late because it ignored the uncertainty aspects. The software was subsequently used to determine a more efficient project duration. The present undertaking was initially planned for a 500-day completion duration. However, after simulation, the duration was adjusted to 604 days, representing a delay of 104 days, or approximately three months. The analysis revealed that the highest sensitivity work activity affecting the overall project duration is cutting off the head pile cap, with a sensitivity of 18.8%. Furthermore, the Oracle Crystal Ball, Fusion Edition User's Guide (Oracle (n.d.) states that (1) Monte Carlo simulation is a statistical technique used to model uncertainty and variability. (2) It involves generating random values for input assumptions based on defined probability distributions. (3) These random inputs feed into formulas or models to produce a range of possible outcomes. And (4) Monte Carlo simulation provides insights into risk, assists decision-makers' understanding of uncertainty, and aids in making well-informed decisions. Nevertheless, it has been studied extensively by educators and academicians but not studied widely among practitioners, particularly in the Thai construction sector. MCS has advanced with computer hardware and software enhancements, supporting the enhancement of statistical tests and experimental data handling. Monte Carlo procedure has been developed to calculate the precision and accuracy of simulated results, generating multiple independent chains of normal random variates. The simulation procedure has been used to generate new critical values for discordancy and significance tests. This emphasizes the importance of outlier-free data arrays as components of a data structure, used to hold several values in a single variable, for accurate estimations. The findings are consistent with Liu and Li (2014), who claimed that MCS has evolved with advancements in computer technology, enabling more effective implementation on personal computers. The simulation method involves generating random numbers, simulating various distributions, and assessing the accuracy of results, making it essential for evaluating data uncertainty. It can be summarized that MCS complements CPM by addressing uncertainty in construction schedule management, enhancing decision-making by identifying key control points, and improving the probability of on-time project completion, as shown

in previous research studies (Liu and Li, 2014; Karabulut, 2017; Chilmi and Wulandari, 2020). Accordingly, the MCS Technique is also used to identify the project completion date for each possible combination of uncertain activities, as Karabulut (2017) stated that while CPM and PERT methods provide a deterministic completion date for the project, MCS provides the completion date based on a probabilistic approach considering all combined uncertain events. MCS Technique, used to model unpredictable processes, is valuable in addressing risk and uncertainty in construction project management. As Fadjar *et al.* (2022) studied, a five-activity project was simulated 2000 times using a spreadsheet application, considering minimum, maximum, and expected durations. The results indicated that the mean, mode, and median project completion times (50, 53, and 48 days respectively) exceeded the initial 42-day expectation. This validates the potential of MCS to assist project managers in creating more realistic and risk-informed schedules, particularly by generating a probabilistic distribution of project completion times that clarifies the likelihood of adhering to specific deadlines. After gathering the relevant knowledge of MCS, the researchers concluded that MCS is a mathematical method employed to estimate the potential outcomes of intricate systems through iterative random sampling. The method is particularly useful when exact solutions cannot be obtained using traditional mathematical methods or when a higher level of confidence is desired. A random variable is a variable whose value is subject to chance. Examples of random variables include the outcome of a coin toss, the number of customers visiting a store each day, or students' test scores. In this context, the number of days required for various construction activities is also considered a random variable (Fadjar *et al.*, 2022).

In the interpretation of MCS, the results are typically in the form of a probability distribution, which can be used to estimate various values such as the mean, median, or variance. However, MCS does not have a single universal equation, as it is a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results. The equation given below is a fundamental concept in statistics and probability theory, representing the sample mean as an estimator for the expected value. This is a core principle underlying the Monte Carlo method. The general principle, or the sample mean approximation of the expected value, is represented as Equation (1).

$$E(X) \approx \frac{1}{N} * \sum(X_i) \quad (1)$$

Where, $E(X)$ is the expected value of a random variable X , N is the number of random samples or simulations, X_i is the outcome of the i -th simulation, and $\sum(X_i)$ is the sum of all the outcomes from the simulations.

A key advantage of MCS is its flexibility in modeling complex systems with multiple random variables. The method is simple to understand and produces reliable results, especially when using a sufficient number of simulations, as demonstrated by the study of Rubinstein and Kroese (2016). The MCS process involves the following steps: (1) Define Inputs, (2) Generate Samples, (3) Compute Deterministically (run the simulation), and (4) Aggregate Results (average the outcomes to estimate the expected value).

In conclusion, MCS offers superior capability to deterministic models by integrating inherent uncertainty. It effectively supplements CPM, leading to the generation of significantly more realistic schedules. This is supported by Santony (2020), Karabulut (2017), Chilmi & Wulandari (2020), and Fadjar *et al.* (2022).

Finally, the researchers utilized MCS principles, drawing upon techniques described by Rubinstein and Kroese (2016) and Taimre *et al.* (2019), while conducting calculations for the construction project schedule based on the original PDM network.

Methodology

For the purposes of this research, the researchers initially gathered project data to perform traditional PDM network calculations, thereby identifying the critical path, critical activities, and the preliminary total project duration, as illustrated in Figure 1. As an initial critical path analysis, based on theoretical principles, the residential building project schedule was developed, representing a typical luxury housing project. This project consists of a two-story reinforced concrete building with a total usable area of 2,166 square meters and a total construction area of 4,450 square meters. The construction work was categorized into mobilization work and structural engineering work (comprising sub-activities B1-B10), architectural work (comprising sub-activities C1-C10), sanitary work (D), building electrical work (E), and commissioning and test run (F). Activity durations were determined and are presented in the Abbreviated Description, along with Box Symbols, as depicted in Figure 1.

