TRIBHUVAN UNIVERSITY

INSTITUTE OF ENGINEERING

PULCHOWK CAMPUS

THESIS NO.: 080/MSCoM/011

A Hybrid Forecasting Model Integrating Earned Value Management and Monte Carlo Simulation for Schedule Risk Prediction in Building Construction Projects

by

Jayan Shrestha

A THESIS

SUBMITTED TO THE DEPARTMENT OF CIVIL ENGINEERING IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN CONSTRUCTION MANAGEMENT

DEPARTMENT OF CIVIL ENGINEERING

LALITPUR, NEPAL

APRIL, 2026

COPYRIGHT

Tribhuvan University
Institute of Engineering
Department of Civil Engineering
Pulchowk Campus

....

Head of Department
Department of Civil Engineering
Pulchowk Campus, Institute of Engineering
Lalitpur, Nepal

DECLARATION

I hereby declare that the thesis entitled "**A Hybrid Forecasting Model Integrating Earned Value Management and Monte Carlo Simulation for Schedule Risk Prediction in Building Construction Projects**" submitted to the Department of Civil Engineering in partial fulfillment of the requirements for the degree of Master of Science in Construction Management, is a record of original work done under the guidance of Er. Subash Kumar Bhattarai. The thesis contains only work completed by me, except for the consulted material, which has been duly referenced and acknowledged.

....

Jayan Shrestha

080/MSCoM/011

TRIBHUVAN UNIVERSITY
INSTITUTE OF ENGINEERING
PULCHOWK CAMPUS
DEPARTMENT OF CIVIL ENGINEERING

CERTIFICATE OF THESIS APPROVAL

The undersigned certify that they have read, and recommended to the Institute of Engineering for acceptance, a thesis entitled "**A Hybrid Forecasting Model Integrating Earned Value Management and Monte Carlo Simulation for Schedule Risk Prediction in Building Construction Projects**" submitted by Jayan Shrestha in partial fulfilment of the requirements for the degree of Master of Science in Construction Management.

....

Supervisor:
Er. Subash Kumar Bhattarai
Visiting Faculty
Construction Management
Centre for Post Graduate Studies
Nepal Engineering College (nec-CPS)

....

External Examiner:
Dr. Dinesh Sukamani
Program Coordinator
M.Sc. in Construction Management
Nepal Engineering College
Prayagpokhari, Lalitpur

....

Program Coordinator:
Asst. Prof. Mahendra Raj Dhital
M.Sc. in Construction Engineering and Management
Department of Civil Engineering
Pulchowk Campus, IOE

24 April 2026

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my supervisor, Er. Subash Kumar Bhattarai, for his invaluable guidance, constructive suggestions, and continuous encouragement throughout the course of this research work. His insightful comments and academic support were instrumental in the successful completion of this thesis.

I am also grateful to the Program Coordinator, Asst. Prof. Mahendra Raj Dhital, M.Sc. in Construction Engineering and Management, Department of Civil Engineering, Pulchowk Campus, Institute of Engineering, for providing the necessary academic environment and support during the study period. I extend my appreciation to the faculty members and staff of the Department of Civil Engineering for their cooperation and assistance.

I would like to sincerely acknowledge the Office of Federal Urban Development and Building Construction under the Department of Urban Development and Building Construction (DUDBC) for providing access to the case study project progress records, which served as an important source of data for this research. Their support and cooperation greatly contributed to the completion of this study.

I sincerely thank all the professionals, experts, and respondents who contributed their time and knowledge during data collection and validation. I am grateful to my friends and colleagues for their continuous support and encouragement. I would like to extend special thanks to Mr. Prabin Shrestha and Ms. Diksha Panta for their invaluable assistance during data collection, and to Mr. Vivek Shrestha for his encouragement and support throughout this research. Finally, I express my deepest gratitude to my family for their constant support, patience, and encouragement, which enabled the successful completion of this study.

Jayan Shrestha
080/MSCoM/011

ABSTRACT

This study develops and evaluates a hybrid forecasting model integrating Earned Value Management (EVM) and Monte Carlo Simulation (MCS) for project schedule risk prediction in building construction projects. Conventional EVM is widely used for project monitoring and forecasting, but its deterministic nature limits its ability to capture uncertainty in future project performance. To address this limitation, the study combines deterministic schedule forecasting from EVM with probabilistic delay estimation using MCS. A quantitative case-study-based research design was adopted. Schedule uncertainty factors were identified through a literature review and validated by nine experts using the Relative Importance Index, resulting in fifteen key factors. A questionnaire survey of 72 construction professionals was then conducted to estimate the probability of occurrence and delay impacts of these factors, which were subsequently analysed using a 5×5 probability-impact matrix for qualitative risk prioritisation. Payment delays emerged as the most critical risk, classified as medium-high, while legal prosecution and land-related disputes represented low-probability but high-consequence risks. A real multi-storey apartment building project was selected as the case project for deterministic EVM and Earned Schedule analysis. The results showed that at the original planned completion point, the project had achieved only 72.13% earned progress, with SPI = 0.72 and SPI(t) = 0.74, indicating significant schedule slippage. The Monte Carlo simulation under the base scenario produced a mean delay of 141.09 days, with P50, P80, and P90 delays of 131.38, 205.59, and 247.16 days, respectively. When simulation outputs were integrated with deterministic forecasts, the ESM1-based hybrid model produced a P50 completion forecast of 1508.65 days and a P80 forecast of 1582.86 days, indicating substantial residual schedule risk even after schedule revision. The study concludes that integrating EVM and MCS provides a more realistic and decision-oriented framework for schedule forecasting than deterministic EVM alone and can support proactive risk-informed planning in Nepalese building construction projects.

Keywords: *Uncertainty Factors, Earned Value Management, Monte Carlo Simulation, Schedule Risk Forecasting, Hybrid Forecasting Model, Earned Schedule, Relative Importance Index, Probabilistic Schedule Forecasting, Probability-Impact Matrix*

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AC	: Actual Cost
ANN	: Artificial Neural Networks
AT	: Actual Time
CPI	: Cost Performance Index
CV	: Cost Variance
DUDBC	: Department of Urban Development and Building Construction
EAC	: Estimate at Completion
ED	: Earned Duration
EDM	: Earned Duration Management
ES	: Earned Schedule
ETAC	: Estimated Time at Completion
ETC	: Estimate to Complete
EV	: Earned Value
EVA	: Earned Value Analysis
EVM	: Earned Value Management
GAM	: Generalized Additive Model
IEAC	: Independent Estimate at Completion
MAPE	: Mean Absolute Percentage Error
MCS	: Monte Carlo Simulation
PERT	: Program Evaluation and Review Technique
PMI	: Project Management Institute
PRM	: Project Risk Management
PV	: Planned Value
QDA	: Quadratic Discriminant Analysis
RII	: Relative Importance Index
S-EVM	: Stochastic Earned Value Management
SCI	: Scheduled Cost Index
SPI	: Schedule Performance Index
SV	: Schedule Variance
SVM	: Support Vector Machine
TCPI	: To-Complete Performance Index
VAC	: Variance at Completion

CHAPTER 1: INTRODUCTION

1.1 Background

The construction industry plays a central role in national infrastructure development, yet projects frequently struggle to meet time and cost targets due to the complex and uncertain nature of construction environments (Giri, 2025). Projects often face unforeseen challenges such as variable activity durations, resource shortages, weather-related delays, environmental risks, and managerial or political instability. These factors significantly increase the likelihood of schedule delays and scope deviations, which can undermine the successful and timely delivery of construction projects (Bhattarai, 2023).

To address project performance measurement challenges, Earned Value Management (EVM) has been widely adopted as a systematic tool that integrates scope, time, and cost to monitor and control project performance. EVM helps quantify deviations from the planned baseline and offers predictive insights into future performance using indicators such as Planned Value (PV), Earned Value (EV), and Schedule Performance Index (SPI) (Jha, 2015). However, EVM is essentially deterministic and retrospective. It relies heavily on past and current progress data to forecast future outcomes and does not account for uncertainty or variability in future project activities (Moradi et al., 2017).

To bridge this limitation, the construction project management field has increasingly turned to probabilistic approaches such as Monte Carlo Simulation (MCS). MCS allows for uncertainty modelling by simulating thousands of possible project scenarios based on probability distributions of key variables like activity durations and schedule impacts (Mubin et al., 2019). This simulation-based method provides a range of possible completion dates with associated confidence levels, which is especially crucial for high-risk environments like Nepal.

Given the strengths of both methods, integrating EVM and MCS into a hybrid forecasting model can provide a more comprehensive understanding of project schedule performance by combining the structured tracking of EVM with the probabilistic foresight of MCS. This hybrid approach enables project stakeholders to not only measure where a project stands in terms of schedule but also understand where it is likely to go under varying risk conditions.

1.2 Problem Statement

Despite the widespread use of Earned Value Management (EVM) in construction project monitoring, its deterministic nature limits its ability to address the uncertainties inherent in real-world project environments (Babar et al., 2017). EVM relies on fixed performance indices and single-point forecasts, which often fail to reflect the stochastic variability associated with activity durations and schedule parameters (Nizam & Elshannaway, 2019).

In the Nepalese construction sector, where infrastructure projects frequently experience significant variability in timelines due to factors such as resource shortages, climatic conditions, and managerial inefficiencies, relying solely on deterministic EVM approaches can lead to misleading schedule forecasts and reactive decision-making.

Moreover, there is currently a lack of localised predictive tools that combine quantitative project performance metrics with probabilistic schedule risk modelling in Nepal. Monte Carlo Simulation (MCS) has been extensively applied internationally to address schedule uncertainty (Akhbari, 2018; Sokolowski, 2010). Its integration with EVM remains rare in Nepalese construction practice. Existing forecasting methods often overlook uncertainty in future progress trends, reducing their effectiveness in dynamic and uncertain project environments.

Several studies have attempted to integrate EVM with probabilistic approaches, such as EVM–MCS hybrid models and stochastic EVM frameworks. However, many existing models involve complex statistical or machine learning techniques and require large datasets. Many studies are industry-specific, with limited real-world validation limiting their applicability in practical construction environments (Acebes et al., 2015; Akhbari, 2018; Bonato et al., 2019).

There is a lack of simple and practical hybrid forecasting frameworks integrating EVM and Monte Carlo Simulation tailored for construction projects in developing countries such as Nepal, where project data availability and forecasting tools are limited.

This gap highlights the need for a hybrid forecasting framework that leverages EVM's schedule tracking capabilities together with MCS's probabilistic modelling strengths. Such a model would enable the generation of probabilistic forecasts of project completion rather than single-point estimates, thereby improving accuracy and supporting more proactive, risk-informed decision-making for construction project managers in Nepal.

1.3 Objectives

The primary aim of this research is to develop a hybrid forecasting model integrating Earned Value Management and Monte Carlo Simulation for schedule risk prediction in building construction projects. To achieve this aim, the study is guided by the following specific objectives:

- To explore key uncertainty factors affecting schedule performance in building construction projects.
- To analyse qualitative schedule risk in building construction projects using a 5x5 probability-impact matrix.
- To develop a hybrid forecasting model integrating EVM and MCS for schedule risk prediction in building construction projects and evaluate its performance against traditional deterministic EVM.

1.4 Significance of the Study

This study holds both theoretical and practical significance in the field of construction project management, particularly in the domain of schedule performance forecasting under uncertainty.

From a theoretical perspective, the research contributes to academic understanding of hybrid forecasting approaches by integrating Earned Value Management (EVM) with Monte Carlo Simulation (MCS). While EVM is widely recognised for its structured and quantitative tracking of project performance, it has limitations when used in isolation, especially in accounting for the dynamic and uncertain nature of construction projects. The incorporation of MCS enhances this framework by introducing stochastic modelling capabilities, thereby enabling more realistic and probabilistic schedule forecasts. This study adds to the existing literature by demonstrating how the fusion of deterministic and probabilistic methods can overcome individual limitations and produce more reliable schedule predictions.

From a practical standpoint, the study is highly relevant to project managers, planners, and policymakers engaged in construction projects in Nepal and similar developing countries. Schedule delays remain a persistent issue in these contexts due to various uncertainty factors such as labour shortages, procurement delays, weather disruptions, and technical challenges. By identifying key schedule-related uncertainties and integrating them into a simulation-based model, the study equips decision-makers with a tool to better understand and anticipate schedule risks. This can lead to improved planning, more realistic scheduling, and proactive timeline control throughout the project lifecycle.

Furthermore, the application of the hybrid model to a real-world Nepalese construction project provides context-specific insights and validates the practical utility of the approach. The comparison with traditional EVM forecasts also highlights the added value of probabilistic schedule risk analysis in decision-making processes, particularly when planning contingencies and allocating resources effectively.

1.5 Scopes and Limitations of the Study

1.5.1 Scope of the Study

This study focuses on schedule risk prediction in building construction projects, specifically during the construction phase. The study identifies and validates key uncertainty factors that influence construction schedule performance through expert input and literature review, followed by a questionnaire survey. These uncertainties are then incorporated into an MCS to generate probabilistic forecasts of project completion.

