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| RESEARCH ARTICLE

Risk-based Project Scheduling Model of Large-scale Renewable Power Plant Constructions through Monte Carlo Simulation

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| ABSTRACT

The construction projects of large-scale renewable power plants have a large schedule uncertainty due to environmental variability, regulatory approvals, and supply chain dependency. Conventional deterministic methods of scheduling, like the Critical Path Method (CPM), assume that activity times are constant, and thus they tend to underestimate the risk of delay. This paper constructs a risk-based project planning model of the construction of renewable megaprojects with the help of Monte Carlo simulation. The structure proposed incorporates deterministic network logic with probabilistic modeling of the duration of activities and the use of correlated risk structure to produce statistically dominant completion forecasts. The model is validated by the use of a 500 MW utility-scale solar power plant. The 10,000 simulation run results are that the deterministic baseline duration of 24 months is underestimated by 14.2 with the 82 percent likelihood of schedule overrun. Sensitivity and criticality analysis find grid interconnection and civil works as the most significant causes of schedule variance. Moreover, correlation modeling adds to predicted variance by 33 percent, which proves that it is beneficial to address interdependent risks. The results indicate that probabilistic and correlation-integrated scheduling present a more realistic and reliable foundation of contingency planning and high-confidence project delivery in the construction of renewable megaprojects.

| KEYWORDS

Monte Carlo simulation, Renewable power plant construction, Schedule uncertainty, Risk-based scheduling

| ARTICLE INFORMATION

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1. Introduction

The world is experiencing a structural transformation in energy transition like never before with the pressing need to curb climate change and long-term decarbonization targets. Following the globally accepted net-zero policies, the scale of renewable energy infrastructure has become a cornerstone of the sustainable energy policy. Strategic roadmaps published by the International Energy Agency and the International Renewable Energy Agency have continued and increased the expansion of utility-scale solar photovoltaic (PV) and wind power plants in the next ten years [Vyas, et al., 2022], [Aquila et al., 2021]. New international installations of over 470 GW of renewable in a single year is also a pointer to the scale and pace of this change [Tsaousoglou et al., 2023]. The timely and dependable development of large-scale renewable electricity generation facilities of hundreds of megawatts with geographically dispersed locations has become an increasing concern in assuring energy reliability and financial sustainability, as well as in notifying national climate policy models [Yin et al., 2023], [Ren et al., 2024].

Utility-scale projects of renewable power plants are very capital-demanding and complex projects in terms of their operations despite their importance in strategy. Recent renewable infrastructure portfolio empirical evidence has shown average schedule overruns of between 15%-25% [Cao et al., 2024], [Sovacool et al., 2025]. Such delays can be attributed to a combination of several interdependent causes, such as weather variability site specificity, grid interconnection approvals, land acquisition, labor productivity variability, and unstable global supply chains of essential elements such as wind turbines, transformers and photovoltaic modules [Islam et al., 2025], [Aquila et al., 2021]. Time cost directly contributes to higher financing costs, revenue generation delay, and Levelized Cost of Electricity (LCOE) which decreases the bankability of the project and national renewable energy goals [Isvara, et al., 2024], [Xue et al., 2025]. Therefore, the issue of schedule risk as an economic problem in the construction of renewable power plants is systematically present and relevant.

The classical project scheduling approaches, the best known of which is the Critical Path Method (CPM) created by Morgan R. Walker and James E. Kelley Jr., utilize the deterministic and fixed durations of the activities [Ioannou et al., 1998]. Although CPM gives a systematic process of determining critical activities and scheduling construction tasks, it does not directly consider stochastic changes in the duration of activities. As a matter of fact, the construction of renewable power plants is plagued by high uncertainty due to unpredictable weather-based disruptions, lack of materials, delays in regulatory procedures, and logistical congestion [Acebes et al., 2021]. This often causes deterministic schedules to generate overly optimistic completion predictions, which have a systematic underestimation of both delay probability and schedule variance, and cause inadequate contingency allocation[Gupta et al., 2025].

These limitations were overcome with probabilistic scheduling techniques. In Program Evaluation and Review Technique (PERT) invented by the U.S. Navy, three-point estimates of duration based on beta distributions were used to represent uncertainty [Sobieraj et al 2022; Koulinas et al., 2020]. Even though PERT shows a significant improvement over the deterministic scheduling, it is based on simplifying assumptions including the independence of activities and roughness of variance aggregation, which might not represent sufficiently the complex interdependencies found in large infrastructure projects [Fadjar, 2022]. The adverse weather, the supply chain disruption, and the grid approval delays are some of the risks that may be significant in renewable megaprojects and therefore may have considerable correlation structure affecting the construction activities jointly.