According to Figure 1, the Box Symbols detail the represent start and finish nodes, encompassing structural engineering work, architectural work,

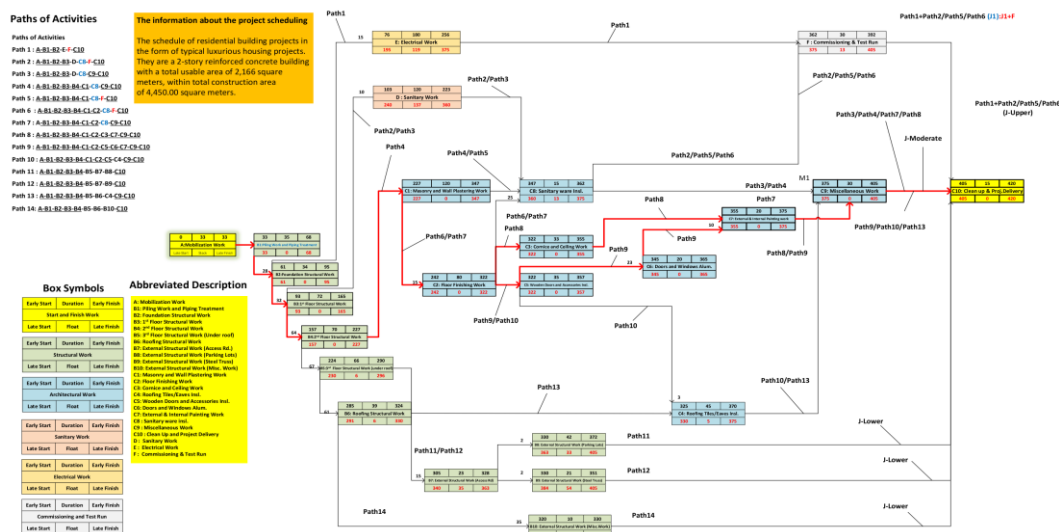


Figure 1. PDM of the luxurious residential housing project

sanitary work, electrical work, and commissioning and test run work. The Abbreviated Description provides further details: A (Mobilization work) and structural engineering work (B1-B10), including B1 (Piling Work and Piling Treatment), B2 (Foundation Structural Work), B3 (1st Floor Structural Work), B4 (2nd Floor Structural Work), B5 (3rd Floor Structural Work - Under Roof), B6 (Roofing Structural Work), B7 (External Structural Work - Access Road), B8 (External Structural Work - Steel Truss), and B10 (External Structural Work - Miscellaneous Work). Architectural work comprises C1-C10, including C1 (Masonry and Wall Plastering Work), C2 (Floor Finishing Work), C3 (Cornice and Ceiling Work), C4 (Roofing Tiles/Eaves Installation), C5 (Wooden Doors and Accessories Installation), C6 (Aluminum Doors and Windows), C7 (External & Internal Painting Work), C8 (Sanitary Ware Installation), C9 (Miscellaneous Work), and C10 (Clean Up and Project Delivery). Sanitary work (D), electrical work (E), and commissioning and test run (F) represent the final stages for project handover. The researchers gathered activity duration data, considering the mean and standard deviation for each activity from A, B1, B2, ..., F, respectively. Data on activity durations were sourced from daily and final work reports of twelve identical buildings, which were verified by the project management team, ensuring the data's reliability within the context of this project. This data was then entered into an Excel spreadsheet, specifying each activity to facilitate calculations according to the sequence depicted in Figure 1, which represents the traditional PDM network calculation. The calculations resulted in 14

activity paths, determined using the PDM method. Upon analysis of these 14 paths (as discussed further in the results section), the critical path with the longest duration for the luxury housing project was identified.

Subsequently, researchers used the calculated mean and standard deviation within a spreadsheet to generate random integers for each project activity (A, B1, B2, ..., F). This was achieved with the formula $\text{INT}(\text{NORM.INV}(\text{RAND}(), \text{AVERAGE}, \text{STDEV.S}))$, which produces integer values that approximate a normal distribution. These values constituted the preliminary data for the MCS. For context, these activities are governed by precedence relationships, meaning certain tasks must be completed before others can start.

The researchers also assigned duration estimates to each activity; for example, activity A had a completion time of 4 to 8 days, and activity C was normally distributed with a mean of 15 days and a standard deviation of 3.75 days. They then used MCS to simulate the project 10,000 times, generating random durations for each activity within each simulation. After running the simulations, a chart was generated to show the total completion time for each of the 10,000 project instances. From these results, researchers could calculate the probability of finishing the project within a specific timeframe. The research procedure, based on the principles of MCS, is as follows:

1. Model Definition: Initiate by defining a mathematical model of the system under consideration, a typical luxury housing project. This MCS model should account for all factors influencing the system's outcomes: each activity in the PDM network and its relevant duration. As

Rubinstein and Kroese (2016) indicate, it is essential to clearly define the problem to be solved and the variables involved, specifically what the researchers are trying to predict or estimate.

2. Random Variable Specification: As Rubinstein and Kroese (2016) mention, the factors that influence the model's outcome are determined. Probability distributions (specifically, a normal distribution with a mean and standard deviation) are then assigned to these variables based on historical data. The normal distribution was selected for the MCS model in the research, as activity durations in project planning tend to follow this pattern. This allows the estimation of the project duration with greater confidence.

3. Objective Function Definition: Random number generators are used to create a large number of possible scenarios based on the input distributions. As Rubinstein and Kroese (2016) explain, this process defines the objective function to be estimated. This function may represent the mean, median, or variance of the system's outcomes, derived from the mean and standard deviation values specified in step 2.

4. Simulation Execution: Random number generators are used to create a large number of possible scenarios based on the input distributions as mentioned by Rubinstein and Kroese (2016). Multiple simulations of the system (10,000 iterations) are then performed, with each iteration utilizing distinct random values for the defined variables to approximate the distribution of potential outcomes.

5. Objective Function Computation: Run the Model: For each set of random inputs, the MCS model is run to generate an output, from which the value of the objective function is computed for each simulation, as suggested by Rubinstein and Kroese (2016).

