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Risk Analysis of Modest Housing Projects Scheduling using Monte Carlo Simulation

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Abstract

It is crucial to address uncertainties in the construction project scheduling to mitigate delays. Probabilistic simulation offers a viable alternative method. This study examined the relationship between project duration and delay risks, as well as identified the most influential activities for modest housing projects using Monte Carlo Simulation. The simulation analysis, which included 2547 iterations, found that, on average, it took 87.39 days to complete a 54-type modest house project, with the shortest and longest durations being 44 and 149 days, respectively. The sensitivity analysis revealed that finishing works, such as painting, doors/windows installation, and cleaning, had the highest uncertainty and significantly affected the project duration. Additionally, the severity analysis showed that wall work was the most impactful activity contributing to delays. Based on these analyses, both finishing works and wall work were identified as the most critical activities significantly influencing the project's completion duration.

Introduction

Planning and scheduling are crucial aspects of construction project management [1]. One of the primary planning challenges is to create a project schedule while considering risks and uncertainties during its execution [2]. According to A. Laufer et al. [3], approximately 80% of projects exhibited a high level of uncertainty at the onset of construction activities. Therefore, project managers must consider and analyze the risks associated with the project completion duration. It is crucial for a project manager to meticulously develop project duration plans while taking uncertainty factors into account [1]. It may consequently mitigate the project completion delay and minimize its impacts on time and costs. Thus, the adoption of scheduling methods that accommodate uncertainty factors as part of risk management is imperative.

Probabilistic scheduling methods are scheduling approaches that incorporate uncertainty into their analysis [4]. One widely utilized probabilistic scheduling method today is Monte Carlo Simulation (MCS) [5].The MCS research was initially introduced in 1949 by Ulam and Metropolis. In the 1990s, this technique became fully operational and applicable to project managers due to the availability of advanced technology to execute MCS [6]. In the context of project scheduling, MCS is used to generate hundreds or thousands of possible output results based on probability distributions for costs and schedules for each activity. The simulation results are utilized to create the project's overall probability distribution [7]. According to Deshmukh et al. [8] and Tysiak et al. [9], MCS provides results that closely approximate real-world durations as observed in the field. MCS is not only more intuitive and accurate but also offers extensive flexibility to present other distributions, correlations, and additional conditions. The advantage of the MCS method, compared to others, lies in its ability to produce sensitivity values for each activity [10]. Sensitivity Analysis

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is used to identify which parameters have the most significant impact on the outcome [11]. This analysis is conducted to identify key factors and how much influence an input distribution of activities has on the total project output variable [11,12]. The higher the sensitivity value of an activity, the greater its potential impact on the entire project duration [10,13]. Considering the advantages of the MCS method in generating data, probabilistic scheduling analysis of simple building projects in Indonesia using the MCS method presents an intriguing avenue for exploration.

Research on MCS and Sensitivity Analysis has been conducted by Kong et al. [12] and Wali et al. [14]. Both studies focused on risk management in scheduling, aiming to explicitly demonstrate the benefits of applying MCS to assess scheduling risks, determine project completion durations, and find potential project duration extensions. Kong et al. [12] used data from construction and installation projects at the Kunming Changsui International Airport cargo area in China. Meanwhile, Wali et al. [14] conducted a questionnaire survey and interviews with 26 civil engineers to obtain estimated duration of residential construction projects in Iraq. However, the usage of overall questionnaire data without conducting reliability tests on the MCS method may produce results with a high level of error. Thus, this study addresses this issue by proposing a new method for checking the data reliability collected from a questionnaire.

This study aimed to investigate the relationship between project completion duration and the risk of delays using MCS probabilistic scheduling and sensitivity analysis for modest housing projects in Indonesia. It also endeavoured to identify the most influential activities affecting the project completion duration. The activity durations used for simulation were gathered through a survey questionnaire. A verification method was assigned to check the reliability of the respondent data responses. A severity analysis to identify the most influential activities toward project duration was also introduced. These two approaches were expected not only to provide a comprehensive understanding of the risks and uncertainties involved in project scheduling but also offers a robust framework since any previous MCS research did not consider them.

Research Data

Research Object

A modest 54-type house in one of the residential areas in Jepara Regency, Central Java, Indonesia, was used as the object of the study. Data associated with the object of the study were obtained through document review, interviews, and observations, which are illustrated in Figure 1.