1.5.2 Limitations of the Study

The following limitations should be considered when interpreting the findings and applying the hybrid forecasting model:

i. Limited Scope of Uncertainty Factors

The model uses a selected set of uncertainty factors derived from a literature review and expert validation. While every effort was made to include the most relevant factors for the Nepalese building construction context, the study does not claim to cover all possible schedule uncertainties that may arise in practice. Therefore, the model focuses on key risks for schedule forecasting rather than providing an exhaustive inventory.

ii. Focus on Construction Phase Only

The research primarily considers uncertainties arising during the construction phase of the project lifecycle. Risks occurring during pre-construction stages (e.g., design development, permitting) or post-construction stages (e.g., commissioning, defects liability) were not included in the analysis. As a result, the model is most applicable for schedule forecasting after construction has commenced.

iii. Assumptions in Monte Carlo Simulation

The simulation relies on probability distributions assigned to each uncertainty factor based on expert and survey responses. These distributions represent professional judgments and approximations of real-world variability, which may differ from actual project conditions. The accuracy of simulation outputs is therefore contingent on the quality and representativeness of the input data.

iv. Single Project Case Study

The model was developed and tested using data from a single multi-storey apartment building project in Nepal. While the methodology is generalisable and can be applied to other projects, the specific numerical results (e.g., delay magnitudes, percentiles) may not fully represent variability across different project types, scales, geographic locations, or contractual arrangements. Future applications should calibrate the model to their specific project context.

v. Generalisability Across Building Types

The findings are based on one case project and survey responses from Nepalese construction professionals. Generalizability to other building types (e.g., commercial, institutional, industrial), project scales (small vs. large), or different national contexts should be validated through further research.

vi. Constant Probability Assumption

Each uncertainty factor is assumed to have a single probability of occurrence that remains constant throughout the project duration. In practice, the likelihood of certain risks may vary significantly depending on project stage (e.g., payment delays may be more likely during later stages, while design issues emerge earlier). The model does not capture these time-varying dynamics.

vii. Independence of Risk Factors

The simulation treats all uncertainty factors as independent events, sampling each factor's occurrence and impact separately. In reality, many construction risks are correlated (e.g., payment delays may exacerbate unreliable supplier issues; political uncertainty may trigger both material price escalation and labour shortages). Due to the lack of reliable dependency estimates in the available data, these relationships were not modelled, which may affect the accuracy of combined risk estimates.

viii. Additive Delay Approximation

The model estimates total project delay by summing the delay impacts of individual uncertainty factors that are sampled to occur. However, in real projects, delays may overlap in time, occur concurrently on parallel work fronts, or affect the same critical path activities. The additive approach does not account for these interactive effects and may therefore slightly overestimate total delay in some cases.

ix. Approximation of Most-Likely Impact

The questionnaire collected only minimum and maximum delay impacts from respondents. The "most likely" impact value was approximated as the midpoint of each respondent's min-max range rather than elicited directly as a three-point estimate (minimum, most likely, maximum). Consequently, the triangular and PERT distributions used in the simulation are based on an estimated rather than directly observed most-likely parameter, which may affect the precision of the distribution shapes.

x. Absence of CPM/Network-Based Schedule Linkage

The hybrid model is not directly linked to a Critical Path Method (CPM) or activity-network schedule. Therefore, the model does not explicitly account for:

- Critical path changes over time
- Activity-level float consumption
- Concurrent delay interactions among activities
- The specific timing of risk occurrence within the project network
- Non-critical path delays that may become critical later

As a result, the model provides an aggregate project-level delay estimate rather than activity-level or path-level forecasts.

xi. Perception-Based Input Data

The probability and impact parameters used in the Monte Carlo simulation are derived from professional perceptions gathered through surveys, not from objective historical project records. While perception-based data is common in exploratory risk research and was appropriate given the absence of systematic delay databases in the Nepalese context, the results should be interpreted as reflecting informed professional judgment rather than statistically validated historical frequencies.

Where possible, the following measures were taken to reduce the impact of these limitations:

- Expert validation (9 experts with 6-27 years' experience) was used to screen and finalise uncertainty factors, reducing the risk of omitting critical factors.
- Multiple risk scenarios (R0-R3) were tested in sensitivity analysis to examine how different assumptions (probability aggregation method, distribution type, impact bounds) influence results.
- Case-based validation was performed by comparing model forecasts against the actual revised completion duration of the selected project.
- Percentile-based bounds (P10/P90 for base model; P5/P95 for sensitivity) were used to reduce the influence of extreme individual responses while preserving collective judgment.
- Triangular distribution was chosen as the baseline for its transparency and minimal shape assumptions, with PERT tested in sensitivity analysis.

CHAPTER 2: LITERATURE REVIEW

2.1 Earned Value Management

Earned Value Management (EVM) provides a systematic method to quantify cost and schedule performance, enabling project managers to monitor deviations, initiate corrective actions, and forecast future performance trends. It is a widely adopted project performance measurement technique that integrates scope, time, and cost parameters to evaluate project progress against a predefined baseline plan. As defined by Chitkara (2014), EVM compares the budgeted cost of work performed with the actual cost incurred and the planned value of work to assess whether the project is progressing as intended.

EVM operates on the principle that as project activities are completed, they earn value based on their contribution to the overall budgeted work. This earned value becomes a true measure of project progress. The method assumes a relatively fixed baseline budget, against which progress is measured using key indicators such as Planned Value (PV), Earned Value (EV), and Actual Cost (AC) (Jha, 2015).

2.1.1 Key EVM Parameters

Earned Value Management involves following three key parameters that are used in tracking the project progress and status.

i. Planned Value (PV)

It is also called the Budgeted Cost of Work Scheduled (BCWS). It represents the cumulative authorised budget for work scheduled to be completed by a specific date. It defines the project cost baseline.

ii. Earned Value (EV)

It is also known as the Budgeted Cost of Work Performed (BCWP). It is the value of work actually completed, measured at the budgeted rate. It is computed as:

$$EV = \%Completion \times Project\ Budget \tag{1}$$

iii. Actual Cost (AC)

It is known as the Actual Cost of Work Performed (ACWP). This refers to the actual expenses incurred for the work completed to date, including management reserves.

2.1.2 Variance Measures

EVM helps track the project status through the variance measures comparing the "Earned Value" against the "Planned Value" and the "Actual Costs". EVM provides two primary variance indicators:

i. Cost Variance (CV)

$$CV = EV - AC \tag{2}$$

A positive CV indicates a cost underrun, whereas a negative CV reflects a cost overrun.

ii. Schedule Variance (SV)

$$SV = EV - PV \tag{3}$$

A positive SV implies that the project is ahead of schedule, while a negative SV denotes that it is lagging.

iii. Variance at Completion (VAC)

$$VAC = BAC - EAC \tag{4}$$

Where, BAC is Budget at Completion, and EAC is Estimate at Completion. This measures the projected cost variance at the project's conclusion.

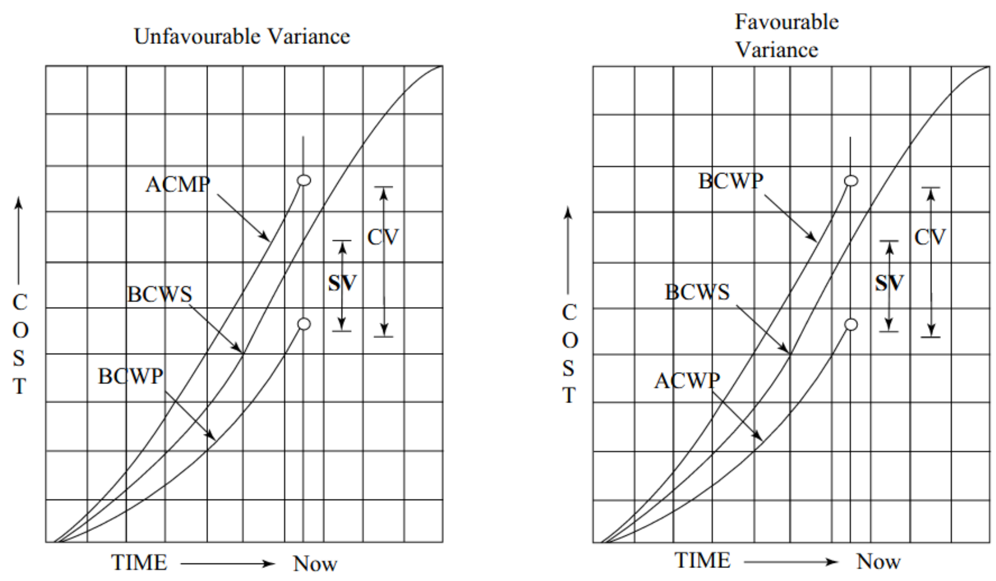


Figure 1: Cost and Schedule Variances

Source: (Chitkara, 2014)

2.1.3 Performance Indices

EVM also provides efficiency indices to assess project performance:

i. Cost Performance Index (CPI)

$$CPI = \frac{EV}{AC} \tag{5}$$

CPI measures the cost efficiency of the work performed. A CPI greater than 1 indicates cost savings, while less than 1 indicates that the project is over budget.

ii. Schedule Performance Index (SPI)

$$SPI = \frac{EV}{PV} \tag{6}$$

SPI reflects schedule efficiency and the degree to which the project is ahead or behind schedule. An SPI greater than 1 indicates that the project is ahead of schedule, while less than 1 indicates that the project is behind schedule.

2.1.4 Forecasting Tools in EVM

EVM is instrumental in forecasting final project cost and completion date through the following estimations:

i. Estimate to Complete (ETC)

It provides a forecasted cost to finish remaining work based on the current cost performance status of the project.

$$ETC = \frac{BAC - EV}{CPI} \tag{7}$$

ii. Estimate at Completion (EAC)

It specifies the revised estimate of total project cost at completion. Common formulas include:

a. Based on current performance and revised estimates:

$$EAC = AC + ETC \tag{8}$$

b. Planned Rate Forecasting (Baseline Performance):

$$EAC = AC + (BAC - EV) \tag{9}$$

This method assumes that future work will be completed at the originally planned rate, regardless of current cost performance.

c. If CPI continues:

$$EAC = \frac{BAC}{CPI} \tag{10}$$

d. Considering schedule impact:

$$EAC = AC + \frac{BAC - EV}{CPI \times SPI} \tag{11}$$

iii. Estimated Time at Completion (ETAC)

It refers to the total time period required for the completion of the work based on the present schedule performance.

$$ETAC = \frac{PD}{SPI} \tag{12}$$

Where, PD is Planned Duration.

While EVM is widely used for monitoring and forecasting project performance, its schedule forecasting outputs are frequently criticised because schedule performance is computed using cost-based information rather than time. Sackey et al. (2020) highlight that this monetary basis can lead to a misleading interpretation of schedule metrics and an underestimation of the time estimate at completion. They also note that toward project completion, schedule indicators become unreliable because the schedule performance index converges to one at completion, reducing its usefulness for late-stage forecasting.

2.1.5 Earned Schedule

Although Earned Value Management (EVM) provides indicators for schedule performance, they are fundamentally cost-based and may become less reliable for time forecasting as a project progresses. To address this limitation, the Earned Schedule (ES) concept was proposed as a time-based extension, where ES represents the time at which the current earned value was planned to be achieved, i.e., the time point at which PV = EV (Lipke, 2014). The formula to calculate the ES is given by

$$ES = C + I \tag{13}$$

C is the largest value of n such that $EV \geq PV_n$, and I is the interpolation given by

$$I = \frac{EV - PV_C}{PV_{C+1} - PV_C} \tag{14}$$

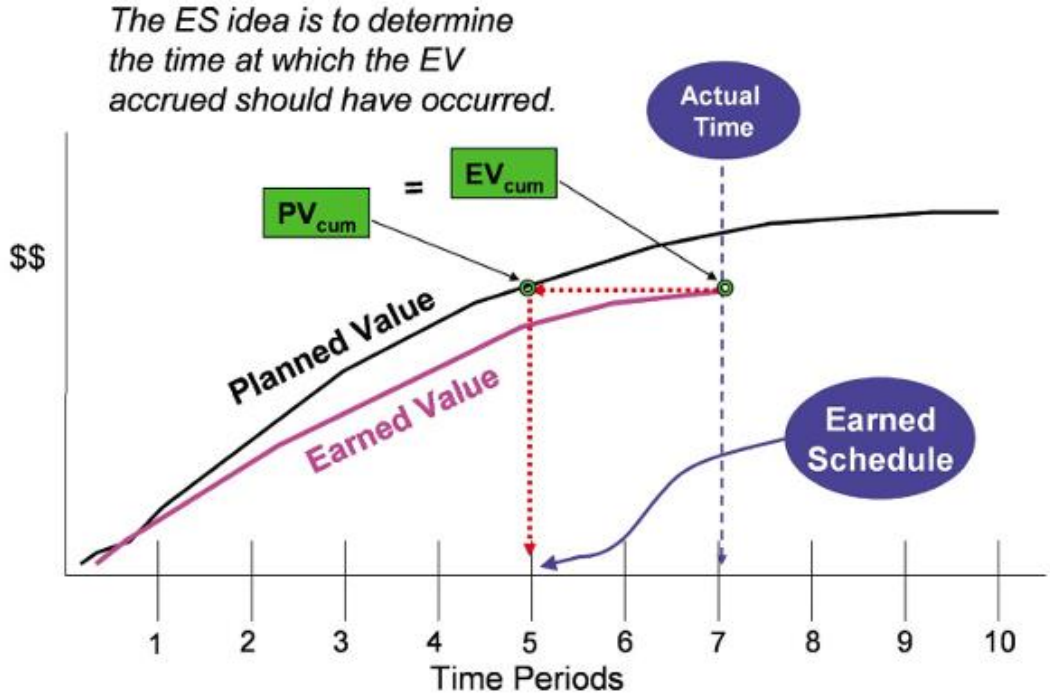


Figure 2: Earned Schedule Concept

Source: (Lipke, 2020)

Using ES, time-based schedule indicators can be computed, such as the schedule variance in time, SV(t).

$$SV(t) = ES - AT \tag{15}$$

and the time-based schedule performance index SPI(t)

$$SPI(t) = \frac{ES}{AT} \tag{16}$$

enabling direct forecasting in time units.