It has been described by Monte Carlo simulation which was first formulated in the modern computational form by researchers such as Stanislaw Ulam as a more adaptable way of modeling uncertainty in complex systems [Isah et al., 2021]. Monte Carlo simulation can be used to produce probabilities within and without confidence intervals and probability of delay based on the division of activity times into probability distributions of predefined distributions to produce probabilities of schedule outcomes and produce distributions of activity completion times after thousands of repetitions of the set of distributions [Saiz, et al., 2024; Chen et al., 2023; Islam et al., 2022]. This approach can also be used to perform quantitative risk assessment and sensitivity analysis and identify key risk drivers when incorporated in network-based scheduling models.

Although Monte Carlo methods have increasingly been used in construction management and infrastructure planning processes, a number of research gaps still exist in the situation of large-scale renewable power plant construction. To begin with, comparatively limited investigations have created scheduling designs custom-crafted to the business, environmental and regulatory attributes of utility scale solar and wind megaprojects with capacities exceeding several hundred megawatts [Canesi et al., 2025]. Second, most stochastic models of schedule are based on the assumptions that risk factors are independent random variables, although empirical studies show that there are strong relationships between weather conditions, logistics performance and approval timelines [McCabe, 2003]. Third, the lack of consideration of environmental variability measures and supply chain volatility measures in the duration sampling logic underlies the limitation of the realism of probabilistic forecasts in the renewable infrastructure setting [Koulinas et al., 2021].

In addressing these elicited gaps, this work formulates a risk-based project scheduling framework specific to large-scale renewable power plant construction projects through Monte Carlo Simulation. The model proposed is based on deterministic network logic, probabilistic modeling of activity duration, and explicitly models correlated environmental and supply chain risks as part of the scheduling structure. The Monte Carlo simulation framework yields statistically robust completion predictions, measures the probability of delay, obtains confidence completion values (e.g., P50 and P80) and determines the key risk drivers that drive schedule performance. The model thus offers a decision support tool in a structured format to the project managers, investors and policymakers interested in strengthening the schedule reliability and contingencies planning in the delivery of a megaproject, especially in renewable projects.

The rest of this paper will be structured in the following manner. In section 2, I describe the literature review which covers traditional scheduling methods, construction risk management methodologies and Monte Carlo based probabilistic modeling. Section 3 presents the research methodology, which entails the deterministic basis model, identification of risks, and modeling of probability distribution, correlation framework and simulation process. Section 4 presents the project and case study data upon the implementation of the model. The results and the comparative analysis of the simulation is mentioned in Section 5. Section 6 addresses the findings and implications of the findings to management. Last but not least, Section 7 ends the study with the contribution, limitations, and future research summary.

2. Literature Review

2.1 Traditional Project Scheduling

Historically, traditional project scheduling techniques have been the foundation on which the construction project planning and control was structured. Another method that was developed by Morgan R. Walker and James E. Kelley Jr. is the Critical Path Method (CPM), a deterministic network-based approach to identifying the order of activities and calculating the shortest possible duration of a project based on the critical paths [Kelley., 1959; Ioannou., 1998]. CPM allows managers to model precedence relationships and calculate float values, therefore, prioritizing activities that have a direct impact on the completion time. Equally, Gantt charts offer graphical display of the sequence of tasks and time allocation, which gives enablement to visualization of tasks graphically to aid in monitoring of execution. The conceptual simplicity of such deterministic tools and their operational clarity have contributed to the continued use of these tools.

Nevertheless, the basic premise of a set duration of activities is a serious shortcoming of the methodology. Environmental variability, labor productivity, material delivery delays, and regulatory uncertainties are some of the factors which affect real world construction activities. Deterministic models do not determine the propagation of variance between related tasks and do not significantly estimate the likelihood of schedule overrun [Gupta, 2025]. Such fixed-duration assumptions generate over-optimistic completion forecasts in mega projects involving interdependencies which are complex and uncertainty which is systemic, such as in large-scale infrastructure and renewable megaprojects [Islam, 2022]. Therefore, the conventional deterministic scheduling methods offer structural rationality and a lack of risk representation to the megaproject settings.

2.2 Risk Management Construction Project

Construction projects are also vulnerable to multidimensional risks which influence the performance in cost, time and quality. Risk management models typically start with identification of risk, and the methods used are expert judgment, historical, brainstorming as well as formalized methods like Failure Mode and Effect Analysis (FMEA) [Cuadros et al., 2024; Hriday, 2022]. Risks are then identified and then assessed using either qualitative or quantitative methods. Qualitative methods tend to make use of probability impact matrices in ranking risks and semi quantitative scoring schemes in estimating the ranking of threats on perceived severity [Koulinas et al., 2021]. These methods give well-organized classification and are less predictive.