6. Results Analysis: The distribution of the model's outputs is analyzed in this step. This analysis provides an understanding of the range of possible outcomes, the most likely outcome, and the probabilities associated with different results. As Rubinstein and Kroese (2016) explain, the values of the objective function obtained from all simulations can be used to estimate the true objective function.

The procedure of this study is presented in Figure 2.

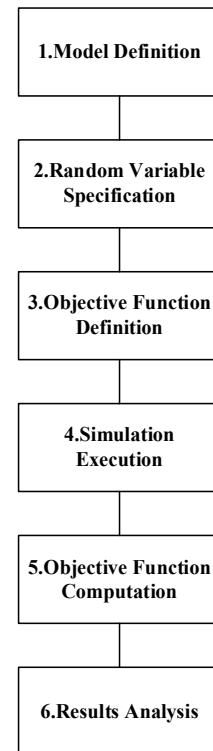


Figure 2 Study Workflow

According to Karabulut (2017), MCS computes deterministic times for 10,000 iterations (or more). The researchers applied this concept to repeatedly simulate end dates for all possible uncertain activities, aiming for more realistic final outcomes. The MCS Technique takes risk factors into account by randomly generating deterministic completion times for each activity in each trial. To simulate the full range of possibilities, the technique yields slightly varying final outcomes for each trial (Liu and Li, 2014; Karabulut, 2017; Taimre *et al.*, 2019; Chilmi and Wulandari, 2020). Following this explanation of the MCS method, the next section presents the results and discussion on the CPM/PDM schedules developed using this technique.

Figure 3. Segment of the Excel spreadsheet showing the TPD calculation via MCS

	A	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	C1	C2	C3	C4	C5	C6	C7	C10	Total Project Duration	Path14	A	B1
1	35	37	54	55	52	13	33	-3	20	19	38	84	67	27	15	43	22	46	11	393	A-B1-B2-B3-B4-B5-B6-B10-C10	35	37
2	26	32	42	41	79	12	36	27	26	11	20	103	69	68	8	21	27	52	10	464		26	32
3	32	26	26	69	44	54	38	33	34	28	0	89	62	101	45	43	13	57	12	467		32	26
4	13	50	43	18	60	34	39	16	33	17	18	96	59	80	29	2	23	1	10	382		13	50
5	46	58	48	55	61	19	24	41	34	44	9	105	49	21	28	42	6	26	5	374		46	58
6	32	44	33	61	9	61	18	2	29	15	17	57	71	69	32	23	25	32	15	392		32	44
7	42	28	29	8	62	36	0	20	12	19	25	41	29	26	49	86	30	70	14	413		42	28
8	49	58	50	60	33	43	23	35	25	41	14	137	79	64	13	61	34	33	8	431		49	58
9	30	43	20	62	16	20	33	49	8	33	20	177	57	74	22	30	9	28	8	369		30	43
10	7	65	38	73	18	44	43	44	17	38	30	121	24	54	24	20	11	22	14	350		7	65
11	4	58	54	55	48	64	23	36	28	50	23	11	95	42	35	10	27	48	17	419		4	58
12	18	1	35	33	19	32	31	64	26	17	25	76	72	62	31	43	22	40	9	374		18	1
13	50	36	46	51	55	33	23	14	10	37	19	113	69	-21	31	73	28	29	15	439		50	36
14	18	27	60	34	40	28	20	22	27	28	7	58	75	52	21	22	18	24	10	378		18	27
9993	17	9	55	44	42	39	28	26	10	32	18	113	104	13	29	64	25	58	3	422		17	9
9994	24	62	55	38	67	76	36	0	35	25	27	109	57	50	28	31	19	26	6	395		24	62
9995	25	39	39	56	82	-23	7	9	27	8	15	119	9	45	43	-7	18	13	14	379		25	39
9996	6	59	34	32	59	29	34	15	41	24	25	60	90	66	40	15	15	55	22	465		6	59
9997	31	56	65	60	42	28	43	19	22	27	17	17	27	83	27	14	12	43	15	410		31	56
9998	22	67	45	52	36	55	41	30	32	16	27	30	46	89	53	43	19	43	11	398		22	67
9999	12	22	12	72	21	52	20	24	36	26	12	76	62	33	49	4	30	52	11	370		12	22
10000	34	30	40	13	70	25	8	41	35	13	0	74	118	46	44	13	27	58	10	507		34	30

Figure 4. Output of Path 14 duration and overlap calculations (10,000 iterations)

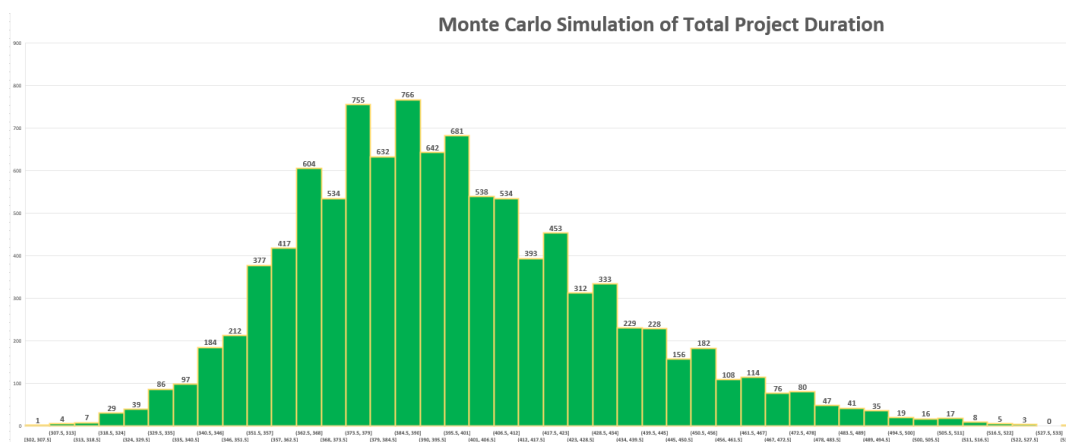


Figure 5. Histogram of the MCS results for the TPD, demonstrating an approximate Normal Distribution

Following this, the calculation will be performed to determine the critical path and total duration of the aforementioned luxury housing project. This calculation will adhere to the conventional PDM Network Diagram approach for identifying the Critical Path and Critical Activities across paths 1 through 14.