For time forecasting, an independent estimate at completion in time units (IEAC(t)) is given by

$$IEAC(t) = \frac{PD}{SPI(t)} = AT + \frac{PD - ES}{SPI(t)} \tag{17}$$

where PD is the planned duration.

Batselier and Vanhoucke (2015) provide a large-scale empirical evaluation of EVM forecasting accuracy, emphasising that prior evidence often relied on simulation or limited datasets. Their study contributes by evaluating both time and cost forecasting and by explicitly examining construction projects, allowing assessment of whether general EVM forecasting observations hold in the construction context. The authors also highlight that time forecasting deserves comparable research attention to cost forecasting and recommend that future improvements should build on the methods that empirically perform best (e.g., ESM-1 for time forecasting).

For ESM-1, the SPI(t) = 1 so that results

$$IEAC(t) = AT + PD - ES \tag{18}$$

de Andrade et al. (2019) emphasise the importance of improving project duration forecasting accuracy for project control decisions and compare ES-based approaches against Earned Duration Management (EDM), noting that although ES expresses performance in time units, it still relies on earned value as a proxy and therefore remains influenced by the project's cost structure; EDM was developed to eliminate this sensitivity by using duration-based metrics.

2.2 Monte Carlo Simulation

2.2.1 Introduction to Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a probabilistic modelling technique that repeatedly samples from input probability distributions to generate a statistical distribution of possible outcomes. It is a probabilistic technique that models uncertainty by generating a number of random samples from input distributions (Hendradewa, 2019). Unlike deterministic models that rely on fixed inputs, MCS captures the inherent randomness of project variables and provides a more realistic approximation of system behaviour (Sokolowski, 2010). Originating in the 1940s at Los Alamos National Laboratory, since then, MCS has been widely adopted across fields such as engineering, finance, and construction for its ability to handle uncertainty in complex systems. It helps in risk assessment, offering an unbiased approach to evaluate complex scenarios and support decision-making where deterministic methods are insufficient (Rezaie et al., 2007; Sadeghi et al., 2010).

The typical procedure of MCS can be summarised in the following steps (Sokolowski, 2010):

Step 1: Define Probability Distributions: Identify uncertain input variables and assign suitable probability distributions (e.g., triangular, normal, uniform). These distributions describe the range and likelihood of possible values.

Step 2: Generate Random Samples: Random numbers are drawn from each distribution using sampling techniques (e.g., inverse transform or Monte Carlo random number generators).

Step 3: Perform Calculations: Deterministic equations are evaluated using the sampled inputs, producing one outcome per trial.

Step 4: Aggregate Results: Repeat the process N times to obtain a distribution of outputs, which can be analysed statistically (mean, variance, percentiles, confidence intervals).

Mathematically, if $Y = f(X_1, X_2, ..., X_n)$ is the output function and X_i are uncertainty inputs, then MCS estimates:

$$\hat{E}[Y] = \frac{1}{N}\sum_{j=1}^{n} f\left(x_{1j}, x_{2j}, \dots, x_{nj}\right) \tag{19}$$

where x_{ij} is the random draw of input X_i in iteration j, and N is the total number of iterations (Bonate, 2001; Raychaudhuri, 2008).

The accuracy of Monte Carlo results depends strongly on the number of iterations. Sokolowski (2010) suggests a two-stage procedure:

Stage I: Pilot Simulation

Run a smaller number of iterations (n_0) to estimate the variance s^2 of the output. Use the estimated variance to calculate the number of runs needed for a given confidence interval:

$$n = \left(\frac{z_{\alpha/2} \cdot S}{E}\right)^2 \tag{20}$$

Where $z_{\alpha/2}$ is the standard normal value for the desired confidence level and E is the acceptable margin of error.

Stage II: Main Simulation

Perform the full simulation with the calculated n iterations to achieve statistically reliable results.

This structured approach ensures computational efficiency while maintaining accuracy in forecasting.

2.2.2 Modelling Uncertainty using Probability

Uncertainty is an inherent characteristic of construction project implementation. Projects frequently face unpredictability in activity durations, estimated costs, resource availability, and adherence to baseline plans. During the early stages of a project, precise values for these variables are unknown, and only estimates can be made. This uncertainty necessitates the use of probability theory to model and quantify the potential range of outcomes.

Probability, defined as the chance of a specific event occurring (with a value between 0 and 1), enables project managers to transition from deterministic to probabilistic thinking. It supports various applications in project management, including network analysis, probabilistic risk assessment, and simulation modelling, such as Monte Carlo Simulation (Chitkara, 2014).

There are two main approaches to assigning probability values in such contexts:

i. Objective Probability: Based on historical data, repeated observations, or known physical properties (e.g., coin toss, dice roll). It is applicable where sufficient empirical data is available.

ii. Subjective Probability: Derived from expert judgment or opinions when data is lacking. Techniques such as the “Delphi Method” and “Nominal Group Technique” are commonly used to elicit expert input, especially for assigning probability distributions in risk assessments.

2.2.3 Probability Distributions in Monte Carlo Simulation

MCS relies on selecting appropriate probability distributions to simulate thousands of project scenarios. The shape and parameters of these distributions depend on the nature of the uncertain variables.

Table 1: Common Probability Distributions used in MCS

Distribution	Shape / Characteristics	Parameters	Key Properties / Description
Normal	Symmetrical, unimodal, bell-shaped	Mean (μ), Standard Deviation (σ)	Extends from –∞ to +∞ Total area under the curve = 1
Triangular	Triangular, can be symmetrical or skewed	Minimum (a), Maximum (b), Most Likely (m)	Defined by three estimates Simple and intuitive
Uniform	Rectangular, flat	Minimum, Maximum	Values between min and max are equally likely, probability is constant in the interval, 0 elsewhere
Beta (PERT variant)	Continuous, bounded, flexible shape	Typically derived from min, max, and most likely (PERT approximation)	Constrained to a finite interval Can be symmetrical, right-skewed, or left-skewed

Source: (Chitkara, 2014)

The probability distributions approximate statistics of simplifying calculations, as summarised in Chitkara (2014)

Table 2: Approximate Statistics of Probability Distributions

Statistics	Triangular	Beta PERT
Expected Value or Mean	$\frac{a+m+b}{3}$	$\frac{a+4m+b}{6}$
Variance, $v = \sigma^2$	$\frac{(b-a)^2+(m-a)\times(b-m)}{18}$	$\frac{(b-a)^2}{36}$
Standard Deviation, σ	$\sqrt{v}$	$\frac{b-a}{6}$

Note: a = Optimistic value, b = Pessimistic value, m = Most likely value

Source: (Chitkara, 2014)

By using these distributions, MCS allows project managers to generate probabilistic forecasts for project duration, total cost, or resource requirements. This provides results in a range of possible outcomes with associated confidence levels rather than a single-point estimate. For instance, instead of stating that a project will be completed in x days, MCS might state there is a y% chance of completing the project within z days.

2.2.4 Application of Monte Carlo Simulation

Akhbari (2018) highlighted that MCS has become one of the most widely used techniques for project time and cost forecasting under uncertainty. By generating thousands of possible scenarios, MCS provides probabilistic estimates instead of single-point predictions. This makes it particularly useful for construction projects where variability is high. In their study, 10,000 simulations were conducted to get a reliable range of outcomes, demonstrating the importance of large-scale iterations in achieving stable forecasting results. This reinforces the suitability of MCS in project management studies, especially in contexts where accurate forecasting is critical (Akhbari, 2018).

Using MCS, Hendradewa (2019) repeatedly simulated activity durations to generate a distribution of total project completion time and then reported results in probability terms (i.e., the likelihood of completing by a specified target duration) and percentile-based completion times. In the case study residential building project, Hendradewa (2019) reports a 62.04% probability of completing within the CPM–PERT estimate of 197 days, while approximately 204 days corresponds to a 95% completion confidence level, illustrating how simulation converts a single deterministic duration into probabilistic schedule forecasts that support contingency decision-making.

By integrating MCS into EVM-based forecasting, project managers can move from deterministic to probabilistic thinking. This integration allows the estimation of confidence levels for project completion costs and dates, improving the reliability of decision-making processes. It enables project teams not just to monitor whether they are on track but also to assess how likely they are to stay on track under varying conditions, which can be a crucial advancement in high-risk construction environments.

So, the deterministic limitation of EVM and the benefits of a probabilistic approach form the rationale for this study. The proposed hybrid model aims to combine the structured metrics of EVM with the forecasting power of MCS to better predict project schedule performance in uncertain construction environments like Nepal.

Mubin et al. (2019) demonstrated the application of MCS in the Dasu Hydropower Project in Pakistan by developing a risk-based schedule and cost model. A triangulation approach of document reviews, expert interviews, and stakeholder surveys was employed to quantify 130 potential risks. The authors proposed a neutral baseline probability of 50%, modifying it upward or downward based on expert input, recognising the subjectivity inherent in the Project Management Institute's (PMI) qualitative risk assessment. Triangular distributions were used to simulate project durations. The risk data was integrated into PERT Master to generate outputs such as probabilistic schedules, cost estimates, and criticality indexes. This case illustrates the capability of MCS to model uncertainty and guide proactive decision-making, especially in complex, high-risk projects like hydropower development.

Urgilés et al. (2019) used PERT distributions with a three-point distribution of minimum, most likely, and maximum values for cost and schedule risk simulation. They showed a typical schedule risk simulation workflow by modelling project schedules as stochastic systems. They assigned probability distributions to activity durations and costs, and ran MCS (10,000 iterations) to generate distributions of completion time and cost outcomes.

Similarly, Allahi et al. (2017) applied MCS for cost contingency estimation in a railway infrastructure project. Their methodology integrated both qualitative and quantitative risk assessments to determine the economic impact of identified risks. By assigning probability distributions using beta and later comparing it with triangular, they demonstrated how the choice of distribution significantly influences contingency estimates and risk coverage levels. Their robustness analysis revealed that triangular distributions, although being simpler, provided conservative yet effective estimations. This reinforces the suitability of triangular distribution in construction projects, particularly in developing countries like Nepal, where empirical datasets are often scarce.

2.3 Integration of EVM and Monte Carlo Simulation

Construction projects are inherently uncertain due to various technical, financial, environmental, and human factors. While EVM offers a structured approach to measure project performance, it primarily relies on historical performance data to forecast future outcomes. This deterministic nature of EVM poses a significant limitation that it assumes past trends will persist without incorporating the probability of future variations.

In contrast, Project Risk Management (PRM) is inherently forward-looking and designed to identify, analyse, and prepare for uncertainties that may affect project objectives (Hillson, 2002). This gap between backward-looking performance measurement (EVM) and forward-looking uncertainty modelling (PRM) has been recognised in the literature. Diamantas et al. (2011) argue that EVM's inability to incorporate uncertainty and risk leads to weaker forecasting and potential loss of valuable risk-related data generated during planning and control phases. Thus, relying solely on EVM can result in oversimplified predictions of final cost and schedule, which may mislead project stakeholders in uncertain environments.

Kim and Reinschmidt (2010) emphasise that effective project control must allow stakeholders to foresee potential future problems and take timely corrective actions. A typical control process includes monitoring actual performance, comparing it with planned performance, identifying variances, and forecasting final outcomes such as Estimate at Completion (EAC). However, when EAC is derived solely from deterministic EVM indicators like CPI and SPI, it provides only single-point estimates, without any insight into the range or probability of different possible outcomes.

This is where Monte Carlo Simulation (MCS) proves to be a powerful complement to EVM, providing a probabilistic technique to model uncertainty by simulating thousands of scenarios using input distributions for key project parameters such as time, cost, or productivity. Instead of a single-point forecast, MCS generates a distribution of potential project outcomes, enabling project managers to assess risks, understand best- and worst-case scenarios, and make more informed decisions under uncertainty.

Vargas (2004) presents an early yet foundational approach to EVM with MCS to produce probabilistic forecasts of project costs. Acknowledging the deterministic limitations of traditional EVM forecasting, the author developed a methodology combining three types of Estimate at Completion (EAC) models - optimistic (constant index), realistic (CPI-based), and pessimistic (SCI-based) to construct a triangular distribution. Using @Risk software, the study simulated 50,000 iterations to model cost uncertainty and derive a probability distribution for final project cost. This integration produced confidence intervals (e.g., 90% range from R$61,102.32 to R$85,078.99), enhancing managerial decision-making under uncertainty.