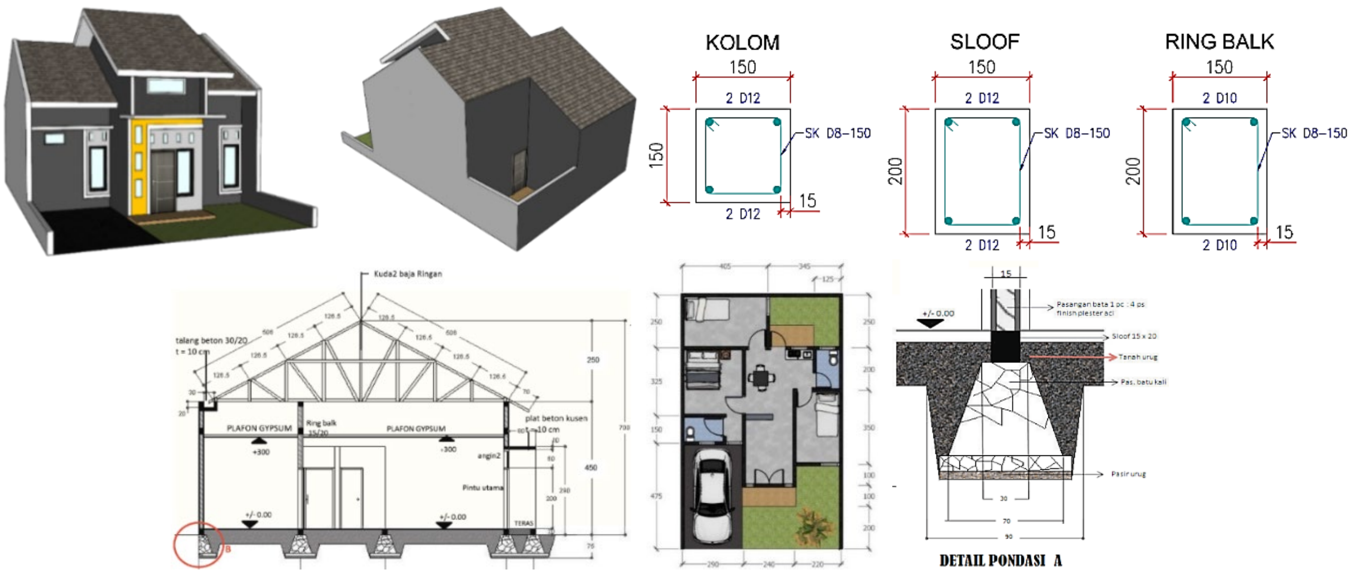

Figure 1. Research Object

Project Network

The project network was developed based on a literature review of some research on house construction projects and clarified by interviewing several construction practitioners. There were 18 activities found as the main activities of the modest housing project, as listed in Table 1.

Table 1. List of Activities

No	ID	Activities	References
1	A	Site Preparation (Site clearing, project fencing, bouwplank, etc.)	[5,15–19]
2	B	Land Work (Excavation &Fill)	[5,16–20]
3	C	Foundation Work	[5,15,16,18–20]
4	D	Sanitary Sewer Pipes Installation	[5,15,18]
5	E	Footing Work	[5,15,16,20]
6	F	Column Work	[5,16,19]
7	G	Masonry (Wall) Work	[5,15,19,20]
8	H	Plumbing	[5,15,16,18,19]
9	I	Window Frames Installation	[5,18–20]
10	J	Door Frames Installation	[5,18–20]
11	K	Beam Work	[5,16,20]
12	L	Roof Frame Work	[5,18,19]
13	M	Roof Covering (Tiles)	[5,15,17,18,20]
14	N	Electrical/Power Installation	[5,15–17,19,20]
15	O	Plastering Work	[5,15,17–20]
16	P	Ceiling Work	[5,15–20]
17	Q	Flooring	[5,15,16,18–20]
18	R	Finishing Work (Painting, varnishing, installation of doors &windows including their accessories, cleaning, etc).	[5,15–20]

According to the literature, among the 18 activities outlined in Table 1, wall, plastering, and finishing work are considered critical due to their longer durations compared to other activities [5,15,17–20]. Finishing work encompasses multiple stages involving various sub-tasks such as wall painting, wood varnishing, installation of doors and windows, and thorough cleaning activities. On the other hand, wall work and plastering work involve handling large areas and substantial volumes. These three activities demand meticulous attention to detail, precision, and careful execution to achieve the desired final result. Hence, effective time management and comprehensive planning are essential to ensure the successful completion of the project.

The 18 activities required to construct the modest housing project were arranged in a network diagram. The diagram was then verified by interviewing four kinds of construction practitioners. This step was conducted as validation of the network which aligns with the real conditions commonly encountered in modest housing projects. The verified network of the eighteen activities is illustrated in Figure 2.

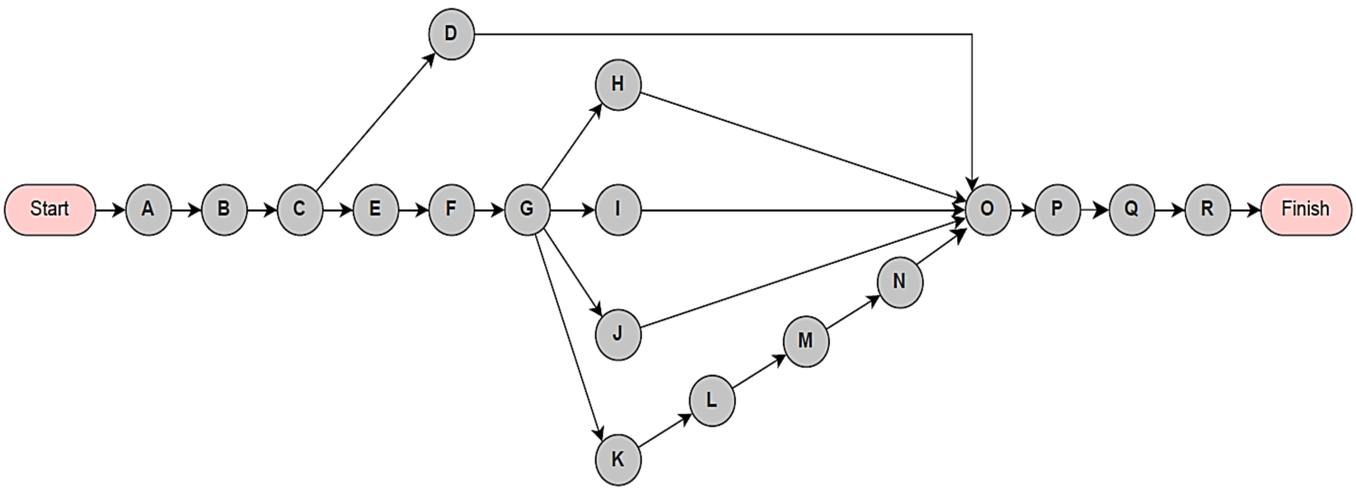

Figure 2. Project Network Diagram

There were two different opinions regarding the sequence and relationship activities of wall (G) and beam (K). Some practitioners argued that beams, as structural elements, should ideally constructed first before non-structural components like brick walls. However, others said that in most single-story modest housing projects in Indonesia, beam is typically carried out after the brick walls. This decision aims to minimize project costs, especially related to formwork and scaffolding expenses.