The researchers conducted an analysis of randomly generated values, adhering to the principles of the MCS method with 10,000 iterations. This involved the stochastic estimation of activity durations for each task (A, B1, B2, ..., F) and the numerical relationships defined within the established PDM Network Diagram. The process entailed generating random values and subsequently analyzing the outcomes to approximate the probability distribution of potential results under conditions of uncertainty. As depicted in Figure 5, the analysis involved a repetitive random sampling of values, totaling 10,000 iterations, from the defined distributions. This iterative process enhances the reliability of the results, bolstering accuracy through simulation under the aforementioned uncertainties.

The initial deterministic calculation using the Conventional PDM Network Diagram yielded a TPD of 420 days. In contrast, the subsequent MCS method produced an average project duration of 396.69 days, with a standard deviation (SD) of 34.11 days derived from the stochastic sampling. Considering the sample size ($n=10,000$) for the confidence interval (CI) calculation, the 95% confidence interval for the population mean project duration, based on the MCS results, ranges from 396.02 days to 397.36 days. This is illustrated in Figure 5, which presents a histogram of the MCS results for the TPD, exhibiting a characteristic Normal Distribution Curve. Regarding the critical path, Paths 8 (A-B1...C10) and 9 (A-B1...C10) emerged as critical in approximately 52% of the iterations. The remaining 48% probability was attributed to other near-critical paths, such as Paths 10 and 13.

Given that the MCS model was constructed through the simulation of randomly generated numerical data conforming to a normal distribution, the researchers performed a continuous evaluation. This involved defining calculations within an Excel

Spreadsheet using the IFS (condition1, value1, condition2, value2, ...) function to determine the probability of project completion within specified timeframes. This allowed for the calculation of the likelihood that the project would be completed in a duration greater than or equal to various conditional time values. These results are presented in Figure 6, illustrating the Percentage Probability of Project Completion. As shown in Figure 5, the results from the PDM-MCS integration and simulation for Conditions 1–8 provide a comparative analysis of the percentage probability of project completion. Specifically, the probability of the project being completed at or beyond the calculated TPD is compared against the probability of completion in less than the specific TPD. This analysis spans the defined TPD range of 350–420 days.

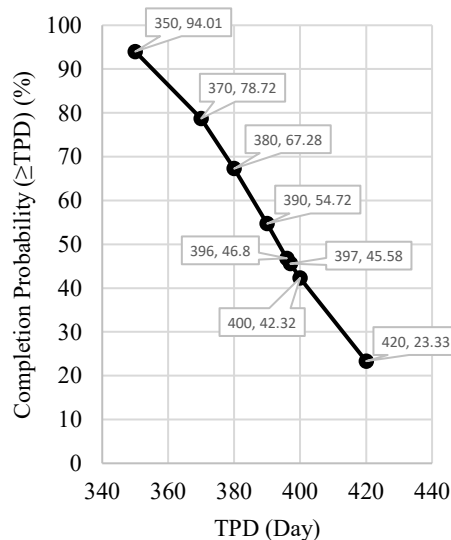


Figure 6. Probability of project completion within the specified TPD

The simulation outcomes indicate that for Condition 1 (1), the probability of the project being completed in more than or equal to 350 days is 94.01%, while the probability of completion in less than 350 days is 5.99%, or approximately 6%. For Condition 2 (2), the probability of project completion in more than or equal to 370 days is 78.72%, while the probability of completion in less than 370 days is 21.28%. For Condition 3 (3), the probability of project completion in more than or equal to 380 days is 67.28%, whereas the probability of completion in less than 380 days is 32.72%. For Condition 4 (4), the probability of project completion in more than or equal to 390 days is 54.72%, with a corresponding probability of less than 390 days being 45.28%. For Condition 5 (5), the probability of project completion in more than

or equal to 396 days is 46.80%, and the probability of less than 396 days is 53.20%. For Condition 6 (6), the probability of project completion in more than or equal to 397 days is 45.58%, with a probability of less than 397 days at 54.42%. For Condition 7 (7), the probability of project completion in more than or equal to 400 days is 42.32%, and the probability of less than 400 days is 57.68%. Finally, for Condition 8 (8), the probability of project completion in more than or equal to 420 days is 23.33%, while the probability of completion in less than 420 days is 76.67%. Subsequently, the researchers recorded and verified the probability of completion for typical luxury housing projects over the final 10 simulation runs. This step intended to corroborate the previously calculated TPD and the conditional timeframes established in Conditions 1 through 8. This verification was conducted in conjunction with an examination of the Histogram of MCS results for the TPD in these final 10 iterations to ensure consistency of the research findings.

To ensure the precision and consistency of the calculations, the researchers recorded and examined the probability of project completion for the final 10 trials (Trial_1 – Trial_10) of the MCS, which involved 10,000 iterations of random value analysis. The results are presented in Figure 7, which illustrates the MCS simulation outcomes for the final 10 trials based on 10,000 iterations. The 10 trials (N=10,002) yielded highly consistent results for completion time (mean, SD): Trial_1 (396.3, 33.31); Trial_2 (396.5, 33.57); Trial_3 (395.8, 33.85); Trial_4 (396.1, 33.84); Trial_5 (396.7, 33.80); Trial_6 (396.3, 33.92); Trial_7 (397.1, 34.31); Trial_8 (395.6, 33.13); Trial_9 (396.7, 33.79) and Trial_10 (397.3, 34.08).