While the approach required no substantial deviation from standard EVM practices, Vargas (2004) noted limitations such as subjectivity in the percent complete method and the lack of empirical validation against real project outcomes. Nonetheless, the study laid the groundwork for hybrid forecasting frameworks that incorporate uncertainty modelling into cost and schedule performance prediction.

Vanhoucke and Vandevoorde (2007) conducted an extensive simulation study to evaluate the accuracy of three EVM-based duration forecasting methods: the Planned Value (PV) method, the Earned Duration (ED) method, and the Earned Schedule (ES) method. They used 3,100 generated project networks and 9 controlled uncertainty scenarios in MCS to assess how well each method predicts project completion time.

Their results consistently showed that the ES method, particularly ES2, which assumes current performance trends persist, outperforms other approaches in both early and late project stages. The study highlights that traditional EVM metrics (e.g., SPI and SV) lose reliability in later stages due to convergence effects (e.g., SPI → 1 regardless of delay), while the ES method, based on time-based indices SPI(t) and SV(t), maintains forecasting accuracy throughout.

The authors also introduce the Serial/Parallel (SP) indicator to demonstrate how the structure of the project network affects forecasting performance. Serial networks offer higher accuracy due to tighter activity dependencies, while parallel structures suffer from variance introduced by slack in non-critical activities. Their findings strongly support the integration of time-based EVM metrics with MCS to build a robust schedule risk forecasting framework.

Acebes et al. (2015) propose a Stochastic Earned Value Management (S-EVM) framework that integrates MCS and statistical learning techniques to overcome the deterministic limitations of traditional EVM. Conventional EVM struggles to distinguish whether observed deviations are due to inherent project variability or structural problems. To address this, the authors introduce the Triad Methodology, a monitoring approach using a triplet of Earned Value (EV), time (t), and cost (c) to track project status probabilistically at any stage of completion. Their hybrid framework employs MCS to generate statistical distributions of cost and time outcomes, anomaly detection algorithms to identify abnormal behaviour, and classification models such as Support Vector Machine (SVM), Quadratic Discriminant Analysis (QDA), and Random Forest to estimate the probability of project success or failure. Regression models using Generalized Additive Models (GAMs) and splines predict the extent of deviations. This framework not only improves predictive accuracy but also provides intuitive dashboards to support real-time managerial decisions. Despite its strengths, the model requires high-quality data and context-specific tuning, making automated model selection a future research direction.

Bonato et al. (2019) present a practical application of integrating EVM with MCS in engineering projects. Their study applied the hybrid method to three industrial plant expansion projects in Brazil, demonstrating that probabilistic forecasting provides enhanced cost estimation capabilities compared to deterministic EVM alone. By using triangular distributions for EAC calculations and simulating 1,000 iterations, the study generated a 95% confidence interval for final cost predictions. This approach enabled early detection of budget deviations and informed managerial decisions under uncertainty.

The authors also noted challenges, such as the variability of the Cost Performance Index (CPI) in short-duration projects and difficulties aligning scope changes with cost tracking. These findings reinforce the value of hybrid models in dynamic environments and highlight the need for adaptive mechanisms in probabilistic forecasting frameworks.

Akhbari (2018) also demonstrated that EVM metrics, when combined with Monte Carlo simulations, provide more realistic forecasting of project performance by considering uncertainty in future trends. Their study further incorporated Artificial

Neural Networks (ANN) alongside MCS, illustrating that machine learning techniques can complement probabilistic simulations in handling complex, non-linear project data. In particular, they proposed a triad methodology that integrates EVM, MCS, and ANN, where project performance can be represented as (x_t, t, AC_t), with x_t denoting progress percentage, t representing time, and AC_t the accumulated cost at time t. By training neural networks on multiple simulated scenarios, the forecasting model can capture both stochastic variability and nonlinear patterns in project performance.

Such approaches highlight the evolution from index-based deterministic models to probabilistic models and further toward intelligent systems such as ANN, support vector machines (SVM), and fuzzy logic (Akhbari, 2018; Babar et al., 2017). However, these advanced hybrid methods often require large datasets and sophisticated calibration, which may not always be practical in construction project settings. This creates an opportunity for research that leverages MCS in a more streamlined way, integrating uncertainty modelling directly with EVM metrics without the complexity of machine learning techniques.

2.4 Uncertainty Factors Affecting the Schedule of Building Projects

Several studies have identified a wide range of factors contributing to schedule delays in construction projects. Based on an extensive review of relevant literature, this study identified 36 uncertainty factors affecting schedule performance in building construction projects, shown in Table 3.

Table 3: Uncertainty Factors Affecting Building Project Schedule from Literature

Uncertainty Factors	(Mishra & Mallik, 2017)	(Giri, 2025)	(Khanal & Ojha, 2020)	(Judson & Paul, 2022)	(Basnet & Shrestha, 2023)	(Ali et al., 2018)	(Rauzana, 2018)	(Wanjari & Dobariya, 2016)	(Sharma & Goyal, 2014)	(Sharma et al., 2020)	(Jangale et al., 2017)	(Pradipbhai et al., 2020)	(Devi & Ananthanarayanan, 2017)	(Murali & Kumar, 2019)
Material price fluctuation / escalation	√			√		√	√	√	√	√	√	√	√	

Uncertainty Factors	(Mishra & Mallik, 2017)	(Giri, 2025)	(Khanal & Ojha, 2020)	(Judson & Paul, 2022)	(Basnet & Shrestha, 2023)	(Ali et al., 2018)	(Rauzana, 2018)	(Wanjari & Dobariya, 2016)	(Sharma & Goyal, 2014)	(Sharma et al., 2020)	(Jangale et al., 2017)	(Pradipbhai et al., 2020)	(Devi & Ananthanarayanan, 2017)	(Murali & Kumar, 2019)
Inflation and macroeconomic instability	√		√	√			√		√	√		√	√	
Exchange rate variability (affecting imported materials)							√			√			√	
Change in material specification					√				√	√		√	√	√
Labour productivity fluctuation				√					√	√	√	√		
Labour skill shortages / availability	√			√					√	√	√		√	√
Labour strikes or union disruptions				√		√			√	√				√
Increase in labour costs	√								√	√			√	
Equipment breakdown or underperformance	√								√	√	√	√	√	√
Equipment availability issues									√	√	√		√	√
Material delivery delays / supply chain issues		√							√	√	√	√	√	√
Unreliable suppliers or subcontractors		√		√					√	√	√			
Design errors and omissions	√	√				√		√	√	√	√		√	

Uncertainty Factors	(Mishra & Mallik, 2017)	(Giri, 2025)	(Khanal & Ojha, 2020)	(Judson & Paul, 2022)	(Basnet & Shrestha, 2023)	(Ali et al., 2018)	(Rauzana, 2018)	(Wanjari & Dobariya, 2016)	(Sharma & Goyal, 2014)	(Sharma et al., 2020)	(Jangale et al., 2017)	(Pradipbhai et al., 2020)	(Devi & Ananthanarayanan, 2017)	(Murali & Kumar, 2019)
Design changes / scope modifications	√			√	√		√	√	√	√	√	√	√	
Late issuance of drawings / revisions				√		√								
Incomplete or ambiguous specifications								√			√	√	√	
Unforeseen technical complexities beyond initial plans							√							
Differing/Unforeseen ground conditions (soil variability, buried utilities)	√			√		√			√	√	√		√	√
Weather uncertainties (rain, storms affecting concrete curing, masonry, etc.)				√	√	√			√	√	√		√	
Environmental disruptions (landslides, flooding near site)			√											
Permit or approval delays			√	√			√		√	√	√	√	√	√
Regulatory or policy changes during construction						√						√	√	

Uncertainty Factors	(Mishra & Mallik, 2017)	(Giri, 2025)	(Khanal & Ojha, 2020)	(Judson & Paul, 2022)	(Basnet & Shrestha, 2023)	(Ali et al., 2018)	(Rauzana, 2018)	(Wanjari & Dobariya, 2016)	(Sharma & Goyal, 2014)	(Sharma et al., 2020)	(Jangale et al., 2017)	(Pradipbhai et al., 2020)	(Devi & Ananthanarayanan, 2017)	(Murali & Kumar, 2019)
Inspection delays, weak monitoring and supervision			√	√		√			√	√		√		
Payment delays		√		√		√			√	√	√		√	√
Fluctuations in interest rates (if loans used)	√													
Contract claims and dispute uncertainties	√			√		√		√	√	√	√	√	√	√
Contractor–subcontractor relationship						√	√							
Community or neighbourhood objections	√													
Political uncertainty	√		√			√	√						√	
Force majeure events (pandemic, earthquake, conflict)	√				√	√		√	√	√				
Improper management by Project Management Team	√			√			√		√	√	√	√	√	
Coordination issues among project stakeholders				√				√	√	√	√	√	√	
Health and safety incidents leading to stoppage	√	√					√		√	√	√			√

Uncertainty Factors	(Mishra & Mallik, 2017)	(Giri, 2025)	(Khanal & Ojha, 2020)	(Judson & Paul, 2022)	(Basnet & Shrestha, 2023)	(Ali et al., 2018)	(Rauzana, 2018)	(Wanjari & Dobariya, 2016)	(Sharma & Goyal, 2014)	(Sharma et al., 2020)	(Jangale et al., 2017)	(Pradipbhai et al., 2020)	(Devi & Ananthanarayanan, 2017)	(Murali & Kumar, 2019)
Poor quality of material and equipment	√	√								√	√	√		√
Wastage on Site								√	√	√			√	
Error in construction/Rework				√				√	√	√	√		√	√

CHAPTER 3: METHODOLOGY

3.1 Research Design

The study adopted a quantitative research design supported by a case study strategy and followed a systematic process beginning with the development of the research concept, research questions, and objectives, followed by data collection, analysis, and interpretation. Literature review and consultation with the supervisor were carried out throughout the research process to refine the study direction, support methodological decisions, interpret findings, and improve the overall rigour of the study.

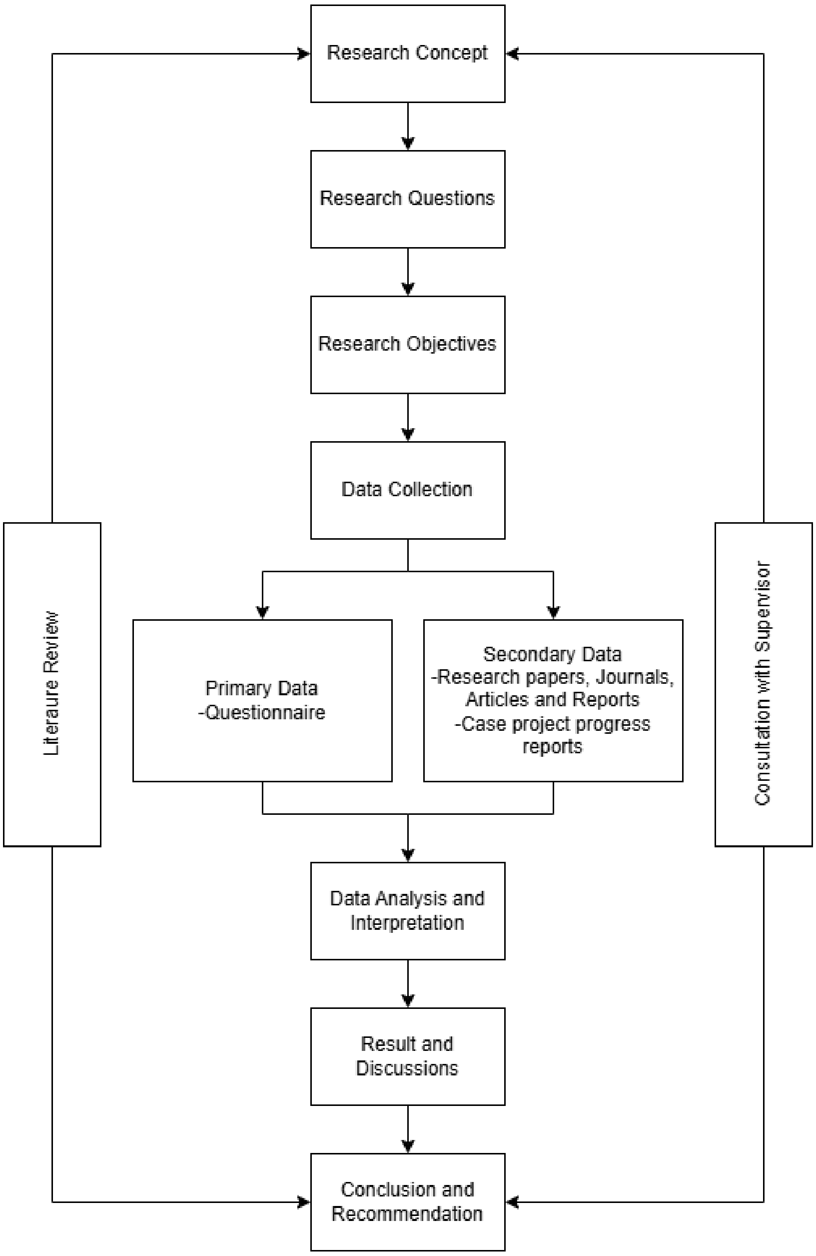


Figure 3: Research Design Framework

3.2 Methodological Framework

The research framework of this study presents the sequential flow followed to achieve the study objectives. The framework begins with the identification of schedule-related uncertainty factors through literature review, followed by expert validation to refine and finalise the most relevant factors for the Nepalese building construction context. These finalised factors were then assessed through a questionnaire survey to obtain the probability of occurrence and the schedule impact data. Based on these responses, qualitative risk was analysed using a 5×5 probability–impact matrix. In parallel, case project records were used to compute deterministic schedule forecasts through EVM and Earned Schedule techniques. Thereafter, Monte Carlo Simulation was applied to model uncertainty under alternative risk scenarios, and the simulated delay outputs were integrated with deterministic forecasts to develop the hybrid EVM–MCS model. Finally, the performance of the hybrid model was evaluated against traditional deterministic EVM forecasts using the revised project completion duration of the selected case project as the practical benchmark.