Survey

The research employed a data collection technique using surveys and questionnaires to gather estimation data from 26 construction practitioners working in small-scale contractor companies. These respondents included engineers (65%), sub-contractors (27%), and forepersons (8%). The majority of respondents (23%) were located in Central Java Province, with the remaining distributed across Yogyakarta Special Region (19%), West Java (15%), Riau (11%), East Java (8%), West Nusa Tenggara (8%), DKI Jakarta (4%), Bengkulu (4%), Central Sulawesi (4%), and North Sulawesi (4%). In terms of experience, 31% respondents had more than ten years of work experience, 27% had 1 to 3 years, 15% had 3 to 5 years, and 27% had 5 to 10 years of experience. There were no respondents with less than one year of experience.

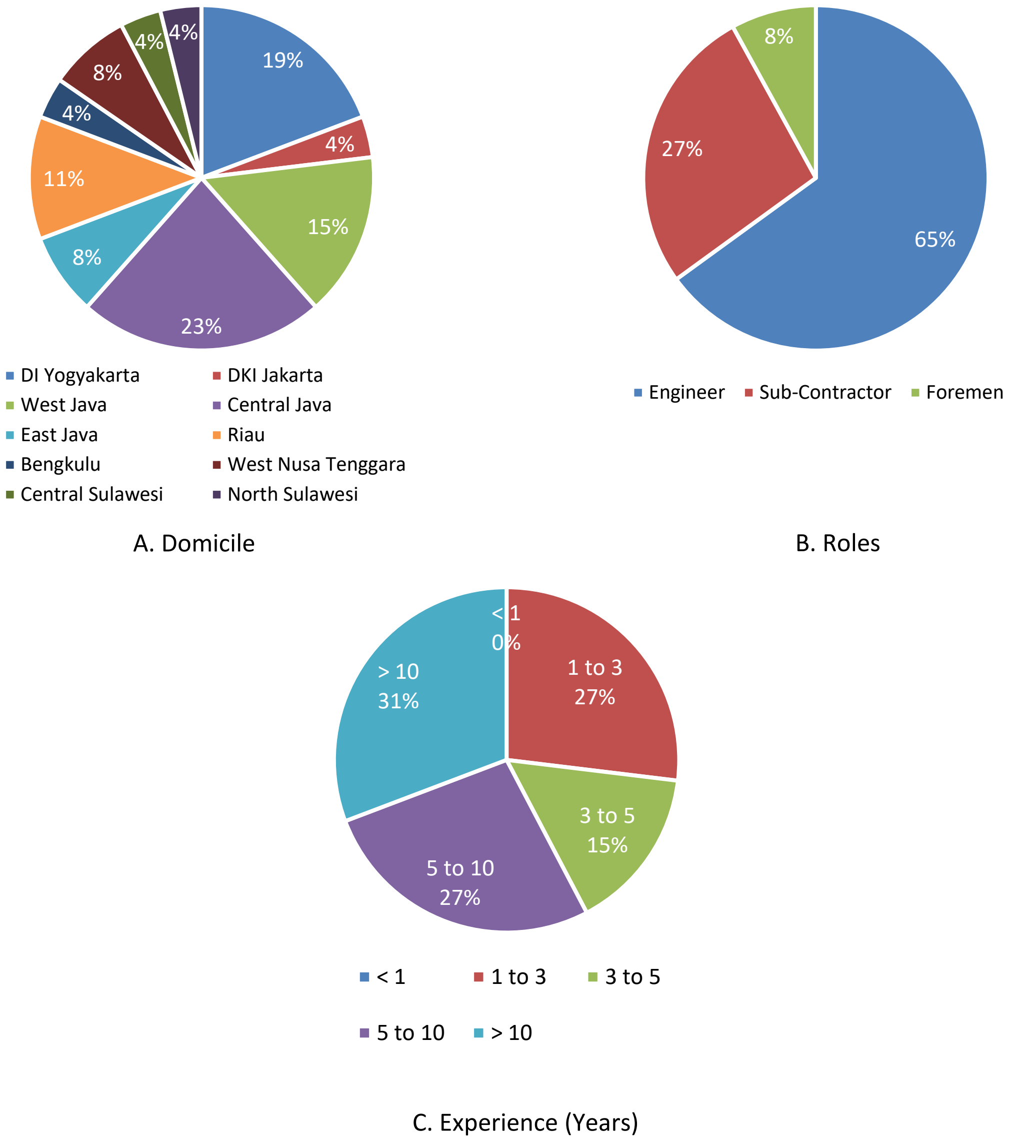

Figure 3. Respondent Demographics: A. Respondent's Domiciles, B. Respondent's Roles in Construction Industry, C. Respondent's Years of Experience

According to the survey findings, the modest housing projects in the case study range from a minimum completion time of 31 days to a maximum of 144 days, with an average duration of 81.69 days. The substantial disparity between the minimum, maximum, and average project durations highlights significant variations in perceptions of construction timelines among construction practitioners in Indonesia.

Monte Carlo Simulation Process

The MCS process, as depicted in Figure 4, involves several steps. Initially, a random number between one and 26 is generated to determine the duration of respondent data for activity A to be used in the simulation. This process is then repeated for activities B through R to determine each activity duration associated with the respondent data. Once the durations for all activities have been determined, the project duration is recorded. As there are 26 potential durations of the respondent data for each of the 18 activities (activity A to activity R), a significant number of iterations, which is equal to 26^{18} or approximately 2.9×10^{25}, is required to ensure each data value has an equal chance of being included in the simulation. Figure 5 illustrates the possible combination of the data for 18 activities with 26 data responses. Therefore, MCS was assigned to simulate these various conceivable scenarios. Using MCS, the number of iterations to run each complete process was stopped when it reached the required sum. MCS analysis was conducted using Microsoft Excel software. Random numbers, determining which respondent data should be taken into account, were generated by employing the function =RANDBETWEEN(**[1]**,**[26]**) on Microsoft Excel's sheet or by utilizing the algorithm Int((**[26]**-**[1]**+1)*Rnd+**[1]**) in Microsoft Excel's Visual Basic.