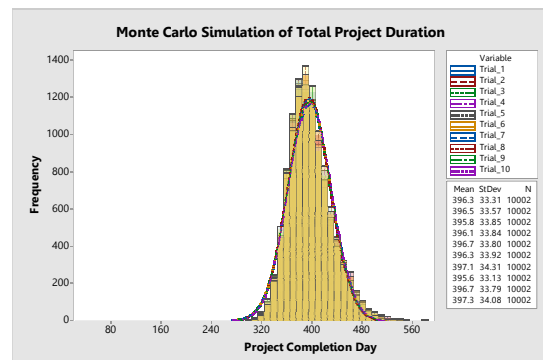


Figure 7. Histogram of the MCS results for the TPD, showing an approximate Normal Distribution

Analysis of the final 10 trials from the 10,000-iteration MCS showed the Mean TPD ranging from 395.60 to 397.30 days. The overall mean across

these 10 trials was 396.44 days, resulting in an estimated project duration of 397 days. The standard deviation across these trials ranged from 33.13 to 34.31 days, with an average standard deviation of approximately 33.76 days. Furthermore, the standard deviation of the 10 mean values was approximately 0.536 days (as presented in Equations (2) and (3)), indicating a relatively low dispersion around the overall average project duration.

This aligns with Equation (2) for calculating the sample standard deviation. The calculated sample standard deviation (s) for these 10 trials is 0.536 days, as presented in Equation (3).

$$s = \sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N-1}} \quad (2)$$

$$s = \sqrt{\frac{\sum_{i=1}^{10} (x_i - 396.48)^2}{(10-1)}} = 0.536 \quad (3)$$

Where, s is the sample standard deviation of the 10 project duration values; x_i represents each individual project duration from the trials; $\bar{x}$ is the sample mean of the project durations; N is the number of data points (10); $N-1$ represents the degrees of freedom for a sample; and the term $\sum_{i=1}^N (x_i - \bar{x})^2$ is the sum of the squared differences between each data point (x_i) and the sample mean ($\bar{x}$).

The mean values from the final 10 trials were re-examined for a more precise, two-decimal place adjustment. An interval plot for these trials was generated at a 95% Confidence Interval (CI), assuming a normal distribution and using the standard deviation from the 10,000 MCS iterations. This analysis yielded an adjusted mean of 396.48 days, which differs by a minimal 0.009% from the previously calculated mean of 396.44 days. Therefore, the adjusted mean project duration is 396.48 days (approximately 397 days), as illustrated in the interval plot in Figure 8.

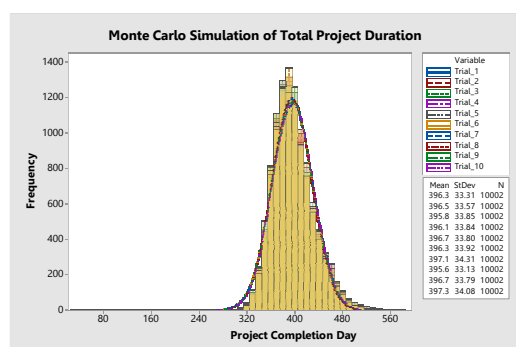


Figure 8. A 95% CI interval plot for the adjusted mean project duration, based on the final 10 trials.

Following this, the final 10 trials (Trial_1 – Trial_10) were examined to draw a conclusion based on the Percentage Probability of Project Completion. The time simulation results from these trials aligned with those from the previously defined Conditions 1 through 8. These conditions encompassed various probabilities, ranging from the probability of project completion being greater than or equal to 350 days to the probability of completion being greater than or equal to 420 days. Figure 9 presents a scatter plot of C3 and C5 versus the probability percentage of project completion. The x-axis represents the TPD (days), while the y-axis represents the percentage values derived from Figure 7. The intersection points of C3 (the blue line) represent the probability of completing the project on or before the specified dates (350, 370, 380, 390, 396, 397, 400, and 420 days), according to Conditions 1-8. The C5 curve (the red line), which represents the probability of project completion, intersects the x-axis (TPD) at a point corresponding to approximately 50% probability. This intersection occurs within the TPD range of 390 to 400 days. By interpolating the values in this range (as indicated by the arrow), the project completion date is estimated to be approximately 394 days. This result is consistent with the simulation outcomes observed in Conditions 4 through 6. Specifically: Condition (4) indicates a 54.72% probability of the project taking 390 days or more to complete, and a 45.28% probability of completion in less than 390 days. Condition (5) shows a 46.80% probability of completion in 396 days or more, and a 53.20% probability of completion in less than 396 days. Finally, Condition (6) reveals a 45.58% probability of completion in 397 days or more, and a 54.42% probability of completion in less than 397 days.

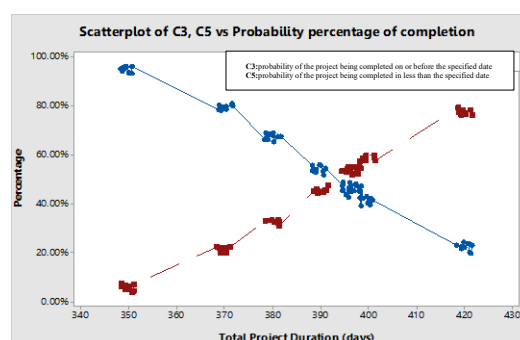


Figure 9. Interval Plot of the Trials with a 95% CI for the Adjusted Mean.

In conclusion, the application of MCS theory and principles to calculate the project completion duration provides a more precise estimate of the

TPD. Based on 10,000 simulation iterations, the calculated TPD is 396.44 days, with an adjusted mean of 396.48 days, which rounds to 397 days. Furthermore, a projection from the scatterplot for the 50% probability level indicates a completion time of 394 days; this value was determined through interpolation. This exhibits a minor difference of only 0.761% compared to the 397 days obtained from the MCS mean, suggesting a strong convergence between the MCS results and this subsequent verification. Conversely, the TPD calculated using the Conventional PDM Network Diagram, which yields a single deterministic value of 420 days, shows a significant difference of approximately 5.793% (23 days) when compared to the MCS-derived TPD of 397 days.