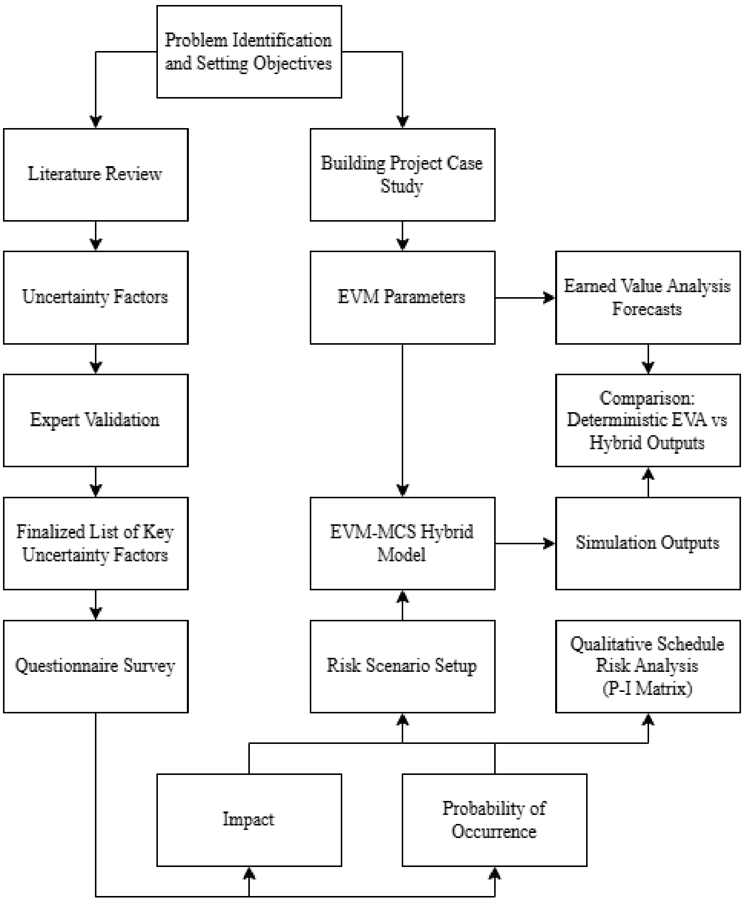


Figure 4: Methodological Flowchart

3.3 Study Area/Case Project Description

This study adopts a case study approach using a multi-storey apartment building project. The project is privately owned and implemented under the approval and monitoring process of the Department of Urban Development and Building Construction (DUDBC). The case project was selected because it provides a complete set of planning and monthly progress records required to compute Earned Value/Earned Schedule indicators and to demonstrate the proposed hybrid forecasting model.

The project was originally planned for a contract period of three years, with a commencement date of 19 Shrawan 2079 and an original completion date of 18 Shrawan 2082. Subsequently, a revised completion date of 18 Magh 2082 was established. The completion date was further revised to 18 Shrawan 2083, as the physical progress till the end of Poush 2082 was only 81.08%, suggesting a notable schedule shortfall and making the project suitable for schedule forecasting and risk analysis. The project scope includes residential apartment units and associated facilities. The baseline approval covered 128 apartment units, while a revised scope of 162 units was under process through design review. Similarly, the building configuration was revised from G+10 storeys (original) to G+13 storeys (revised), with the structural design reportedly considering future expansion potential.

For model development and testing, the study uses the project's monthly progress dataset, including planned progress percentage and actual progress. These progress curves were used to derive the Planned Value (PV) and Earned Value (EV) time series required for Earned Value/Earned Schedule computation and deterministic forecasting at different status dates.

A summary of key project particulars used in this study is presented in Table 4.

Table 4: Project Particulars

Contract Amount	NRs. 2,89,70,61,432.16 (Including VAT and PS)
Original Contract Period	3 Years
Commencement Date	19 Shrawan 2079
Original Completion Date	18 Shrawan 2082

Revised Completion Date	18 Shrawan 2083
Original Built-up Coverage	5643.51 sq.m.
Revised Built-up Coverage	6074.81 sq.m.
Built-up Coverage Area	1913.21 sq.m. (31.60 %ex)
Greenery Area	1348.22 sq.m. (22.7%)
Total Number of Apartment	Originally 128, Revised 162
Original Total Floor	G+10 Story
Revised Total Floor	G+13 Story
Physical Progress as of Poush 2082	81.08%

3.4 Population, Sample and Sampling Design

The study involved two categories of respondents: experts for the validation of uncertainty factors and construction professionals for the questionnaire survey. The population for the expert validation stage consisted of professionals with substantial knowledge and experience in building construction planning, scheduling, execution, and project management in the Nepalese context. A purposive sampling method was adopted to select experts who possessed relevant professional qualifications, practical experience, and familiarity with schedule-related risks in building construction projects. Accordingly, nine experts were selected for the validation process.

For the questionnaire survey, the target population comprised construction professionals involved in building projects in Nepal, including site engineers, contractors, consultants, government/client representatives, and project managers. Since the study required responses from individuals with practical knowledge of construction schedule risks, purposive sampling was adopted for survey distribution.

The required sample size for the questionnaire survey was determined using Cochran's formula (Cochran, 1977):

$$n = \frac{z^2 \times p \times (1-p)}{e^2} \tag{21}$$

Where,

z = standard normal value at 90% confidence level (1.645),

p = estimated proportion of the population (0.5 for maximum variability),

e = margin of error (0.1).

Substituting the values, we get,

$n = 67.5 \approx 68$

Since no prior population proportion was available, p = 0.5 was adopted because it assumes maximum variability and gives a conservative sample size under Cochran's formula. The sample size of 68 was selected based on a 90% confidence level and a 10% margin of error, following Cochran (1977) formula for large populations. This size is further justified by the homogeneity of the study population, as reduced variability in participant characteristics decreases the likelihood of sampling error and allows for reliable insights with a more efficient sample (Cochran, 1977; Krejcie & Morgan, 1970). The target respondents were restricted to professionals directly involved in building construction projects, which provides domain homogeneity (Kish, 1965). However, because purposive sampling was used and the respondents differed by role and experience, the results are interpreted as informed professional perceptions rather than statistically generalizable estimates for the entire construction industry. Thus, a minimum sample of 68 respondents was adopted as an appropriate target for an exploratory professional-judgement survey. A total of 72 valid responses were ultimately obtained and used for analysis.

Table 5: Sampling Design for the Study

S.N.	Study Unit	Population	Sample	Sampling Design
1	Experts for validation	Construction professionals with substantial knowledge and experience in building construction planning, scheduling, execution, and project management (Purposive expert pool)	9	Purposive sampling
2	Questionnaire respondents	Construction professionals involved in building projects in Nepal (Treated as effectively infinite for sample size calculation)	72	Purposive sampling
3	Case project	Building construction projects with sufficient planning and monthly progress records for EVM/Earned Schedule analysis	1	Purposive / criterion-based case selection

3.5 Methods of Data Collection

3.5.1 Primary Data Collection

Primary data were collected in two stages. First, expert validation was carried out to assess the relevance of uncertainty factors identified from the literature. A structured validation form was prepared (Appendix I), and the selected experts were requested to rate the relevance of each uncertainty factor using a five-point Likert scale: 1 = Not relevant, 2 = Slightly relevant, 3 = Moderately relevant, 4 = Relevant, and 5 = Highly relevant. Experts were also invited to suggest additional uncertainty factors relevant to the Nepalese building construction context. The expert responses were later analysed using the Relative Importance Index (RII) to retain the most important factors for further study.

Second, a structured questionnaire survey was conducted among construction professionals involved in building projects in Nepal. The questionnaire consisted of two sections: the first section collected background information of respondents, and the second section collected responses on the probability of occurrence and minimum and maximum schedule impacts of the finalised uncertainty factors, which are shown in Appendix III. The survey was administered through KoboToolbox, and the collected responses were used as inputs for probabilistic modelling and Monte Carlo Simulation.

3.5.2 Secondary Data Collection

Secondary data were collected from two main sources. First, an extensive review of journal articles, conference papers, reports, and other relevant publications was undertaken to identify uncertainty factors affecting the schedule performance of building construction projects. The literature review focused primarily on studies conducted within developing country contexts to ensure relevance to the Nepalese construction industry, while also incorporating globally recognised findings. This review provided the initial list of uncertainty factors and helped establish the theoretical basis of the study.

Second, project-related secondary data were collected from the selected case project. These included project particulars, planned progress, actual progress, cumulative time data, and other relevant planning and monthly progress records. These project documents were used to calculate Planned Value (PV), Earned Value (EV), Schedule

Performance Index (SPI), and Earned Schedule parameters, which formed the basis for deterministic forecasting and hybrid model validation.

3.6 Data Analysis Techniques

3.6.1 Expert Validation of Uncertainty Factors

The identified schedule uncertainty factors were subjected to expert validation using the Relative Importance Index (RII) technique, adapted from Akadiri et al. (2013). This approach was employed to assess the perceived importance of each factor based on expert judgment.

The Relative Importance Index for each factor was calculated using the following expression:

$$RII = \frac{\sum W}{A \times N} \tag{22}$$

Where,

w = weight assigned to each factor by respondents (ranging from 1 to 5),

A = the highest possible weight (5 in this study), and

N = total number of respondents.

The RII values range between 0 and 1, with higher values indicating greater perceived importance. The RII values were interpreted using five importance levels (Akadiri et al., 2013):

i. High (H): $0.80 \leq \text{RII} \leq 1.00$
ii. High–Medium (H–M): $0.60 \leq \text{RII} < 0.80$
iii. Medium (M): $0.40 \leq \text{RII} < 0.60$
iv. Medium–Low (M–L): $0.20 \leq \text{RII} < 0.40$
v. Low (L): $0.00 \leq \text{RII} < 0.20$

In this study, only factors with an RII value of 0.80 or above were retained for further analysis, while those below the cutoff threshold were excluded. This ensured that only the most critical uncertainty factors, as agreed upon by domain experts, were considered in the subsequent modelling and simulation stages.

3.6.2 Descriptive Statistics of Questionnaire Survey Responses

3.6.2.1 Choice of Central Tendency for Probability of Occurrence

Central tendency for the responses of probability of occurrence was summarised using the median and interquartile range (IQR) for a base model. This choice was made because the item distributions were bounded and showed non-normality with predominantly positive skewness across variables (skewness values generally > 0). Under skewed distributions, the mean can be disproportionately influenced by higher responses, whereas the median provides a more robust estimate of the typical response. So, the median value of probability of occurrence was used as a base model, and mean values were also retained and later used in sensitivity analysis to test the influence of an alternative central tendency assumption. The mode was not selected as the primary measure because several items exhibited multiple modes, and mode does not reflect the overall distribution as effectively as median for comparative ranking. The descriptive results are presented in section 4.2.1.2, and full diagnostic outputs are provided in Appendix IV.

3.6.2.2 Representative Values for Impacts

For each uncertainty factor, respondents provided a minimum and maximum schedule impact (days). A midpoint value was computed for each respondent as

$$EI_{ij} = \frac{Min_{ij} + Max_{ij}}{2} \tag{23}$$

Where,

'i' denotes factor, 'j' denotes respondent, and 'EI_{ij}' denotes the Expected Impact of the i^{th} factor derived from the response of the j^{th} respondent. The ‘most likely’ impact parameter m_i was represented by the median of EI_{ij} across respondents to obtain a robust central estimate. The optimistic and pessimistic bounds were derived using percentiles to reduce the influence of extreme responses: $a_i = P10(Min_i)$, which is the 10^{th} percentile of the minimum impact values, and $b_i = P90(Max_i)$, which is the 90^{th} percentile of the maximum impact values for the i^{th} factor.

This percentile-based approach reflects collective judgment while limiting outlier dominance. Sensitivity analysis was subsequently performed using alternative bounds P5/P95 to evaluate the robustness of simulation outputs to parameter selection.

3.6.3 Probability-Impact Matrix

For a Probability-Impact Matrix of the size 5x5, probability classes (P1–P5) were derived from the 20th/40th/60th/80th percentiles of all respondent probability entries, yielding cutoff values. Similarly, impact classes (I1–I5) were derived from respondent-level expected impact values (EI). Each factor was then assigned a probability code and impact code based on its median probability and median expected impact, respectively. Finally, factors were grouped into qualitative risk levels for prioritisation.