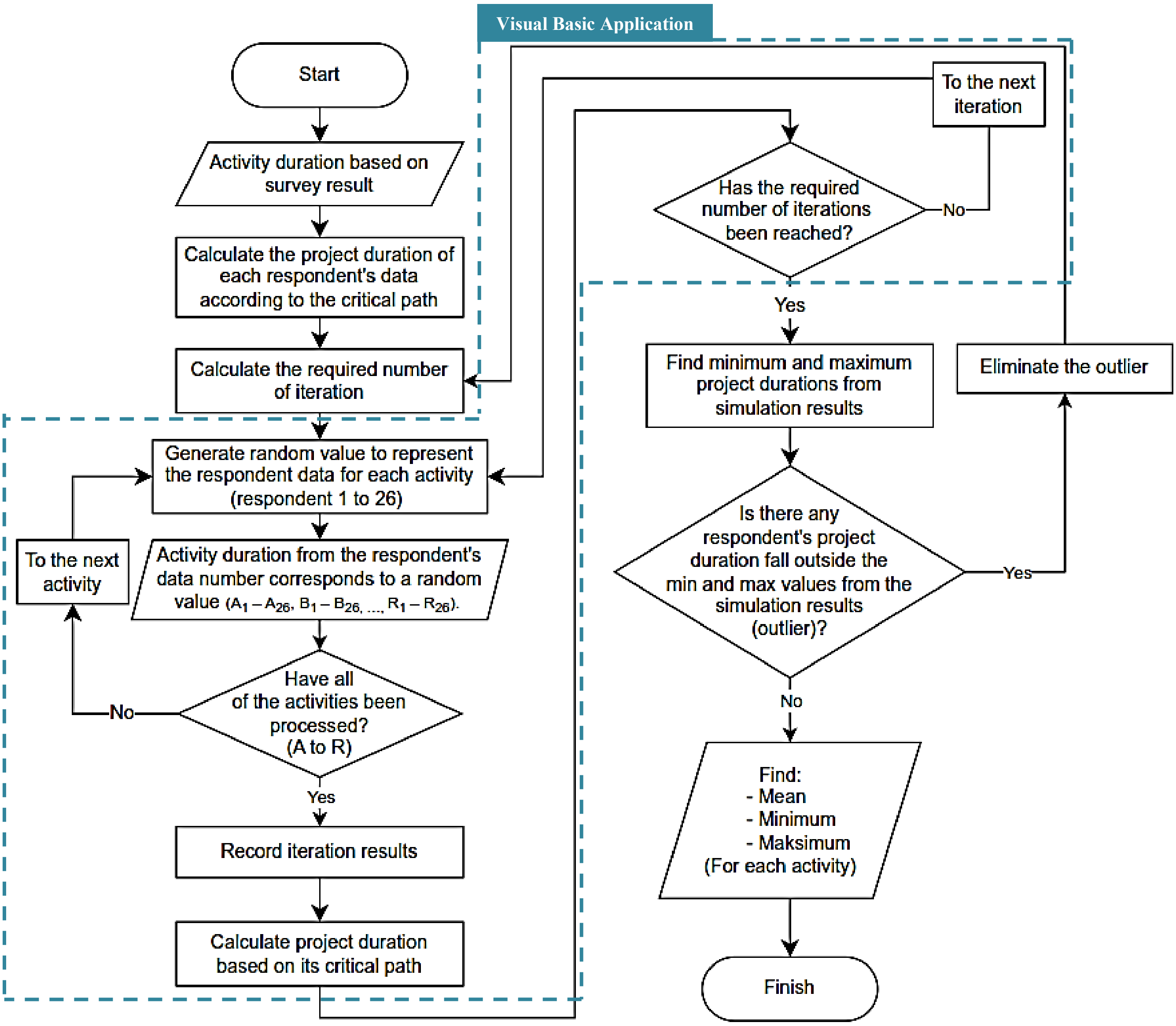

Figure 4. Flow Chart of Monte Carlo Simulation Process

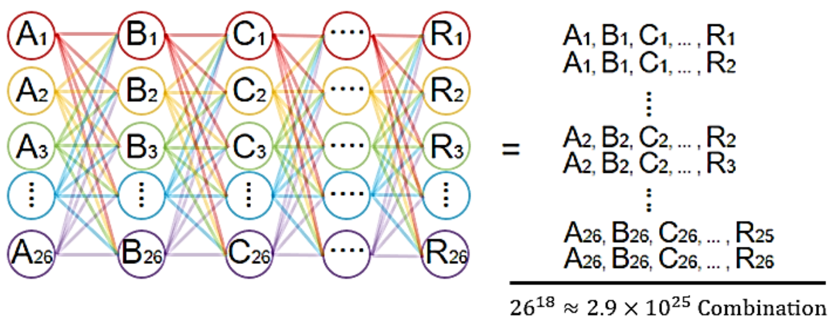

Figure 5. Illustration of the Possible Data Combination

Determination of the Required Number of Iteration

MCS simulation error is depended on its number of iterations [21]. When the standard deviation and absolute error are expected to be less than 2%, the MCS then required number of iterations is calculated based on the following calculation:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{k}(x_i - \bar{x})^2}{k-1}} \tag{1}$$

$$\varepsilon = \frac{\bar{x}}{\left(\frac{1}{RE}\right)} \tag{2}$$

$$n = \left(\frac{3\sigma}{\varepsilon}\right)^2 \tag{3}$$

Where σ is the standard deviation, x_i is the data value of each population member, $\bar{x}$ is the overall data mean, k is the number of data, ε is the absolute standard error, RE is the maximum error value (in this study taken as 2%), and n is the number of iterations [21,22].