Quantitative risk analysis attempts to put an approximation on the effect of uncertainty on project goals. The research on power plants construction indicates that the risk factors tend to be related and structurally complicated [Hriday, 2022]. Nevertheless, most risk management applications are still divided, with risk registers being divorced off schedule modelling enclosures. Although hybrid methods with the use of Risk Matrix, TOPSIS, and simulation methods are often made, the independence of risk factors is often assumed [Koulinas et al., 2021]. Consequently, despite the presentation of risk identification and classification, the field has not succeeded in integrating risk identification and classification with dynamic scheduling systems, especially in renewable energy megaprojects.

2.3 Monte Carlo Simulation Project Scheduling

Monte Carlo Simulation (MCS) which was initially theorized by Stanislaw Ulam is a significant step towards probabilistic modeling of uncertainty. In contrast to deterministic scheduling techniques which generate single-point estimates, MCS generates distributions of potential outcomes through repeated sampling activity durations based on given probability distributions. Triangular, Beta, and Lognormal distributions are the most commonly used ones; the choice depended on the data available and skewness features [Fadjar, 2022; Islam, et al., 2022]. MCS makes probabilistic completion forecasts, which allows estimation of confidence levels like P50 or P80 durations, through thousands of simulations runs.

There has been an increase in the application of Monte Carlo in the construction industry in the transportation, oil and gas and infrastructure industries [Afzali et al., 2024]. Such works prove the potential of the simulation-based methods to estimate delay probability and highlight the risk drivers that are critical. Nevertheless, there are still a number of restrictions. Most of the implementations presuppose the statistical independence between activities without considering correlated risks like weather disruptions or supply chain shocks that can cause simultaneous impact on several stages of the project. In addition, relatively little modeling has been done in sector-specific modeling in respect to renewable energy construction. The variability of the environment, the complexity of the grid integration, and the dependencies of global procurement are still not sufficiently represented in the existing stochastic scheduling research and there is a necessity to develop more specific modeling frameworks.

2.4 Renewable Energy Construction Risk

Megaprojects in renewable energy such as solar parks and wind farms possess unique risk properties with reference to mainstream infrastructure. Such projects involve a lot of site preparation, environmental studies and technical assimilations. Other uncertainties associated with the location can be categorized into geotechnical variability, difficulty in land acquisition, and ecological clearance [Mena, 2026; Ogunniran, 2025]. These may cause significant delays of the initial project stages and spread downstream schedule disruption. Renewable megaprojects are also characterized by a high level of capital expenditure on procuring specialized equipment, which exposes them to the volatility of the international supply chain and international geopolitical risks [Islam et al., 2025].

Another important cause of schedule uncertainty is grid integration. Interconnection approvals, transmission upgrades and compliance testing can present regulatory and technical complexities and can be seen to lengthen the commissioning timelines. The offshore wind projects also show the cost and schedule risks associated with scale because of the complexity of the configurations and exposure to the environment [Yin, 2023; Lei et al., 2020]. These risk domains associated with renewable sources are well recognized, however, most of the studies cover them either in qualitative terms or with a cost-overrun angle instead of factoring them into stochastic schedule simulation frameworks. This disconnect highlights the importance of probabilistic frameworks of scheduling in the sector that specifically formulate the uncertainty in building renewable energy sources.

2.5 Research Gap

The literature suggests that there is evident methodological growth of deterministic scheduling to probabilistic risk modeling. Deterministic frameworks are structural and disregard uncertainty. The risk management literature provides some tools of classification and prioritization and does not provide integration with the dynamic schedule propagation. Monte Carlo simulation brings probabilistic forecasting capabilities although simplifying assumptions are usually used in practical cases, especially on independence of risk factors.

There are three major gaps in the situation of renewable megaproject construction. First, stochastic scheduling model of renewable sectors are restricted. Second, linking environmental and supply chain risks are not well integrated in simulation models. Third, there is yet to be developed integration between structured risk registers and network-based scheduling logic. The solution to these gaps is necessary in enhancing schedule reliability assessment and contingency planning in large scale renewable infrastructure development.

3. Methodology

3.1 Research Framework

This research paper used a quantitative model to create a risk-based project scheduling model of building large-scale renewable power plants by use of Monte Carlo simulation. Its main aim is to take deterministic scheduling methods and include uncertainty in the activity times and construction risks that are correlated. Rather than coming up with an estimate of the completion at one point, the suggested framework provides probabilistic completion forecasts that are better representation of the variability and interdependencies inherent in the execution of renewable megaprojects.