3.6.4 Earned Value Analysis

The EVA was performed on the real project data, taking multiple baselines. The key forecasting tools used for the Estimated Time at Completion (ETAC) involve equations 12, 17 and 18.

$$ETAC_{EVA} = \frac{PD}{SPI_{Classic}}, using\ Classical\ Cost\ based\ EVM\ Parameters \tag{12}$$

$$ETAC_{EVA} = AT + \frac{PD - ES}{SPI(t)}, using\ Time\ based\ EVM\ Parameters \tag{17}$$

$$ETAC_{EVA} = AT + PD - ES, using\ ESM - 1\ method\ taking\ SPI(t) = 1 \tag{18}$$

3.6.5 Monte Carlo Simulation Model

The simulation model was implemented in Python using NumPy for random sampling, Pandas for data handling, and Matplotlib for visualisation. A total of 5,000 iterations were used in the simulation. The algorithm for the code is shown in Appendix XIII, and the full simulation code is shown in Appendix XIV.

3.6.5.1 Choice of Probability Distribution

Impact uncertainty for each factor was modelled using a three-parameter distribution defined by (a_i, m_i, b_i). The base model adopted a triangular distribution due to its transparency and minimal shape assumptions. A Beta-PERT distribution was evaluated in sensitivity analysis as it concentrates probability mass around the most likely value, m_i. Since m_i is derived from survey midpoints rather than directly collecting from the respondents, the triangular distribution was retained as the baseline choice. The input probability distributions for various risk scenarios are shown in Appendices IX, X, XI, and XII.

3.6.5.2 Sensitivity Analysis Design

A structured sensitivity analysis was performed to examine the influence of parameter and distribution assumptions on forecasted delay. Scenarios varied: (i) aggregation of probability (median vs mean), (ii) impact distribution (triangular vs PERT), and (iii) impact bounds (P10/P90 vs P5/P95). Results were compared using P50/P80/P90/P95 delays.

Table 6: Alternative Risk Scenarios

Risk Scenario	Probability of Occurrence (p)	Impact Distribution	Impact Bounds
R0	Median	Triangular	P10/P90
R1	Mean	Triangular	P10/P90
R2	Median	PERT	P10/P90
R3	Median	Triangular	P5/P95

For each of the risk scenarios, the estimated time at completion from the EVA was calculated from ESM1, SPI(t), and the $SPI_{Classic}$ methods.

3.6.5.3 Hybrid Integration Equation

The hybrid model was implemented using an additive delay factor from the simulation results, integrating with the estimated completion time from the deterministic EVM. Mathematically shown as,

$$ETAC_{Hybrid} = ETAC_{EVA} + Delay_{MCS} \qquad (24)$$

3.6.6 Model Validation and Evaluation

The proposed hybrid forecasting model was evaluated using the selected building construction case project. The purpose was to assess whether the developed model could generate schedule forecasts that are reasonably consistent with the actual project outcome and whether it improves the practical usefulness of schedule prediction compared with traditional deterministic Earned Value Management (EVM) methods.

Since the study is based on a single case project, the validation was designed as a case-based comparative evaluation rather than a universal statistical validation. Accordingly, the model was assessed by comparing the forecasting outputs of deterministic EVM methods and the hybrid EVM–Monte Carlo Simulation (MCS) framework against the revised project completion duration. In addition, sensitivity analysis was performed to evaluate the interpretability of the model.

For validation purposes, the revised project completion duration was used as the practical benchmark. The case project originally had a planned duration of 1096 days, but the completion date was later extended through the revised project plan. Therefore, the revised duration was considered the most appropriate reference for comparing model forecasts, since it reflects the project's actual updated execution context more realistically than the original baseline.

3.7 Research Matrix

Table 7: Research Matrix

Objectives	Research Question	Data Source	Methods / Analysis	Outcomes
1. To identify key uncertainty factors affecting schedule performance in building construction projects.	What are the major uncertainty factors that affect schedule performance in building construction projects?	Secondary data: literature review of journal articles, conference papers, reports, and related publications. Primary data: expert validation ratings from 9 purposively selected experts using a structured validation form.	Initial uncertainty factors are identified from literature. Experts assess factor relevance on a five-point Likert scale. Expert responses are analysed using the Relative Importance Index (RII). Factors with RII ≥ 0.80 are retained for further analysis.	A finalised set of key uncertainty factors affecting schedule performance in building construction projects.
2. To analyse qualitative schedule risk in building construction projects using a 5×5 probability-impact matrix.	How can the identified uncertainty factors be prioritised qualitatively based on their probability of occurrence and schedule impact?	Primary data: questionnaire survey responses from 72 construction professionals. Respondents provide the probability of occurrence and minimum and maximum schedule impacts for each finalised factor.	Descriptive statistics are used to summarise the responses. Median and IQR are used for the probability of occurrence in the base model. Expected impact is computed as ($EI_{ij}=(Min_{ij}+Max_{ij})/2$). The most likely impact is represented by the median EI, while impact bounds are taken from P10/P90, with P5/P95 used in sensitivity analysis. Probability and impact classes are then assigned through percentile cutoffs and combined in a 5×5 probability–impact matrix for qualitative risk prioritisation.	Qualitative classification of uncertainty factors into different risk levels and identification of the most critical schedule risks for building construction projects.

Objectives	Research Question	Data Source	Methods / Analysis	Outcomes
3. To develop a hybrid forecasting model integrating EVM and Monte Carlo Simulation for schedule risk prediction in building construction projects and evaluate its performance against traditional deterministic EVM.	Can a hybrid EVM–MCS model provide more realistic and useful schedule forecasts than traditional deterministic EVM methods?	Secondary data: case project records, including project particulars, planned progress, actual progress, cumulative time data, and other planning / monthly progress records. Primary-data-derived inputs: probability and impact parameters from the questionnaire survey.	Earned Value Analysis (EVA) is performed using project data to compute deterministic time forecasts through SPI Classic, SPI(t), and ESM1. A Monte Carlo Simulation model is then implemented in Python using 5,000 iterations. Impact uncertainty is modeled using triangular distribution in the base model, while PERT is used in sensitivity analysis. Four risk scenarios are tested: R0, R1, R2, and R3. The hybrid model is formed using the additive relation: $ETAC_{Hybrid} = ETAC_{EVA} + Delay_{MCS}$. Model performance is evaluated by comparing deterministic and hybrid forecasts against the revised project completion duration of the selected case project.	A hybrid EVM–MCS forecasting model for schedule risk prediction; probabilistic completion forecasts (such as mean, P50, P80, P90, P95); comparison of hybrid and deterministic forecasts; and evidence on whether the hybrid model improves practical schedule prediction.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Key Uncertainty Factors Affecting Schedule Performance in Building Construction Projects

Based on the calculated RII values (shown in Appendix II) and a cutoff threshold of 0.8, twelve factors were retained as the most critical for schedule performance in building construction projects. In addition, experts were provided the opportunity to suggest any additional factors they considered important. Three additional factors were recommended through this process and included, bringing the final set of schedule uncertainty factors to fifteen.

Table 8: Key Uncertainty Factors Affecting Building Project Schedule

S.No.	Uncertainty Factors	RII	Importance Level/Remarks
1	Payment delays	0.93	High (H)
2	Design changes / scope modifications	0.87	High (H)
3	Design errors and omissions	0.84	High (H)
4	Political uncertainty	0.84	High (H)
5	Coordination issues among project stakeholders	0.84	High (H)
6	Material delivery delays / supply chain issues	0.82	High (H)
7	Unreliable suppliers or subcontractors	0.82	High (H)
8	Labour skill shortages / availability	0.80	High (H)
9	Material price fluctuation / escalation	0.80	High (H)
10	Inflation and macroeconomic instability	0.80	High (H)
11	Inspection delays, weak monitoring and supervision	0.80	High (H)
12	Fluctuations in interest rates	0.80	High (H)

S.No.	Uncertainty Factors	RII	Importance Level/Remarks
13	Legal prosecution, court-issued stay orders	-	Added from the expert's suggestion
14	Local interference, vandalism and site-level social disturbances	-	Added from the expert's suggestion
15	Land-related disputes	-	Added from the expert's suggestion

4.2 Qualitative Schedule Risk Analysis in Building Construction Projects

4.2.1 Survey Results on Probability and Impact

72 valid questionnaire responses were obtained for the questionnaire survey. Respondents represented key stakeholder groups involved in building projects in Nepal, including site engineers, contractors, consultants, government/client officials, and project managers.

4.2.1.1 Profile of Respondents

Site engineers constituted the largest share (25 respondents; 34.7%), followed by government officials/clients (18; 25.0%) and contractors (14; 19.4%). Consultants contributed 10 responses (13.9%), while project managers contributed 3 (4.2%), and others were 2 (2.8%), including structural designers. Regarding experience, the sample was dominated by early-to-mid career professionals: 39 respondents (54.2%) had less than 5 years of experience, 26 respondents (36.1%) had 5–10 years, 5 respondents (6.9%) had 10–15 years, and 2 respondents (2.8%) had more than 15 years of experience.

Table 9: Profile of Respondents (Role*Experience)

Role * Experience Crosstabulation						
Count						
		Experience				**Total**
		<5	5-10	10-15	>=15	
Role	Project Manager	0	2	1	0	**3**

	Site Engineer	16	9	0	0	**25**
	Contractor	4	7	2	1	**14**
	Consultant	5	4	1	0	**10**
	Government Official/Client	12	4	1	1	**18**
	Others	2	0	0	0	**2**
Total		**39**	**26**	**5**	**2**	**72**

4.2.1.2 Descriptive Statistics of Probability of Occurrence

As shown in Table 10, Payment delays recorded the highest median probability of 0.50 (mean = 0.490), indicating that respondents generally perceive payment-related issues as a frequently occurring schedule risk in Nepalese building projects. Similarly, design changes/scope modifications, material delivery delays/supply chain issues, and material price fluctuation/escalation exhibit relatively high median probabilities of 0.30. These findings suggest that both client-driven changes and market-driven uncertainties are routinely expected during project execution. In particular, design and scope changes highlight weak upstream planning and evolving client requirements, while supply chain and price fluctuations reflect external market volatility and import dependency in construction materials.

Moderate probability values (median = 0.20–0.25) are observed for factors such as coordination issues among project stakeholders, local interference and social disturbances, unreliable suppliers or subcontractors, design errors and omissions, political uncertainty, land-related disputes, labour shortages, inflation, and supervision-related delays. These factors represent systemic and operational inefficiencies that, while not as frequent as payment or supply chain issues, still occur regularly enough to contribute to cumulative schedule risk.

The lowest median probability was observed for legal prosecution/court-issued stay orders (median = 0.10). Although such events may have substantial schedule consequences when they occur, respondents view them as comparatively less frequent.

A noticeable pattern across factors is that the mean probabilities are consistently higher than the medians for most items, suggesting positively skewed response distributions where a subset of respondents reported relatively higher probabilities. The descriptive statistics and histogram of responses for the probability of occurrence of the uncertainty factors are shown on Appendix IV and VII, respectively. This further supports the use of the median probability values as base-case inputs for the Monte Carlo simulation, while the mean values were retained for sensitivity analysis to evaluate the influence of alternative aggregation assumptions.

Table 10: Descriptive Statistics of Probability of Occurrence of Various Uncertainty Factors

S.N.	Uncertainty Factors	Mean p	Median p
1	Payment delays	0.490	0.500
2	Design changes / scope modifications	0.411	0.300
3	Material delivery delays / supply chain issues	0.411	0.300
4	Material price fluctuation / escalation	0.387	0.300
5	Coordination issues among project stakeholders	0.342	0.200
6	Local interference, vandalism and site-level social disturbances	0.340	0.250
7	Unreliable suppliers or subcontractors	0.336	0.250
8	Design errors and omissions	0.325	0.200
9	Political uncertainty	0.323	0.200
10	Land-related disputes	0.311	0.200
11	Labour skill shortages / availability	0.298	0.200
12	Inflation and macroeconomic instability	0.293	0.200
13	Inspection delays, weak monitoring and supervision	0.286	0.200
14	Legal prosecution, court-issued stay orders	0.208	0.100
15	Fluctuations in interest rates	0.190	0.150

4.2.1.3 Descriptive Statistics of Impact

As shown in Table 11, Legal prosecution/court-issued stay orders recorded the largest expected delay with a median Expected Impact (EI) of 60 days, indicating that although the probability of occurrence may be lower, the potential consequences are substantial when such events occur. Land-related disputes also show high impacts with a median EI of 37.5 days, reflecting the severity of access and right-of-way issues in practice. Political uncertainty also presents a comparatively high typical impact with a median EI of 32.5 days.

Payment delays remain a critical driver of schedule disruption, with a median EI of 25 days. Design changes/scope modifications have a median EI of 22.5 days, and design errors and omissions have a median EI of 18.25 days. These values suggest that design quality and change management can materially influence schedule performance in building projects. Table 11 shows the descriptive statistics of minimum and maximum impact responses and the expected impact for each uncertainty factor.

The dispersion statistics indicate considerable variability across respondents, particularly in the upper tails of maximum impacts. For example, payment delays have a reported maximum impact of up to 400 days, with a P90 maximum of 120 days and a P95 maximum of 244.75 days, indicating a pronounced long-tail risk.