Examination of Respondent Data Reliability

Probabilistic analysis using MCS generally considers that each respondent's data is valid and reliable to be used in the simulation. However, the use of doubtful data will certainly provide an inappropriate result. This research examined the reliability of the data. The proposed project duration of each respondent was examined to ensure whether it fell within the range of the minimum and maximum values of the MCS results. Any proposed project duration dropped outside the range was categorized as unreliable, and the respondent was declared as a doubtful respondent. All data given by this respondent was then eliminated and not used for subsequent simulation. This process was repeated until the minimum and maximum values of the simulation results covered the entire proposed project duration of the respondent.

Statistical analysis found that, from 26 respondents' data, the average project duration was 81.69 days, the standard deviation was 32.06, and the absolute standard error was 1.63. Applying these three values (average, standard deviation, and absolute error) into equations (1), (2), and (3) obtained the required number of iterations (n) is equal to 3465 iterations.

Table 2. Simulation Results

	1st Sim.	2nd Sim.
Number of respondent data	26	23
Number of simulation result data	3465	2547
Minimum duration values (days)	47	44
Maximum duration values (days)	146	149

Table 3. Results of Respondent Data Reliability Examination

No.	ID	Project Duration	1st Sim.	2nd Sim.	No.	ID	Project Duration	1st Sim.	2nd Sim.
1	R1	67	Ok	Ok	14	R14	52	Ok	Ok
2	R2	139	Ok	Ok	15	R15	125	Ok	Ok
3	R3	80	Ok	Ok	16	R16	78	Ok	Ok
4	R4	107	Ok	Ok	17	R17	54	Ok	Ok
5	R5	65	Ok	Ok	18	R18	133	Ok	Ok
6	R6	76	Ok	Ok	19	R19	52	Ok	Ok
7	R7	114	Ok	Ok	20	R20	38	Outlier	-
8	R8	49	Ok	Ok	21	R21	67	Ok	Ok
9	R9	77	Ok	Ok	22	R22	44	Outlier	-
10	R10	31	Outlier	-	23	R23	62	Ok	Ok
11	R11	99	Ok	Ok	24	R24	80	Ok	Ok
12	R12	87	Ok	Ok	25	R25	118	Ok	Ok
13	R13	86	Ok	Ok	26	R26	144	Ok	Ok

Table 2 presents the maximum and minimum duration given by the MCS analysis, whereas Table 3 displays the results of the reliability test. In the first MCS analysis, with 3465 iterations, the given minimum project duration was

47 days, and the maximum duration was 146 days. In fact, three proposed project durations did not fall within the range of the minimum and maximum durations. These three data were R10, R20, and R22, which provided durations of 31, 38, and 44 days, respectively. These durations were smaller than the minimum duration provided by MCS, which was 47 days. Therefore, these three data were deemed unreliable and should not be considered in the simulation. The simulation was then continued using 23 remaining data. The same statistical analysis was again conducted to obtain values of average, standard deviation, and absolute error. Based on the statistical value of the 23 data, 2547 iterations were required to do the second MCS analysis. The second simulation granted minimum and maximum values of 44 days and 149 days, respectively. These results convinced that the 23 data were in the range of minimum and maximum values and met the reliability criteria. Table 4 shows the final values of each activity duration obtained from the MCS analysis.

Table 4. Final Results of Monte Carlo Simulation

Activities	Mean	Min	Max
A	3.39	1	14
B	4.30	2	7
C	5.66	2	14
D	2.78	1	10
E	5.07	2	14
F	6.53	3	21
G	1.10	5	25
H	2.41	1	7
I	2.97	1	8
J	2.79	1	6
K	7.29	2	21
L	5.11	2	8
M	4.52	1	10
N	4.77	1	14
O	9.55	3	20
P	5.56	1	14
Q	5.91	3	20
R	8.63	2	25
Total Duration	**87.39**	**44**	**149**

Figure 6 displays a visual representation of the variation in average duration across different iteration counts. The graph illustrates a consistent pattern where an increase in the number of iterations leads to a decrease in the difference in average duration. The results depicted in the graph confirm that the MCS analysis of 23 respondent datasets with iteration counts of 2547 and 3465 has reached a stable state, with the difference in average duration being less than 0.5 days or a margin error less than 1%.

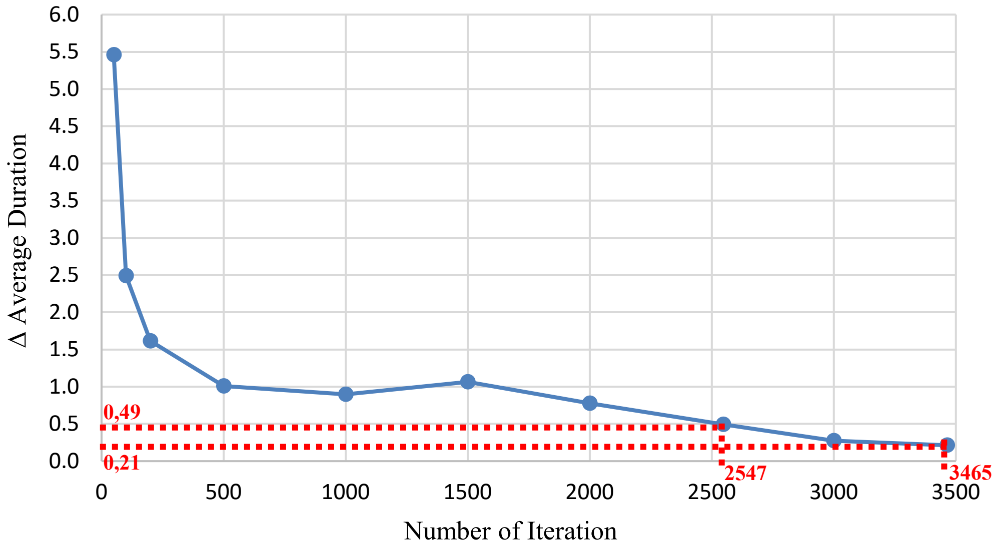

Figure 6. Delta Average Duration Across Various Iteration Counts

Normality Tests

A series of normality tests were carried out to assess the distribution of data in relation to the independent and dependent variables in the regression model [23]. There are more than 40 statistical tests available for examining the normality of a dataset [24]. Some of the well-known tests include the Skewness Kurtosis (SK) test, Jarque Bera (JB) test, Shapiro Wilk (SW) test, Lilliefors (LF) test, and Kolmogorov Smirnov (KS) test [25–27]. The selection of the normality test is based on the number of data points, as outlined in Table 5.