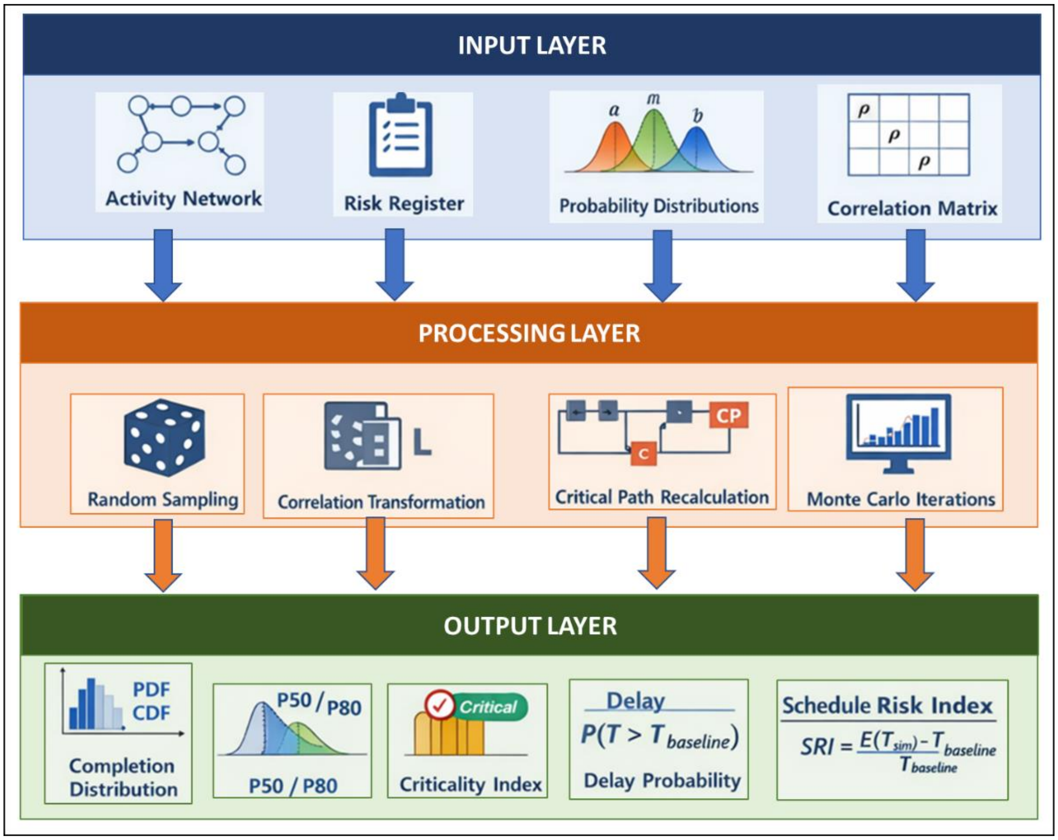

Figure 1: Overall Proposed Framework

The research model includes four consecutive steps. A deterministic baseline schedule is first made on the Critical Path Method (CPM). Second, the identification of construction risks is done and the risks mapped to project activities. Third, the duration of the activities is modeled and incorporated into a Monte Carlo simulation framework to produce stochastic completion results. Lastly, schedule risk measures are calculated to measure the level of delay probability, behavior of activity criticality and levels of confidence-based completion. The framework is applied and justified using a real-life case study of a huge project related to the construction of a renewable power plant. To better understand how it works, the general layout of the suggested model will be provided in Figure 1 that will show the input (activity network, risk register, probability distributions, correlation matrix), processing (random sampling, correlation transformation, critical path recalculation, simulation iterations) and the output (completion distribution, risk metrics) layers.

3.2 Deterministic Baseline Model

The modeling process is initiated by the development of a deterministic baseline schedule to define a base completion time. A work breakdown structure (WBS) is created in a structured manner to identify key project stages such as site preparation, civil works, foundation construction, structural installation, electrical works, grid interconnection and testing and commissioning. The activities are defined in terms of precedence relationships to create a directed project network. Define the set of activities as:

$$\mathrm{A} = \{a_1, a_2, \ldots\ldots\ldots\ldots\ldots\ldots, \ldots. a_n\}$$

Where all activities ai are known to take a deterministic period di. A precedence matrix is created to depict dependency relationship amongst activities. With the Critical Path Method, the critical path (CP) is defined as the longest path of any dependent activity that defines the minimum time a project will take. Deterministic minimizing baseline completion time is estimated:

$$T_{baseline} = max \sum_{i \epsilon CP} d_i$$

This baseline period is the parameter used to compare stochastic schedule results created by simulation.