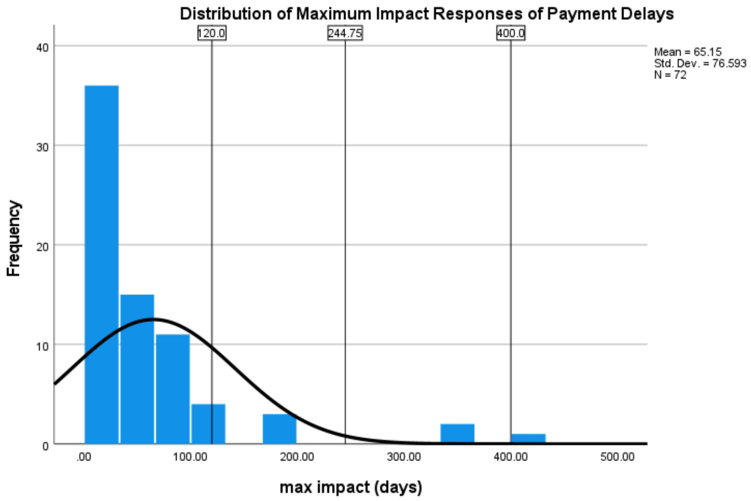


Figure 5: Distribution of Maximum Impact Responses of Payment Delays

Similarly, political uncertainty shows maximum impacts up to 500 days, with a P90 maximum of 120 days and a P95 maximum of 235 days. Long-tail behaviour is also evident for legal prosecution/stay orders and land-related disputes, where P95 maximum impacts exceed 250 days. The histogram of responses for the minimum and maximum impact of the uncertainty factors is shown in Appendix VIII. These patterns support the use of percentile-based bounds (e.g., P10 minimum and P90 maximum) for simulation inputs to represent collective judgment while reducing the influence of extreme individual responses.

Overall, the impact results indicate that while some risks, including payment and supply chain related issues, have moderate-to-high expected impacts, a smaller set of risks, including legal action, land disputes, and political uncertainty, exhibit relatively higher expected delays and heavier tails, which is critical for schedule risk planning and contingency estimation in Nepalese building projects.

Table 11: Descriptive Statistics of Impacts

S.N.	Uncertainty Factors	Minimum Impact (days)			Maximum Impact (days)			EI (days)
		Min.	Percentiles		Max.	Percentiles		
			5th	10th		90th	95th	
1	Payment delays	1	2	3	400	120	244.75	25
2	Design errors and omissions	0	0.65	1	325	84	130.5	18.25
3	Design changes / scope modifications	0	0.65	1	300	88.5	128	22.5
4	Political uncertainty	0	0	0	500	120	235	32.5
5	Coordination issues among project stakeholders	0	0	0.3	365	97	148	15
6	Material delivery delays / supply chain issues	1	1	1	200	90	107	15
7	Unreliable suppliers or subcontractors	0	0.65	1.3	350	90	180	18.5
8	Labour skill shortages / availability	0	0	1	200	60	93.5	15
9	Material price fluctuation / escalation	0	0	0	250	84	107	12
10	Inflation and macroeconomic instability	0	0	0	200	78.5	120	10
11	Inspection delays, weak monitoring and supervision	0	0	1	100	48.5	90	11
12	Fluctuations in interest rates	0	0	0	365	60	100	7.5
13	Legal prosecution, court-issued stay orders	0	0	0.3	365	180	257.75	60
14	Local interference, vandalism and site-level social disturbances	0	0.65	1	400	90	103.5	20
15	Land-related disputes	0	0	1	400	180	256	37.5

4.2.2 Probability Impact Matrix

The cutoff values for the probability classes (P1–P5) were found to be 0.10, 0.20, 0.30, and 0.50. Similarly, Impact classes (I1–I5) have cutoffs of 6.4, 15.0, 22.5, and 46.7 days. Table 12 shows the qualitative risk levels for the key uncertainty factors based on the assigned probability code and impact code.

Table 12: Risk Level of Uncertainty Factors

S.N.	Uncertainty Factors	p	Probability Level	EI	Impact Level	Risk Level
F1	Payment delays	0.5	4	25	4	Medium High
F2	Design errors and omissions	0.2	2	18.25	3	Low Medium
F3	Design changes / scope modifications	0.3	3	22.5	3	Medium
F4	Political uncertainty	0.2	2	32.5	4	Medium
F5	Coordination issues among project stakeholders	0.2	2	15	2	Low Medium
F6	Material delivery delays / supply chain issues	0.3	3	15	2	Low Medium
F7	Unreliable suppliers or subcontractors	0.25	3	18.5	3	Medium
F8	Labour skill shortages / availability	0.2	2	15	2	Low Medium
F9	Material price fluctuation / escalation	0.3	3	12	2	Low Medium
F10	Inflation and macroeconomic instability	0.2	2	10	2	Low Medium
F11	Inspection delays, weak monitoring and supervision	0.2	2	11	2	Low Medium
F12	Fluctuations in interest rates	0.15	2	7.5	2	Low Medium
F13	Legal prosecution, court-issued stay orders	0.1	1	60	5	Medium
F14	Local interference, vandalism and site-level social disturbances	0.25	3	20	3	Medium
F15	Land-related disputes	0.2	2	37.5	4	Medium

The matrix (Figure 6) highlights that most schedule risks fall in the low–medium band in terms of qualitative severity.

Among all factors, payment delays (F1) emerges as the most significant risk, classified as 'Likely' with a 'Significant' impact, resulting in a 'Medium-High' risk level. This reflects the dual effect of relatively high occurrence probability and meaningful schedule disruption when payment issues arise. Payment delays often cascade into secondary effects such as reduced contractor cash flow, delayed procurement, slowed labour mobilisation, and interruptions in subcontractor payments, thereby amplifying their overall schedule impact.

In contrast, land-related disputes (F15) and political uncertainty (F4) are categorized as 'Unlikely' but 'Significant' impact risks, leading to a 'Medium' risk classification. These factors represent contextual and external risks that are not part of routine project operations but are strongly influenced by institutional, regulatory, and socio-political environments. Although their likelihood is comparatively lower, their occurrence can result in severe disruptions such as work stoppage, redesign requirements, or extended approval delays.

A particularly important observation is legal prosecution/court-issued stay orders (F13), which is classified as 'Very Unlikely' but 'Severe' impact, positioning it as a classic low-probability, high-consequence risk. While respondents perceive such events as rare, their potential consequences include complete suspension of project activities, contractual disputes, or indefinite delays. This highlights the importance of legal and regulatory preparedness, even for risks that may not frequently materialise in practice.

On the other hand, factors such as coordination issues among stakeholders (F5), material delivery delays (F6), labour skill shortages (F8), and macroeconomic variables including inflation (F10) and interest rate fluctuations (F12) fall within the low to medium risk range. These factors are generally perceived as recurring but manageable disruptions rather than critical threats. Their relatively lower impact classification suggests that while they contribute to inefficiencies and minor delays, they are less likely to individually drive major project overruns compared to institutional or financial bottlenecks.

An important pattern emerging from the matrix is that most risks cluster in the middle risk zone, indicating a predominance of moderate uncertainty rather than extreme volatility. This suggests that Nepalese building construction projects are characterised more by cumulative operational inefficiencies than by isolated catastrophic risks.

However, the presence of a few high-impact, low-probability risks implies that risk management strategies should not focus solely on frequent issues but also incorporate contingency planning for rare but disruptive events.

Overall, the probability–impact matrix provides a structured prioritisation of uncertainty factors, enabling decision-makers to focus on critical risks such as payment delays, land acquisition issues, and legal disruptions, while also managing recurring operational inefficiencies through routine project controls.

		Impact				
Probability		Negligible (1)	Minor (2)	Moderate (3)	Significant (4)	Severe (5)
	Very Likely (5)					
	Likely (4)				F1	
	Possible (3)		F6, F9	F3, F7, F14		
	Unlikely (2)		F5, F8, F10, F11, F12	F2	F4, F15	
	Very Unlikely (1)					F13

Risk Levels	
	Low
	Low Medium
	Medium
	Medium High
	High

Figure 6: Probability-Impact Matrix

4.3 Hybrid Forecasting Model Integrating EVM and MCS for Schedule Risk Prediction in Building Construction Projects

4.3.1 EVM Analysis of Case Project

Figure 7 presents the S-curve of Planned Value (PV) and Earned Value (EV) for the case project. The figure 7 shows that at the early stage of the project, the EV curve was slightly above the PV curve, indicating that the initially progressed ahead of schedule. However, from Baisakh 2080 onwards, the EV curve remained consistently below the PV curve, and the gap between the two curves continued to widen over time. This divergence indicates persistent schedule underperformance and confirms that the project progressively fell behind the planned schedule.

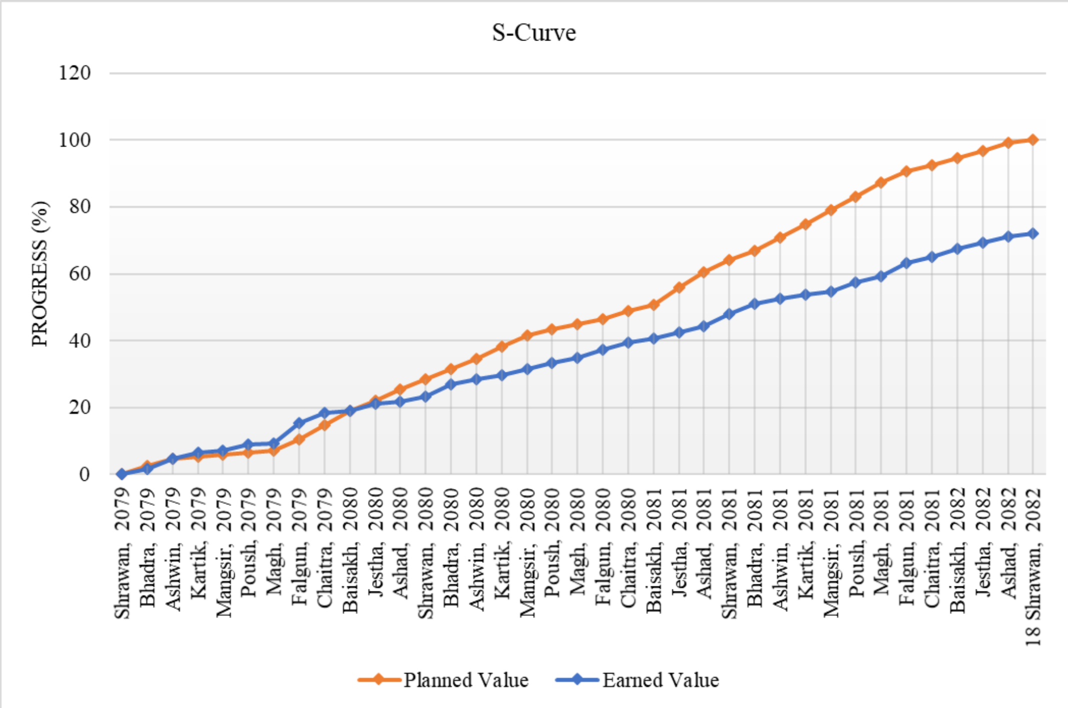


Figure 7: S-Curve of Planned Value and Earned Value

Table 13 shows the EVM and Earned Schedule parameters at the selected status dates. In the first monitoring period (Magh 2079), the project was ahead of schedule, with SPI = 1.33 and SPI(t) = 1.11. The Earned Schedule (ES) of 213.33 days also exceeded the actual time elapsed (AT = 193 days), confirming an early schedule advantage.

Table 13: EVM and ES Parameters

Status Month	AT (days)	PD (days)	PV	EV	SPI	ES	SPI(t)
Magh, 2079	193	1096	7.02	9.31	1.33	213.33	1.11
Shrawan, 2080	379	1096	28.4	23.4	0.82	328.00	0.87
Magh, 2080	558	1096	45	35	0.78	442.65	0.79
Shrawan, 2081	744	1096	64.2	48.1	0.75	608.87	0.82
Magh, 2081	924	1096	87.4	59.2	0.68	703.04	0.76
18 Shrawan, 2082	1096	1096	100	72.13	0.72	814.73	0.74

However, this trend did not continue. By Shrawan 2080, the project had fallen behind schedule, with PV = 28.4% and EV = 23.4%, resulting in SPI = 0.82 and SPI(t) = 0.87.

From this stage onwards, all monitoring periods recorded SPI < 1 and SPI(t) < 1, indicating continued schedule slippage. At the original planned completion date (18 Shrawan 2082), the project had achieved only 72.13% earned progress, with SPI = 0.72 and SPI(t) = 0.74. The corresponding ES of 814.73 days shows that after the full planned duration of 1096 days, the project had earned schedule progress equivalent to only about 815 days of planned work.

Table 14 shows the deterministic completion forecasts using ESM1, SPI(t), and the classical SPI-based method. At the early stage (Magh 2079), all three methods predicted completion earlier than the planned duration, which is consistent with the project's initial ahead-of-schedule condition. However, once delays emerged, the predicted completion durations increased steadily over time. At the final status date (18 Shrawan 2082), the forecasted completion durations were 1377.27 days for ESM1, 1474.37 days for SPI(t), and 1519.48 days for the classical SPI method. Compared with the original planned duration, these imply projected overruns of about 281 days, 378 days, and 423 days, respectively.