Table 5. Normality Tests Based on The Number of Data Points [28,29]

Test	Number of Samples							
	3 ≤ N ≤ 4	5 ≤ N ≤ 6	7 ≤ N ≤ 9	9 ≤ N ≤ 50	51 ≤ N ≤ 200	201 ≤ N ≤ 2000	2001 ≤ N ≤ 5000	5001 ≤ N
Skewness Kurtosis				V*	V*	V**	V**	V**
Jarque Bera	V**	V*	V*	V*	V*	V**	V**	V**
Shapiro Wilk			V**	V**	V	V		
Lilliefors		V	V	V	V**	V	V	V
Kolmogorov Smirnov		V	V	V	V*	V*	V	V

Explanation:
V = Valid to use
V* = Valid and a good choice to use
V** = Valid and the best choice to use

In accordance with Table 5, utilizing a sample size of 2547 data points, the Skewness Kurtosis (SK) and Jarque Bera (JB) methods are determined to be the most favorable approaches for testing normality. These two methods are subsequently employed as the normality tests, in addition to three others commonly utilized methods: Shapiro Wilk (SW), Lilliefors (LF), and Kolmogorov Smirnov (KS).

The SK method employs a *Z-test*, while the JB, SW, KS, and LF methods utilize the *p-value* to ascertain whether a data sample adheres to a normal distribution [30,31]. According to the SK test, a data sample is deemed normally distributed if the values of $Z_{skewness}$ and $Z_{kurtosis}$ lie within the range of -1.96 to +1.96 (at a 95% confidence level or *alpha* = 0.05). On the other hand, in the JB, SW, KS, and LF tests, a data sample is identified as normally distributed if the *p-value* is below 0.05 (at a 95% confidence level). The normality tests SW, KS, and LF are executed using the SPSS program, while the SK and JB tests are carried out using the following calculations:

$$SE_{skewness} = \sqrt{\frac{6}{n}} \tag{4}$$

$$SE_{kurtosis} = \sqrt{\frac{24}{n}} \tag{5}$$

$$Z_{skewness} = \frac{S}{SE_{skewness}} \tag{6}$$

$$Z_{kurtosis} = \frac{K}{SE_{kurtosis}} \tag{7}$$

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{8}$$

Where $SE_{skewness}$ is the standard error of skewness, $SE_{kurtosis}$ is the standard error of kurtosis, n is the number of samples, S is the skewness values (obtained from SPSS or using the formula =SKEW() in Microsoft Excel), K is the kurtosis values (obtained from SPSS or using the formula =KURT() in Microsoft Excel), and JB is the values of Jarque Bera test result [28,29,32].

Table 6. Normality Tests Results

Tests	Notation	Values	Requirements	Conclusion
Skewness	*Z*	10.28	-1.96 < *Z* < 1.96	NOT OK
Kurtosis	*Z*	3.48	-1.96 < *Z* < 1.96	NOT OK
Jarque Bera	*p-Value*	6E-187	*p-Value* > 0.05	NOT OK
Shapiro Wilk	*p-Value*	< 0.001	*p-Value* > 0.05	NOT OK
Kolmogorov Smirnov & Lilliefors	*p-Value*	< 0.001	*p-Value* > 0.05	NOT OK

Table 6 displays the results of the normality test analysis for the data derived from the MCS results. The table indicates that, according to the five normality test methods (SK, JB, SW, KS, and LF), the data from the MCS results did not satisfy the criteria for a normal distribution.

Probability, Sensitivity, and Severity Analysis

The Monte Carlo simulation effectively produced data suitable for probabilistic analysis. However, as the normality test results suggested that the simulation results data are not normally distributed, we proceeded with a Cumulative Density Function (CDF) analysis assuming that the data represents a population to calculate the probability of project durations. The results of the CDF analysis are depicted in Figure 7.

The accuracy of contractors' project duration estimates directly impacts the level of risk involved in completing the project. The optimistic estimate represents a 50% chance of the project being finished within the projected timeframe. Conversely, the pessimistic estimate reflects a 5% risk of delay or a 95% likelihood of successfully completing the work within the estimated timeframe. The optimistic duration estimate is 86 days, while the pessimistic duration estimate is 112 days.

At a 95% confidence level, the fastest possible project duration is 65 days, and the latest acceptable duration is 116 days, excluding the 2.5% probability range on the extreme ends of the CDF analysis curve. Project durations exceeding 116 days or falling below 65 days can be deemed unreasonable.