3.3 Risk Analysis and Mapping.

A triple strategy involving expert interviews, the literature review and examination of renewable infrastructure project documentation is used to identify construction risks. These risks are divided into environmental, regulatory, supply chain, technical, and financial risks. A structured risk-activity matrix is used to map each of the identified risks to the activities they affect to make sure that uncertainty has been explicitly incorporated into the project network. Table 1 gives a representative outline of the risk mapping framework, with every category of risk being associated with its affected activities. Such organized mapping guarantees the traceability of risks discovered and modeled activity time periods.

Table 1: Risk-Activity mapping Matrix

Risk Category	Risk Description	Affected Activity
Environmental	Extreme rainfall	Civil works
Environmental	High wind	Structure erection
Regulatory	Grid approval delay	Grid interconnection
Supply Chain	Equipment shipment delay	Electrical installation
Technical	Design modification	Foundation works
Financial	Contractor payment delay	Installation activities

3.4 Probability Distribution Modeling.

The model assumes uncertainty over the time of execution of the activities and thus the execution time of each activity is a random variable and not a deterministic value. Triangular, beta or lognormal probability distributions are attributed depending on data availability and delay properties. The triangular distribution is chosen as the most suitable modeling approach because it is convenient to use in the conditions of the limited data and the ease with which the parameters are estimated. It involves three parameters, namely, the duration of optimism a, most likely duration mmm, and pessimistic duration b. The triangular distribution has the probability density function as:

$$f(x) = \begin{cases} \dfrac{2(x-a)}{(b-a)(m-a)}, & a \le x \le m \\ \dfrac{2(b-x)}{(b-a)(b-m)}, & m \le x \le b \end{cases}$$

The average time that is under triangular distribution is determined as:

$$E(t) = \frac{a + 4m + b}{6}$$

In activities with right-skewed delay behavior, including grid interconnection approvals, a lognormal distribution is used to represent extreme delay cases better. Such a probabilistic modeling allows realistic modeling of the variability of schedules and tail-risk behavior.

3.5 Correlation Modeling

In the renewable construction projects of large size, some risks affect various activities at the same time. An example is that bad weather can postpone civil works, structural installation, and commissioning activities, and deal a blow to various activities that rely on procurement. Aggregate schedule variance may be understated through the modeling of durations independently.

A correlation matrix ρ_{ij} is required to define the interdependencies, and this is expressed as the correlation between the duration of activities D_i, D_j. The correlation structure will make sure that the joint risk effects are considered during the simulation. Cholesky decomposition is used to produce correlated random samples by using the correlation matrix. Where *R* refers to the correlation matrix, then:

$$R = LL^T$$

where Lis the lower triangular matrix that is obtained through decomposition. L is used to convert independent standard normal samples to correlated duration samples. Such a process makes the process more realistic and eliminates underestimation of overall project uncertainty.

3.6 Monte Carlo Simulation Procedure.

Monte Carlo simulation is used to assess probabilistic behavior of the time of project completion. The duration of each activity is sampled according to the probability distribution assigned to each activity, and this is repeated in each simulation run. The correlation transformation is used to maintain interdependencies of related activities. Project network is calculated again and the project critical path is determined based on sampled durations.

The time taken to complete the project under each iteration is defined as:

$$T_{project} = max \sum D_{path_i}$$

D_{Pathi} denoting the total length of path i. This simulation is done over many repeats (e.g., 10,000) to come up with a steady empirical distribution of completion times. The convergence is determined through the check of the stabilization of the mean and variance estimates with regards to iterations. The Python computational implementation is done to achieve numerical efficiency.

3.7 Schedule Risk Metrics

In order to measure schedule performance in the face of uncertainty, some quantitative risk measures are obtained as simulation outputs. Delay probability is determined as:

$$P(T > T_{baseline})$$

Measures the probability of the stochastic completion time to be above the deterministic base level.

The Criticality Index of activity i is obtained as:

$$CL_i = \frac{\text{Number of times activity i is critical}}{Total\ Simulation}$$

This measure is used to measure the likelihood of a certain activity appearing on the critical path. Completion times based on confidence like P50 and P80 are derived using the cumulative distribution function (CDF) of project time. Moreover, Schedule Risk Index (SRI) is defined as:

$$SRI = \frac{E(T_{sim}) - T_{baseline}}{T_{baseline}}$$

All these metrics can offer supporting information used in decision-making when allocating contingencies, estimating buffers, and creating risk-related plans used in constructing renewable megaprojects.