The conventional deterministic PDM is a planning approach that assigns a single, fixed-point estimate for the duration of each activity, without accounting for the inherent uncertainties and variabilities of on-site execution (Fadjar *et al.*, 2022). In the reality of construction work, which is fraught with variables such as adverse weather conditions, material delivery delays, labor issues, and other unforeseen events, these predetermined durations often deviate from actual performance. This discrepancy is a primary cause of schedule delays, which in turn directly impacts costs, leading to consequences such as (1) liquidated damages and opportunity costs from late completion, (2) escalated resource costs due to extended overhead and labor, and (3) depletion of contingency funds to manage unforeseen events, amplifying the risk of cost overruns as highlighted by PMI (2017).

While these findings differ from those of Fadjar *et al.* (2022), whose PDM calculations yielded mean, mode, and median completion times (50, 53, and 48 days, respectively) that all exceeded the 42-day target, they align with the principle demonstrated by Nuntiya *et al.* (2023). In their study of highway construction, PERT/CPM predicted a 63-day duration, whereas MCS provided a shorter estimate of 61 days.

Conclusion and Discussion

In this study, 10,000 iterations from the entire simulation dataset were used to determine the final probability distribution. Then, 10 Trials were implemented, in addition to the iterations, to confirm the convergence of the 10,000-iteration result. A critical path analysis of this luxury housing project using a conventional PDM network diagram identified Paths 8 (A-B1-B2-B3-B4-C1-C2-C3-C7-C9-C10) and 9 (A-B1-B2-B3-

B4-C1-C2-C5-C6-C7-C9-C10) as critical, with a deterministic Total Project Duration (TPD) of 420 days. The researchers then employed MCS, simulating a range of potential durations for each activity (A, B1, B2, ..., F) based on randomly generated numerical data conforming to a normal distribution. This method estimates the average project duration by considering the inherent variability in activity completion times, unlike the single-point estimate of the conventional critical path method.

Subsequently, the researchers analyzed randomly generated numerical values based on the principles and methods of MCS. This aligns with the research of Fadjar *et al.* (2022), who noted that MCS is a prevalent simulation technique for modeling processes with unpredictable random variables and highlighted its practical application for project simulation using spreadsheet functions. Similar to this study, their research employed 10,000 iterations to stochastically estimate the durations of activities A, B1, B2, ..., F, based on their numerical relationships within a PDM network diagram. This approach is also consistent with the methodology suggested by Karabulut (2017), which involved generating random numerical values and analyzing the resulting probability of potential outcomes under uncertain conditions, yielding an average project duration ranging from 396.02 to 397.36 days.

The 10,000 iterations of the MCS were subsequently analyzed, with a specific focus on the final 10 trials to validate the findings. This examination revealed a mean TPD ranging from 395.60 to 397.30 days, with a mean of 396.44 days across these final trials (approximating 397 days when rounded). The finding indicates that the project has only a 45.6% probability of meeting the traditional TPD. The standard deviation observed across these trials ranged from 33.13 to 34.31 days, yielding a mean standard deviation of 33.76 days. This methodological approach is consistent with the principle articulated by Fadjar *et al.* (2022), who stated that “the difference is that the Monte Carlo method tests a number of random variables and then averages, rather than starting out with an average.”

A key advantage of this approach is its ability to overcome the Merge Bias or Path Convergence inherent in PDM networks, which often causes deterministic (single-critical-path) analysis to be overly optimistic. In contrast, MCS evaluates all potential paths and the probability that non-critical paths may become critical. Furthermore, when the 95% Confidence Interval (CI) for the mean duration was estimated to range between 395.78

and 397.09 days, the resulting very narrow range. This narrow CI, achieved after 10,000 iterations, strongly suggests that the model has converged to a stable value, thus confirming the high reliability of the 397-day mean estimate.

Subsequently, the researchers recorded and examined the probability of project completion for the final 10 trials (Trial_1 – Trial_10) derived from the 10,000-iteration MCS analysis. An interval plot of Trial_1-Trial_10 at a 95% Confidence Interval (CI) for the mean yielded a value of 396.48 days, a minimal 0.010% difference from the previously calculated 396.44 days. Thus, the adjusted mean project duration is 396.48 days (approximately 397 days), as depicted in Fig. 7. The application of MCS principles to estimate project completion duration enhances the accuracy and reliability of the TPD. The use of 10,000 simulation iterations-distinguishes this study from that of Fadjar *et al.* (2022), who simulated a project with five activities 2000 times using minimum, maximum, and expected durations.

The reasons that the MCS yielded shorter TPD than the conventional deterministic method are as follows:

1. The project schedule is highly parallel. Therefore, any change in activities' duration may cause shifts in the critical path.
2. The variance of activity durations is high.
3. This study adopted a normal distribution, which is symmetric. Hence, the results are equally distributed between early and delayed completions. This contrasts with the typical skewed delay characteristics in construction projects.

For the luxury housing project in this research, the MCS yielded a mean completion time of 396.44 days and an adjusted mean of 396.48 days, which was approximated to 397 days when rounded. The projection from the scatterplot's x-y intersection, representing the 50% probability of completion determined by interpolation, indicated a completion time of 394 days. This 3-day (0.756%) difference between the MCS result and the projection is less than 1%, demonstrating a strong convergence between the two analyses. Conversely, the TPD calculated using the conventional PDM network diagram yielded a single deterministic value of 420 days, a difference of approximately 23 days (5.793%) when compared to the MCS-derived TPD of 397 days. This case study, which involves the application of MCS in construction planning, aligns with the methodological principles outlined by Taimre *et al.* (2019).

As described, MCS inherently involves testing multiple random variables and their associated probabilities through a suite of computational algorithms that rely on repeated random sampling to obtain numerical results. Fundamentally, MCS

simulates the likelihood of various outcomes in processes that are not easily predictable due to the influence of random variables. The method involves creating a mathematical model of a system or process and then running numerous simulations (often thousands or millions) with randomized input variables to observe the range of potential results.