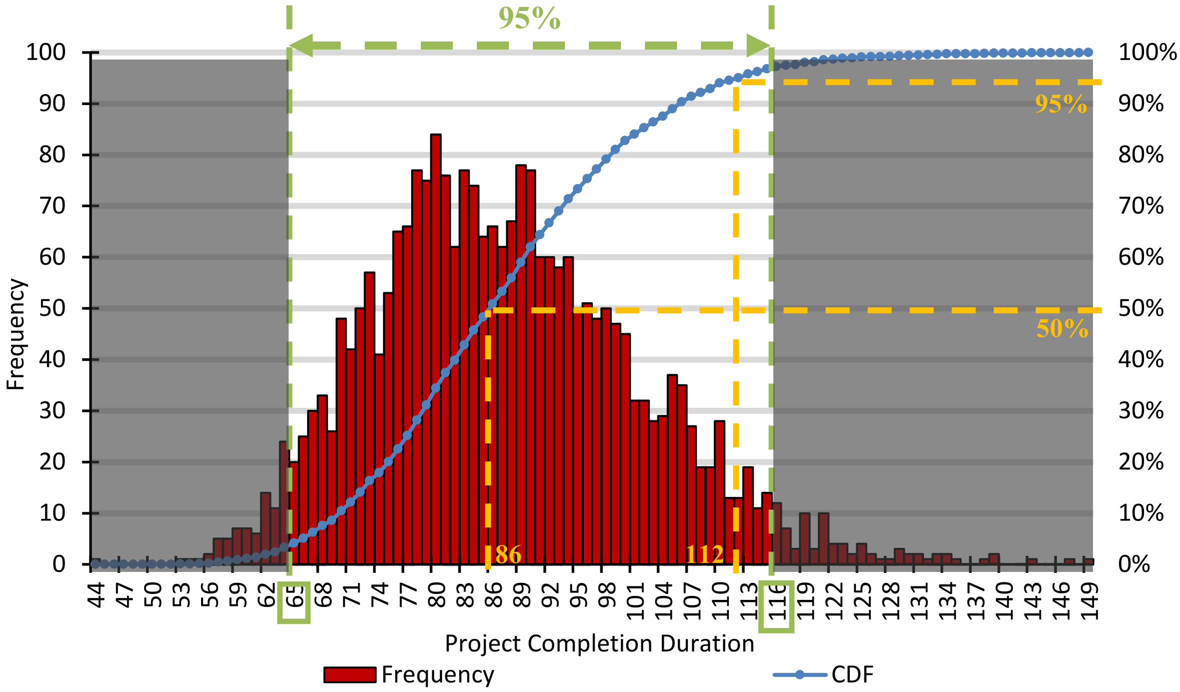

Figure 7. Results of CDF Analysis

The results of the CDF analysis at a 95% confidence level, as depicted in Figure 7, form the basis for conducting sensitivity analysis. In this analysis, the total project duration is calculated when a particular activity is completed in the shortest or longest timeframe, while other activities maintain their average durations. The magnitude of the difference between the potential shortest and longest project durations resulting from an activity reflects the uncertainty associated with that activity's impact on the project duration. Equation (9) is used to calculate the sensitivity analysis.

$$SnI = \frac{\Delta T}{\sum_{i=1} \Delta Ti} \tag{9}$$

Where SnI is the Sensitivity Index values, and ΔT is the gap between the maximum and the minimum project duration.

The sensitivity analysis results are depicted in
Figure 8 using a tornado diagram, showcasing the impact of each activity on the project duration. Four activities, namely J (door frames installation), I (window frames installation), H (plumbing), and D (sewer pipes installation), exhibited a sensitivity index of 0%, indicating that they did not affect the project duration at their minimum or maximum values due to their non-critical nature. On the other hand, activity R (finishing work) emerged as the most influential, contributing to the highest potential fluctuation in project duration, with a value of 11.7%. Following closely, activities G (wall work), K (beam work), and F (column work), demonstrated sensitivity indices of 10.2%, 9.6%, and 9.1%, respectively, signifying their significant impact on project duration.

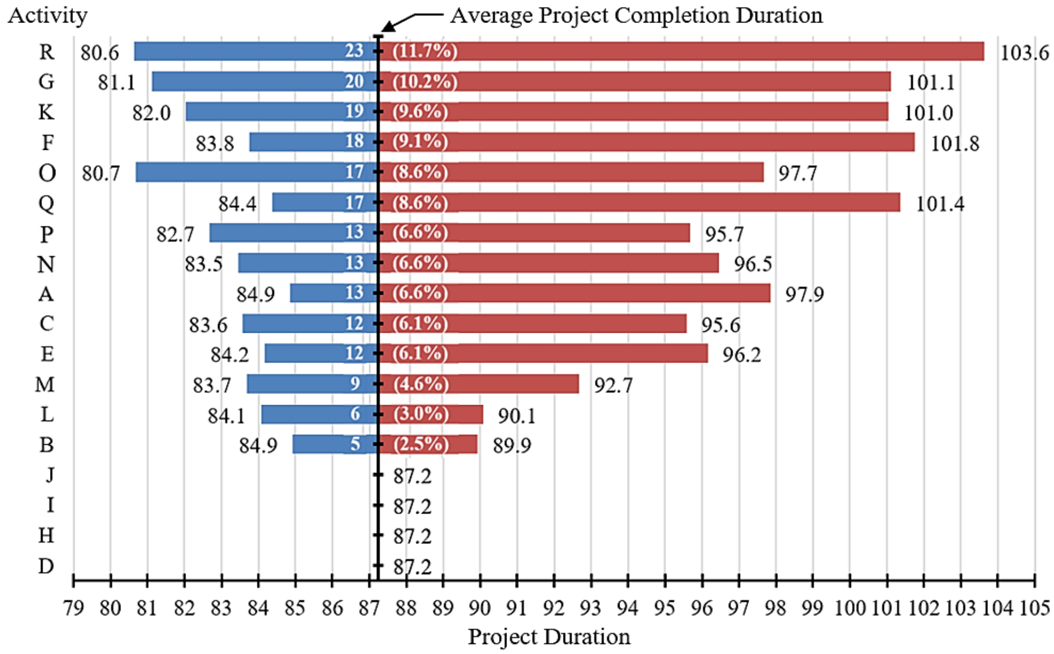

Figure 8. Activity Sensitivity Index

In reality, the activity with the highest sensitivity index, encompassing the widest range of uncertainty in duration affecting project completion, may not always be the most likely cause of project delays. Considering the triangular data distribution of each activity as generated by the Monte Carlo simulation, project completion duration should be determined not only by the potential gap between the fastest and slowest durations, but also by the most likely duration of each activity. Consequently, we introduced a severity index analysis to assess the threat level posed by each activity to the project's completion duration. The severity index analysis was calculated using equations (10), (11), and (12).

$$\bar{t} = \frac{\sum_{i=1}^{n} ti}{n} \tag{10}$$

$$Sv = SnI \times \bar{t} \tag{11}$$

$$SvI = \frac{Sv}{\sum_{i=1} Svi} \tag{12}$$

Where $\bar{t}$ is the average duration of each activity, ti is the duration of each activity, n is the number of data, Sv is Severity values, SnI is Sensitivity Index values, dan SvI is Severity Index values.