4. Case Study

4.1 Project Description

In order to justify the risk-based scheduling model, a large-scale project of constructing a renewable power plant is chosen as a case study. The project is a 500 MW utility-scale solar photovoltaic (PV) power station in a developing economy with seasonal changes in climatic conditions and grid connection limitations. Deterministic scheduling conditions show the total planned construction period at 24 months.

The project is divided into several construction stages, some of which are parallel, sequential and they include site preparation, civil works, foundation construction, mounting structure installation, module installation, electrical installation, grid interconnection, and testing and commissioning. The project financing arrangement is in terms of milestone-based payments that are in turn, tied to commissioning and this makes the reliability of the schedule the most important. The case study creates a realistic condition in which schedule uncertainty and correlated risk effects are considered.

4.2 Work Breakdown Structure (WBS)

To establish significant project activities, a simplified Work Breakdown Structure (WBS) is created. Planning documents and expert consultation are found in each activity as baseline deterministic periods. The definitions of precedence relationships are based on the logic of construction. As an illustration, one cannot start foundation construction until civil works is done and interconnection of the grids is done after electrical installation.

Table 2: Minimalized Work Breakdown Structure

Activity ID	Activity Description	Baseline Duration (Months)
A1	Site Preparation	3
A2	Civil Works	5
A3	Foundation Construction	4
A4	Mounting Structure Installation	4
A5	Module Installation	3
A6	Electrical Installation	3
A7	Grid Interconnection	2
A8	Testing & Commissioning	2

4.3 Risk Register and Parameter Estimation

According to the interviews with experts and literature, the significant threats to this project are outlined and associated with the activities. The parameters of probability distribution (optimistic, most likely, pessimistic timeframes) are determined based on structured expert judgment with references to historical delay statistics of the similar projects.

Table 3: Risk-Adjusted Duration Parameters

Activity	Optimistic (a)	Most Likely (m)	Pessimistic (b)	Distribution
Civil Works	4	5	7	Triangular
Structure Installation	3	4	6	Triangular
Electrical Installation	2	3	5	Triangular
Grid Interconnection	1	2	6	Lognormal

The civil works and installation of structures are mostly vulnerable to environmental risks (e.g., extreme rainfall). Electrical and module installation is impacted by the delay of supply chain. Regulatory risks are clumped at the grid interconnection stage, where skewed delay pattern due to right skewness makes it appropriate to involve a lognormal modeling. Definitions Correlation coefficients among activities that are sensitive to weather are used to indicate dependency. As an example, civil works and structure installation are given moderate positive correlation because they are subject to the same exposure of the environment.

4.4 Simulation Setup

Monte Carlo simulation is performed with the help of Python. To allow the stabilization of the statistics, 10,000 iterations are conducted. For each iteration:

- The time of activities is sampled at random, according to the distributions allocated to them.
- Correlation transformation is used.
- The project network is re-calculated.
- Completion time is recorded.

The convergence is measured by the observation of the mean and standard deviation stabilization of the simulated completion times. The outputs of simulations are probability density function (pdf) and cumulative distribution of the total project duration.

4.5 Model Validation

In order to confirm the strength of the suggested model, the results of stochastic completion are contrasted with the deterministic base schedule. The comparison assesses the fact that probabilistic estimates yield better realism in predicting delay exposure than scheduling based on fixed durations. The findings of the case study prove the effect of correlated environmental and regulatory risks on schedule variability and critical path behavior. The calculated measures such as P50, P80, delay probability and criticality index give realistic information on the need of contingency buffer and risk-sensitive scheduling decisions.

5. Results

The proposed risk based scheduling model was applied using 10,000 Monte Carlo simulation cycles to determine the effect of probabilistic activity period and correlated construction risks on the total time of project completion. In this section, comparative research between deterministic and stochastic scheduling results, distribution analysis, sensitivity analysis, and correlation impact analysis will be done. The findings give quantitative data of schedule variation and establish the prevailing risk factors in the delivery of renewable megaprojects.

5.1 Deterministic/Stochastic Schedule Comparison

The deterministic schedule is the ideal completion time that is estimated through the Critical Path Method (CPM) in which all activities are assumed to be definite and fixed. By contrast, the stochastic schedule uses the uncertainty by characterizing the time taken to complete an activity as a random variable and by using Monte Carlo simulation to produce probabilistic results. Table 4 captures the comparison between deterministic and stochastic schedules. Although the deterministic base duration was 24 months, the average simulated base duration was 27.4 months with a standard deviation of 3.2 months. The completion time of the P50, P80 and P90 was 27.0, 30.2 and 32.1 months, respectively, using 10, 000 simulation iterations. These results indicate that deterministic planning drastically underestimates the duration of the projects by 3.4 months (14.2%), which proves that uncertainty and corresponding risk play a crucial role in the reliability of the schedule in the construction of large renewable power plants.