The resulting output provides a comprehensive overview of the risks and uncertainties involved, thereby enabling businesses to make more informed decisions. Ultimately, MCS surpasses deterministic models by integrating inherent uncertainties in complex systems, providing more realistic project outcome projections than conventional single-point estimates. Utilizing probability distributions and numerous simulations, MCS generates a range of potential results, acknowledging the prediction challenges in real-world construction (Rubinstein and Kroese, 2016). Its relevance in effective planning and risk management grows with project scale and complexity, where increased stakeholders and interdependencies amplify potential deviations. Unlike conventional deterministic methods that struggle with the cascading effects of uncertainty, MCS offers crucial probabilistic analysis for project management and scheduling.

This alignment can be attributed to the mean project duration from MCS often being lower than that from standard CPM/PDM, reflecting a more realistic probabilistic assessment. MCS systematically incorporates the variance and uncertainty of each activity's duration, resulting in a skewed distribution of potential completion times. Consequently, the MCS mean is frequently lower than the single-point estimate from CPM/PDM, which tends to be overly optimistic because it fails to account for the cumulative impact of potential delays on converging paths. This optimism can be compounded if users set unrealistically low "most likely" durations for activities (PMI, 2017).

This enables a shift from reactive to proactive risk management, thereby improving contingency planning and resource allocation. This aligns with the PMBOK framework's handling of uncertainties in project variables (duration, cost, resources). By estimating project timelines through a range of durations based on probabilistic inputs, MCS facilitates more realistic, data-driven cost and schedule estimates (PMI, 2017). The findings of Rubinstein and Kroese (2016), along with the PMBOK Guide (PMI, 2017), indicate that the bell-shaped curve, or normal distribution — a symmetrical probability distribution — is frequently employed in MCS analysis. This curve illustrates that the majority of potential outcomes tend to cluster around the mean or average, with fewer occurrences at the extremes. Consequently, it offers

valuable insights into the most probable outcomes and the extent of potential deviations from the mean. Therefore, this research aligns with the PMBOK Guide.

The implications of this finding are as follows:

Theoretical Implication: It enhances the accuracy of duration estimates by incorporating inherent uncertainties for probabilistic assessment, moving beyond the single-point estimates typical of conventional planning. It mitigates the discrepancies and errors in duration values that are inherent in fundamental deterministic scheduling models.

Practical Implication: for complex bespoke luxury projects, this probabilistic approach offers a realistic completion range, enabling better contingency planning and transparent communication of schedule risks, moving beyond misleading deterministic dates. Furthermore, the method's effectiveness hinges on the commitment of stakeholders, particularly policymakers and practitioners, to gather high-quality historical data for building accurate probability distributions.

A limitation of the current model is its reliance on the Normal Distribution for duration estimates. While functional for high-level approximations, this distribution inadequately captures the inherent positive skewness (i.e., a higher tendency for delay) common in construction tasks. Future validation should incorporate the Beta Distribution, which offers greater fidelity at the activity level and enhances the simulation's realism, aligning with established PDM-MCS methodologies (e.g., Hajdu & Isaac, 2016).

Furthermore, this study was limited to schedule variability. Future research should extend the stochastic framework to include cost and resource fluctuations. This extension is necessary for a more comprehensive time-cost-resource trade-off evaluation, moving beyond the current, purely duration-centric model.

While acknowledging the limitations of this study, it is crucial to note that accurate MCS requires comprehensive, high-quality data; its reliability also depends on the validity of assumptions regarding variable independence and the shapes of the probability distributions. Furthermore, the PMBOK Guide suggests that MCS can be applied to other aspects of construction management, such as cost estimation and resource availability.

The integration of PDM and MCS yields a more realistic risk-based schedule because MCS systematically accounts for the variability and uncertainty in the duration of each activity, providing a sounder basis for accurate risk planning.