Table 7. Severity Analysis Results

Activity	SnI		$\bar{t}$	Sv	SvI	
	value	rank			value	rank
R	11.7%	1	8.59	1.00	14.8%	2
G	10.2%	2	11.12	1.13	16.6%	1
K	9.6%	3	7.20	0.69	10.2%	4
F	9.1%	4	6.47	0.59	8.7%	5
O	8.6%	5	9.56	0.82	12.2%	3
Q	8.6%	6	5.87	0.51	7.5%	6
P	6.6%	7	5.55	0.37	5.4%	7
N	6.6%	8	4.77	0.31	4.6%	9
A	6.6%	9	3.38	0.22	3.3%	11
C	6.1%	10	5.65	0.34	5.1%	8
E	6.1%	11	5.07	0.31	4.6%	10
M	4.6%	12	4.55	0.21	3.1%	12
L	3.0%	13	5.15	0.16	2.3%	13
B	2.5%	14	4.30	0.11	1.6%	14
J	0.0%	15	2.78	0.00	0.0%	15
I	0.0%	16	2.95	0.00	0.0%	16
H	0.0%	17	2.43	0.00	0.0%	17
D	0.0%	18	2.77	0.00	0.0%	18

In Table 7, the severity index analysis results are presented, illustrating the impact of each activity on the project's success. Notably, activity G (wall work) has the highest severity index at 16.6%, making it the most influential activity. Surpassing activity R (finishing work), which was previously considered the most critical, these two activities interchange ranks based on the sensitivity and severity index calculations. Despite Activity G having a smaller uncertainty gap of 20 days compared to Activity R's 23 days, it has a greater potential to impact project completion delays. Hence, activity G should be given greater attention than activity R. Similarly, activities O (plastering work), K (beam work), and F (column work) occupy the third, fourth, or fifth positions based on sensitivity or severity index analysis, necessitating close attention following activities G and R to ensure timely project completion.

In this research, sensitivity and severity analysis revealed that finishing work (R) and wall work (G) exhibit the highest sensitivity and severity index values. These findings align with a study by Wali et al. [14], which conducted a sensitivity analysis on a house construction project in Iraq. Their study highlighted that ceramic wall tiling had the most significant impact on project duration. Although wall finishing methods differ between Iraq, where ceramic tiling is common, and Indonesia, where paint is typically used, both are integral to architectural work and significantly impact project schedules.

The study's findings are supported by other research, as noted in the paragraph below Table 1. Six other studies have highlighted finishing work and wall work as primary focuses due to their relatively longer compared to other activities. Finishing work involves numerous stages, including wall painting, wood varnishing, installation of doors and windows along with all accessories, cleaning activities, and more. The complexity and variety of these tasks contribute to their unpredictability. Wall work, which encompasses large areas and substantial volumes, also requires meticulous attention to detail and precision to achieve the desired outcomes.

Six additional studies have emphasized the importance of focusing on finishing work and wall work due to their longer duration compared to other activities [5,15,17–20]. Finishing work involves several stages, such as wall painting, wood varnishing, and installation of doors and windows, as well as the associated cleaning activities. The complexity and diversity of these tasks contribute to their unpredictability. Wall work, which involves large areas and significant volumes, also requires meticulous attention to detail and precision to achieve the desired results. Moreover, both finishing and wall work require a substantial labour force. The larger the workforce, the higher the potential for variability and uncertainty due to coordination challenges, differences in skill levels, and fluctuations in productivity. This increased labour intensity inherently elevates the level of risk.

Conclusions

The study effectively performed a reliability test on the data generated from the Monte Carlo Simulation (MCS). This involved comparing the project duration produced by 3465 MCS analyses with the proposed project duration from respondent data. The analysis identified three invalid respondents' data that were unsuitable for MCS data generation.

The findings of the MCS Analysis revealed that small-scale housing projects in Indonesia exhibit a relatively high degree of uncertainty. The expected duration with a 50% risk of project delay is 86 days, while the worst-case scenario with a 5% risk of delay is 112 days. The variation between the best and worst-case scenarios represents a 30% potential delay in the project completion.

The sensitivity analysis results indicate that finishing work is the most uncertain activity, with a sensitivity index of 11.7%. Any inaccuracies in managing the finishing activity could potentially cause delays, impacting the overall project completion time. However, based on the distribution of data from the MCS analysis, the severity test reveals that wall work has the most significant influence on project completion. Furthermore, both sensitivity and severity analyses highlight the importance of paying attention to plastering, beams, and columns, which are the third, fourth, and fifth most critical activities in avoiding project completion delays. Interestingly, activities with the widest potential gap between the fastest and slowest completion times are not always the ones that demand the most attention to prevent project delays.

The study primarily employed Monte Carlo Simulation for analyzing project completion durations. However, it's important to note that Monte Carlo Simulation has a broader application beyond scheduling. This method is effective in evaluating risks from various perspectives, including costs, human resource allocations, and even construction quality. Furthermore, there is significant potential for further research and development of Monte Carlo methodologies, especially in their application to project cost management. This is essential to pursue, as cost management is a critical aspect and a primary focus in project management and risk management within the construction industry.

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