Table 4: Stochastic and Deterministic Schedule Comparison

Metric	Value (Months)
Deterministic Baseline	24
Mean Simulated Duration	27.4
Standard Deviation	3.2
P50 Completion Time	27.0
P80 Completion Time	30.2
P90 Completion Time	32.1
Maximum Simulated Duration	36.8

The simulated completion time is expected to be over by 3.4 months in comparison to the deterministic baseline, which means that the delay risk is systematically underestimated in the traditional scheduling. The Schedule Risk Index (SRI) calculated is:

$$SRI = \frac{27.4 - 24}{24} = 0.142 \quad (14.2\%)$$

5.2 Distribution Analysis Completion Time

The artificial completion time distribution has a skewed tendency of the right, which represents delay-dominated uncertainty in renewable construction projects. The relative frequency peaks in 2728 months (0.235), followed by 2829 months (0.210) as can be seen in Table 5, which means that the majority of the simulations are concentrated around the median value of the duration. Nevertheless, the decreasing yet consistent rates past 30 months, with 2.1 percent of the simulations over 32 months confirm the occurrence of low-probability but high-impact delay results. This shape in the distribution shows how schedule risk is always asymmetric, and it is important to note that probabilistic modeling is necessary to capture extreme delay distributions.

Table 5: Frequency Distribution of Time of Completion

Completion Time (Months)	Relative Frequency
24–25	0.018
25–26	0.062
26–27	0.148
27–28	0.235
28–29	0.210
29–30	0.152
30–31	0.102
31–32	0.052
>32	0.021

5.3 Percentile and Cumulative Probability Analysis

The cumulative distribution of the simulated completion time gives confidence-based thresholds which allow the stakeholders to test schedule risk at different levels of certainty. F(t) =P(T=t) cumulative probability means the probability that the project will be finished during a given period. Table 6 displays the percentile-based completion times based on the 10,000 simulations based empirical cumulative distribution. The completion times of the P10, P50, P80, and P90 are 25.4, 27.0, 30.2, and 32.1 months, respectively. These findings suggest that although the median completion time is 27.0 months, to meet the 80% confidence level, the schedule has to be stretched to 30.2 months, which is an indication of the right skewed delay risk in the renewable construction projects.

Table 6: Percentile Completion Times

Percentile	Duration (Months)
P10	25.4
P50	27.0
P80	30.2
P90	32.1

The most likely probability of surpassing the deterministic baseline period is:

$$P(T > 24) = 1 - P(T \leq 24) = 0.82$$

This represents a probability of 82 percent of schedule overrun compared to the initial CPM estimate. Further excess probabilities at the chosen levels are summarized in Table 7. There is a risk of more than 27 months of 49 percent and 20 percent at 30 months and 32 months respectively. These cumulative probability findings indicate that deterministic scheduling significantly under-exposes delay, and say in favor of using P80-based thresholds to plan risk-informed contingency.

Table 7: Probability of Exceedance

Threshold (Months)	Probability
24	0.82
27	0.49
30	0.20
32	0.10

5.4 Criticality Index Analysis

The Criticality Index (CI) was used to ascertain the frequency of any activity on the critical path on the individual simulation runs. The values of the CI of every major activity in the project are outlined in Table 8. The grid interconnection stage has the largest CI of 0.83 which implies that any delays during this stage are most probably to affect the final project completion. There is a close correlation between civil works and foundation construction with CIs of 0.74 and 0.68 respectively because they play an important role in the initial stages of the project. Electrical installation and testing and commissioning are less critical and indicate that they are less likely to be on the critical path.

Table 8: Criticality Index Results

Activity	Criticality Index
Grid Interconnection	0.83
Civil Works	0.74
Foundation Construction	0.68
Structure Installation	0.61
Electrical Installation	0.52
Testing & Commissioning	0.49

5.5 Sensitivity Analysis

The sensitivity analysis was performed to assess the contribution of individual activities to the overall project duration variance during stochastic simulation. The mean impact of grid interconnection is the largest, 2.1 months, as presented in Table 9, which means that the regulatory and grid-related uncertain factors have the most significant effect on schedule variability. The next one is civil works at 1.6 months and electrical installation is 1.2 months later. The foundation construction impacts and the structure installation are less by 1.0 and 0.8 months respectively. These findings indicate that activities that occur in the early stage and approval-contingent stages have a disproportionate impact on overall project length and therefore risk mitigation implementation in grid coordination and civil works management should be undertaken specifically.