References

- Asyrofi, H. R., & Arumsari, P. (2023). Comparative analysis of CPM, PDM and PERT method on the duration of bridge work (Case study: Gelam Bridge Project). *IOP Conference Series: Earth and Environmental Science*, 1169(1), 012011. <https://doi.org/10.1088/1755-1315/1169/1/012011>
- Avlijaš, G. (2019). Examining the value of Monte Carlo simulation for project time management. *Journal of Sustainable Business and Management Solutions in Emerging Economies*, 24(1), 11-23. <https://doi.org/10.7595/management.fon.2018.0004>
- Chilmi, M., & Wulandari, D. A. R. (2020). Optimization of project duration using CPM method and Monte Carlo Crystal Ball simulation. *Neutron*, 19(2), 17-25. <https://doi.org/10.29138/neutron.v19i2.32>
- Danfulani, U. B., Mohammed, M., Reuben, B. Z., Yakubu, J. A., & Digil, S. I. (2023). Application of critical path method (CPM) to optimal project scheduling: A case of Mosul Building Company, Yola North Local Government Adamawa State, Nigeria. *Fudma Journal of Sciences*, 7(3), 186-192. <https://doi.org/10.33003/fjs-2023-0703-1860>
- Durdyev, S., & Hosseini, M. R. (2020). Causes of delays on construction projects: A comprehensive list. *International Journal of Managing Projects in Business*, 13(1), 20-46. <https://doi.org/10.1108/IJMPB-09-2018-0178>
- El-Far, M. E., Kotb, M., & Sabry, R. (2023). Controlling fast-track construction method variables (time, cost and quality). *Infrastructure Asset Management*, 10(2), 103-112. <https://doi.org/10.1680/jinam.23.00001>
- Fadjar, A., Nirmalawati, N., & Hidayat, N. (2022). Estimating project completion time with Monte Carlo simulation. *Rekonstruksi: Tadulako Civil Engineering Journal of Research and Development*, 3, 21-26. <https://doi.org/10.3390/buildings12122173>
- Hajdu, M., & Isaac, S. (2016). Sixty years of project planning: History and future. *Organization, Technology & Management in Construction: An International Journal*, 8(1). <https://doi.org/10.1515/otmcj-2016-0013>
- Hansen, S., Fassa, F., & Wijaya, S. (2023). Factors influencing scheduling activities of construction projects. *Journal of Legal Affairs and Dispute Resolution in Engineering and Construction*, 15(1), 06522004. [https://doi.org/10.1061/\(ASCE\)LA.1943-4170.0000594](https://doi.org/10.1061/(ASCE)LA.1943-4170.0000594)
- Harshavardhan, T., Reddy, V. S., Vardhani, P. S. R. P. S. S., Shrihari, S., Alawadi, A. H. R., & Sharma, S. D. (2023). Resource allocation, scheduling and planning of a multi-storied residential building. *E3S Web of Conferences*, 391, 01217. <https://doi.org/10.1051/e3sconf/202339101217>
- Hendradewa, A. P. (2019). Schedule risk analysis by different phases of construction project using CPM-PERT and Monte-Carlo simulation. *IOP Conference Series: Materials Science and Engineering*, 528(1), 012035. <https://doi.org/10.1088/1757-899X/528/1/012035>
- Hosseini, R., Chileshe, N., Zou, J., & Baroudi, B. (2012). Approaches of implementing ICT technologies within the construction industry. *Australasian Journal of Construction Economics and Building – Conference Series*, 1(2), 1-12. <https://doi.org/10.5130/ajceb-cs.v1i2.3161>
- Kamandang, Z. R. (2021). Risk assessment of construction project scheduling. In *Proceedings of the International Conference on Rehabilitation and Maintenance in Civil Engineering* (pp. 863-872). Springer Nature Singapore. https://doi.org/10.1007/978-981-16-9348-9_77
- Karabulut, M. (2017). Application of Monte Carlo simulation and PERT/CPM techniques in planning of construction projects: A case study. *Periodicals of Engineering and Natural Sciences*, 5(3), 408-420. <https://doi.org/10.21533/pen.v5i3.152>

- Lepage, M. (2017). *Types of schedule delays in construction projects*. Top Primavera P6 Educators.
- Liu, Y., & Li, Y. (2014). Study on application of Monte Carlo simulation in construction schedule management. *Advanced Materials Research*, 859, 284-288. <https://doi.org/10.4028/www.scientific.net/AMR.859.284>
- Mejia, G., Sánchez, O., Castañeda, K., & Pellicer, E. (2023). Stakeholders' issues as a source of project delays: A meta-analysis between building and road projects. *Revista de la Construcción*, 22(1), 51-73. <https://doi.org/10.7764/RDLC.22.1.51>
- Naguib, M., Eldamhouri, E. S., Hanna, A. S., & Lotfallah, W. (2022). An integrated framework to quantify the impact of competency factors on project performance. In *Construction Research Congress 2022* (pp. 863-873). <https://doi.org/10.1061/9780784483978.088>
- Nuntiya, A., Sittiraj, S., Chaisiri, K., Tapanon, J., Buachart, C., & Rinchumphu, D. (2023). Application of PERT/CPM and Monte Carlo simulation techniques for scheduling in reinforced concrete pavement project. In *International Conference on Green Urbanism* (pp. 147-159). https://doi.org/10.1007/978-3-031-86095-9_12
- Oracle. (n.d.). *Oracle Crystal Ball, Fusion Edition user's guide*. Retrieved June 4, 2025, from https://docs.oracle.com/cd/F25597_01/document/products/epm/111130/E12825_01/epm.111/cb_user/frameset.htm?copyrite.html
- Perminova, O., Gustafsson, M., & Wikström, K. (2008). Defining uncertainty in projects – A new perspective. *International Journal of Project Management*, 26(1), 73-79. <https://doi.org/10.1016/j.ijproman.2007.08.005>
- Project Management Institute. (2017). *The standard for portfolio management*. Project Management Institute.
- Rathod, R., & Patil, A. R. (2016). Efficient planning scheduling and delay analysis of residential project. *International Journal of Engineering Research and Applications*, 6(9), 39-45. <https://doi.org/10.13140/RG.2.2.24776.26886>
- Rosalinda, R., Nizmah, N., Makmur, M., & Rarasanti, D. (2023). Analysis of project time and cost control with CPM, PERT and crashing project methods in shop building projects at CV. Mentari Permai. *Scientific Journal of Reflection: Economic, Accounting, Management and Business*, 6(1), 85-94.
- Rubinstein, R. Y., & Kroese, D. P. (2016). *Simulation and the Monte Carlo method*. John Wiley & Sons.
- Santony, J. (2020). Simulasi penjadwalan proyek pembangunan jembatan gantung dengan metode Monte Carlo. *Jurnal Informasi dan Teknologi*, 30-35. <https://doi.org/10.37034/jidt.v2i1.34>
- SCB Economic Intelligence Center. (2024). *Construction industry trends in 2024*. Retrieved June 5, 2025, from <https://www.sceic.com/th/detail/product/construction-100124/>
- Taimre, T., Kroese, D. P., & Botev, Z. I. (2019). Monte Carlo methods. *Wiley StatsRef: Statistics Reference Online*, 10, 1-17. <https://doi.org/10.1002/9781118445112.stat03619.pub2>
- Tang, H., Guo, S., Huang, L., Li, L., & Li, Y. (2015). Research and development on key models and technology of PDM system. *The International Journal of Advanced Manufacturing Technology*, 78, 1865-1878. <https://doi.org/10.1007/s00170-014-6765-8>
- Zhou, J., Love, P. E., Wang, X., Teo, K. L., & Irani, Z. (2013). A review of methods and algorithms for optimizing construction scheduling. *Journal of the Operational Research Society*, 64(8), 1091-1105. <https://doi.org/10.1057/jors.2012.174>