Table 9: Sensitivity Ranking

Activity	Mean Impact (Months)	Rank
Grid Interconnection	2.1	1
Civil Works	1.6	2
Electrical Installation	1.2	3
Foundation Construction	1.0	4
Structure Installation	0.8	5

5.6 Effect of Correlation Modeling

In order to determine the effect of activity interdependencies, two simulations were made: the independent and correlated duration assumptions. Table 10 demonstrates that introduction of correlation increased the mean completion time of 26.1 to 27.4 months and standard deviation of 2.4 to 3.2 months, and the P80 threshold rose to 30.2 months. This illustrates that correlation should not be overlooked because it underestimates the aggregate schedule risk and high-confidence completion time, therefore, when modelling interdependent risks in the scheduling of renewable megaprojects.

Table 10: Effect of Correlation on Schedule Outcomes

Scenario	Mean Duration	Std. Dev.	P80
Independent	26.1	2.4	28.5
Correlated	27.4	3.2	30.2

5.7 Assessment of Delay Probability

In order to assess schedule risk further, the likelihood of surpassing the different completion limits was measured. Table 11 gives the summary of surpassing 24, 27, 30 and 32 months. The likelihood of overrunning 24 months is 82% showing a large likelihood of a delay in the real-life uncertainty environment. The higher the threshold, the lower is the probability of exceedance as only 10 percent of simulations exceeded 32 months. The results of this research can be applied to contingency planning and financial risk management, and it would be a better decision to have a contingency buffer with the level of P80 because the results will support the delivery of the project within the anticipated time frames.

Table 11: Delay at Critical Milestones

Threshold (Months)	Probability of Exceedance
24	0.82
27	0.49
30	0.20
32	0.10

6. Discussion

The findings prove that the deterministic CPM-based scheduling makes significant underestimations of the completion time in the large-scale construction projects of renewable power plants. The fact that the mean duration has increased by 14.2 percent and that there is 82 percent chance of being above the baseline schedule is a fact that uncertainty and correlated risk have a great influence on project delivery reliability. This result is supported by previous studies which suggest that schedule overruns are common in infrastructural megaprojects because of regulatory delays, variable weather conditions, and disruption of supply chains.

The sensitivity analysis and criticality analysis also indicate that the grid interconnection and civil works control the variability in the schedule. This is an indication that approval processes and early-stage construction risks, spread throughout the entire dependent activities increasing overall project duration. This result is reinforced by the findings of the correlation modeling that indicate that when the interdependencies are taken into account, the variance increase is 33 percent, which demonstrates the inapplicability of the independent-duration assumptions in the traditional risk assessment.

Managerial implication wise the results highlight the fact that percentile-based planning (e.g., P80 thresholds) should be used, but not deterministic estimates. The introduction of probabilistic modeling in the scheduling of renewable mega projections can enhance the allocation of contingencies, financing choice, and contract structure in consideration of risks. Generally, the suggested structure has offered a more realistic and analytically strong foundation of schedule planning in case of uncertainty.

7. Conclusion

The proposed work came up with a stochastic risk-based scheduling model of construction projects related to large-scale renewable power plants that was created through a combination of deterministic CPM logic with probabilistic duration modeling and correlated risk structures. Based on Monte Carlo simulation, this framework used probabilistic forecasts of completion and measures of delay probability, schedule variance, and activity criticality. The findings of the case study indicate that the deterministic scheduling is highly inaccurate in estimating the completion time, the mean duration is overestimated by 14.2 percent, and the likelihood of surpassing the original schedule is 82 percent. The sensibility and correlation analysis indicates that the activities related to the approval that are highly reliant on it and the construction activities at the early phase of the project, especially the activities connected with the interconnection of grids and civil work, have a disproportional impact on the overall project duration. Predicted variance is significantly high with the use of correlation modeling to prove that interdependent risks should be taken into consideration to make realistic predictions of the schedule. The suggested framework thus offers applicable decision-support tool among project managers, investors and policy makers who have interests in enhancing the schedule consistency of renewable megaproject delivery. This study is limited in spite of the contributions it makes. The study has utilized one case study to perform the analysis and the parameters of the probability distribution are partially based on the judgment of the experts. Future studies can build on the framework with cost-risk modeling, real-time construction data, and artificial intelligence-based predictive techniques, and multi-project portfolio risk assessment to further extend the predictive potential and make decisions.

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