Table 14: Deterministic EVA Forecasts

Status Month	EAC (days)			EAC vs PD (Delay Days)		
	ESM1	SPI(t)	SPI	ESM1	SPI(t)	SPI
Magh, 2079	1075.67	991.57	826.41	-20.33	-104.43	-269.59
Shrawan, 2080	1147.00	1266.41	1330.19	51.00	170.41	234.19
Magh, 2080	1211.35	1381.62	1409.14	115.35	285.62	313.14
Shrawan, 2081	1231.13	1339.24	1462.85	135.13	243.24	366.85
Magh, 2081	1316.96	1440.46	1618.08	220.96	344.46	522.08
18 Shrawan, 2082	1377.27	1474.37	1519.48	281.27	378.37	423.48

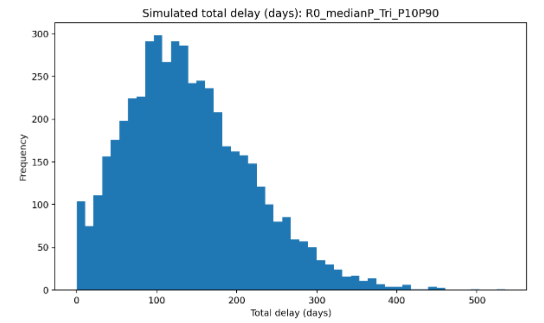
4.3.2 Monte Carlo Simulation Results

The results show that the simulated delay distribution is substantial under all scenarios. Under the base case scenario (R0), the mean delay is 141.09 days, while the median (P50) delay is 131.38 days. This indicates that even under moderate assumptions, the identified uncertainty factors are capable of causing major schedule overrun. At higher confidence levels, the projected delay increases to 205.59 days at P80, 247.16 days at P90, and 284.59 days at P95, showing the presence of significant tail risk.

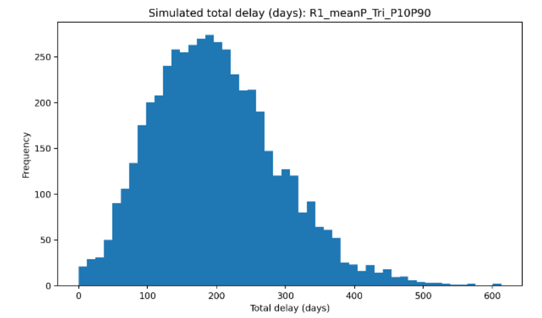
When mean probabilities are used instead of median probabilities (R1), the mean delay increases to 199.12 days, indicating that higher assumed occurrence likelihoods increase forecast delay. The PERT-based scenario (R2) generates comparatively lower delay estimates, suggesting that the smoother PERT distribution moderates extreme outcomes. In contrast, the wider percentile-bounded triangular scenario (R3) produces the largest delay estimates, with a mean delay of 209.88 days and a P95 delay of 431.62 days, reflecting the influence of long-tail impacts in the survey responses. Overall, the Monte Carlo results demonstrate that schedule forecasting based only on single-point deterministic estimates would under-represent the magnitude of uncertainty affecting the case project.

Table 15: Summary of Simulated Schedule Delay under Alternative Risk Scenarios

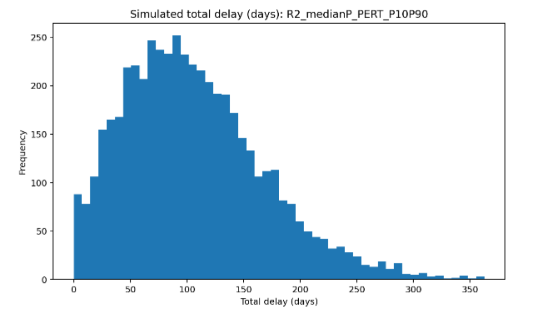
Risk Scenario	Mean	Std	p50	p80	p90	p95
R0	141.093	78.5357	131.384	205.593	247.158	284.586
R1	199.116	90.8751	191.408	271.71	320.471	360.259
R2	106.143	61.7971	98.6004	154.626	188.859	221.123
R3	209.883	121.571	193.644	309.408	374.534	431.62



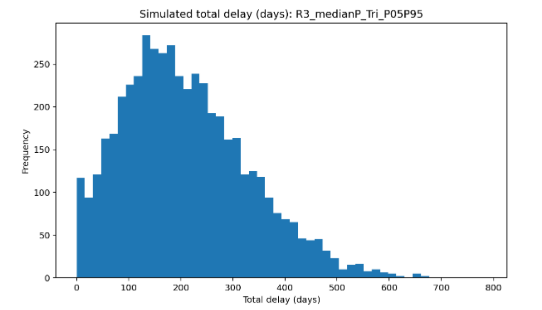
(a) Risk Scenario R0



(b) Risk Scenario R1



(c) Risk Scenario R2



(d) Risk Scenario R3

Figure 8: Simulated Delay Distributions Under Alternative Risk Scenarios

4.3.3 Model Validation Results

The original contract duration of the case project was 1096 days, corresponding to the original completion date of 18 Shrawan 2082. The revised plan extended the completion date to 18 Shrawan 2083, representing the extension of approximately 378 days. Thus, the reference completion duration for comparison is about 1474 days. This revised schedule was used as the practical benchmark for comparing deterministic and hybrid forecasting outputs.

At the final status date (18 Shrawan 2082), the deterministic forecasting results obtained from the EVM/Earned Schedule analysis were 1377.27 days for ESM1, 1474.37 days for SPI(t), and 1519.48 days for the classical SPI method. This shows that, in purely deterministic terms, the SPI(t)-based forecast provided the closest estimate to the revised completion duration, with an absolute error of only 0.37 days, whereas ESM1 underestimated the revised duration and the classical SPI method overestimated it.

Table 16: Validation of Deterministic Forecasting Methods against Revised Completion Duration

Forecasting Method	Predicted Completion Duration (days)	Delay Beyond Original Plan (days)	Absolute Error vs Revised Duration (days)
ESM1	1377.27	281.27	96.73
SPI(t)	1474.37	378.37	0.37
SPI Classic	1519.48	423.48	45.48

However, when Monte Carlo-based schedule risk was integrated with the deterministic forecasts, the relative performance changed. In the hybrid model, the ESM1-based forecasts consistently produced completion durations closer to the revised project completion than the SPI(t)-based and SPI-based hybrid forecasts. Full simulation results are shown in Appendix XV. Under the base case hybrid scenario R0, the final ESM1 hybrid P50 forecast was 1508.65 days, compared with 1605.75 days for SPI(t) and 1650.86 days for the classical SPI method. This indicates that although SPI(t) was the best deterministic predictor, ESM1 served as the better baseline once probabilistic delay was added in the hybrid framework.

Table 17: Hybrid Forecasting Model Results for Scenario R0

Status Period	Method	AT	PD	Finish mean	Finish P50	Finish P80	Finish P90	Finish P95
Magh, 2079	ESM1	193	1096	1216.77	1207.06	1281.27	1322.83	1360.26
Shrawan, 2080		379	1096	1288.09	1278.38	1352.59	1394.16	1431.59
Magh, 2080		558	1096	1352.45	1342.74	1416.95	1458.51	1495.94
Shrawan, 2081		744	1096	1372.22	1362.51	1436.72	1478.29	1515.72
Magh, 2081		924	1096	1458.05	1448.34	1522.55	1564.11	1601.54
18 Shrawan, 2082		1096	1096	1518.36	1508.65	1582.86	1624.43	1661.85
Magh, 2079	SPI(t)	193	1096	1132.67	1122.96	1197.17	1238.73	1276.16
Shrawan, 2080		379	1096	1407.51	1397.80	1472.01	1513.57	1551.00
Magh, 2080		558	1096	1522.71	1513.00	1587.21	1628.77	1666.20
Shrawan, 2081		744	1096	1480.34	1470.63	1544.84	1586.40	1623.83
Magh, 2081		924	1096	1581.55	1571.84	1646.05	1687.61	1725.04
18 Shrawan, 2082		1096	1096	1615.46	1605.75	1679.96	1721.53	1758.96
Magh, 2079	SPI	193	1096	967.51	957.80	1032.01	1073.57	1111.00

Status Period	Method	AT	PD	Finish mean	Finish P50	Finish P80	Finish P90	Finish P95
Shrawan, 2080		379	1096	1471.28	1461.57	1535.78	1577.35	1614.77
Magh, 2080		558	1096	1550.24	1540.53	1614.74	1656.30	1693.73
Shrawan, 2081		744	1096	1603.95	1594.24	1668.45	1710.01	1747.44
Magh, 2081		924	1096	1759.17	1749.46	1823.67	1865.24	1902.67
18 Shrawan, 2082		1096	1096	1660.57	1650.86	1725.07	1766.64	1804.06

For completeness, it is also noted that among all tested hybrid configurations, the numerically closest result to the revised completion duration was obtained using the ESM1 + R2 combination, which produced a P50 completion of 1475.87 days, only about 1.87 days above the revised project duration. Nevertheless, for the main validation under the selected base-case risk scenario, the important finding is that SPI(t) performed best deterministically, whereas ESM1 performed best in the hybrid framework.

4.3.4 Sensitivity Analysis

The sensitivity results show that the hybrid completion forecast remains above the revised planned duration under all scenarios. Under the base-case scenario (R0), at the final status date, the project is expected to finish at 1508.65 days at P50 and 1582.86 days at P80, which indicates that even after revision of the project schedule, additional schedule overrun remains likely if the identified risks materialise. This corresponds to an additional delay of about 34 days at P50 and 108 days at P80 beyond the revised duration.

Among the tested scenarios, R2 produced the lowest forecast values, with a P50 completion of 1475.87 days, which is very close to the revised planned completion. In contrast, R3 produced the highest forecasts, reflecting the effect of wider impact bounds and greater tail risk. The results therefore show that the hybrid model is sensitive to both the probability aggregation approach and the assumed impact distribution. However, the overall conclusion remains unchanged across all scenarios that the revised project schedule still carries significant residual schedule risk.

4.4 Discussion of Key Findings

The findings of this study demonstrate that schedule forecasting for building construction projects can be significantly improved by integrating deterministic earned value analysis with probabilistic risk simulation. The expert validation process and questionnaire survey confirmed that project schedule performance in the Nepalese building construction context is affected by a combination of financial, technical, institutional, and supply-chain related uncertainties. Although some risks occur more frequently than others, the analysis showed that both the probability of occurrence and magnitude of impact are important in determining overall schedule risk.

Further evidence supporting the relevance of the identified uncertainty factors was obtained from a review of the case project's monthly progress reports. The reported delay causes included design review requirements arising from DUDBC comments, structural design revisions, changes in low-voltage system design, and delays in issuing ground floor and structural drawings. Regulatory factors included changes in FAR legislation affecting design approvals and social disturbances due to civil movements that were treated as force majeure events impacting site activities. Supply chain disruptions included crusher closures, causing material shortages and delays in damper shipment due to cash flow constraints. Environmental disruptions included heavy rainfall affecting construction activities. These observed delay causes correspond directly with the validated uncertainty factors, including design changes and scope modifications, political uncertainty, material delivery delays, and supply chain issues, thereby strengthening the practical relevance of the developed hybrid model.

The descriptive analysis of the survey responses showed that payment delays had the highest median probability of occurrence, while legal prosecution/court-issued stay orders, land-related disputes, and political uncertainty had the largest expected impacts. The Probability-Impact Matrix further showed that payment delays occupied the most critical practical position because it was found to have a relatively high likelihood with significant schedule consequences. This indicates that frequent operational risks may be more influential in project control than rare risks unless they have very extreme impacts.

The EVA of the case project confirmed schedule underperformance. At the original planned completion point, the project had reached only 72.13% earned progress, resulting in SPI = 0.72 and SPI(t) = 0.74. The deterministic forecasting results showed that SPI(t) gave the closest estimate to the revised completion duration of the project, suggesting that time-based earned schedule indicators are more reliable than classical SPI for duration forecasting.

However, when uncertainty was incorporated through MCS, the relative performance of the forecasting methods changed. The validation results showed that the ESM1-based hybrid forecasts were closer to the revised planned completion than the SPI(t)-based hybrid forecasts. This suggests that SPI(t) is the stronger method for deterministic duration prediction, whereas ESM1 provides a more suitable baseline when probabilistic delay is added. It shows that the most accurate deterministic predictor is not necessarily the most appropriate anchor for a hybrid risk-adjusted forecast.

The hybrid results further show that the revised project schedule may still be optimistic. Under the base case scenario, the ESM1-based hybrid forecast produced a P50 completion of 1508.65 days and a P80 completion of 1582.86 days, which are both later than the revised project duration. This indicates that even after formally revising the schedule, the project remains exposed to additional delay if the validated uncertainty factors continue to affect project execution.

Overall, the study demonstrates that the proposed hybrid EVM-MCS framework provides a more realistic basis for schedule forecasting than deterministic EVM alone. It not only shows the current performance status of the project but also quantifies the range of possible future outcomes under uncertainty. As such, the model offers a more decision-oriented approach for project managers, planners, and clients seeking to manage schedule risk proactively.

CHAPTER 5: CONCLUSION AND RECOMMENDATION

5.1 Conclusions

This study was carried out to develop and evaluate a hybrid forecasting model integrating Earned Value Management (EVM) and Monte Carlo Simulation (MCS) for schedule risk prediction in building construction projects. The study addressed the limitations of conventional deterministic schedule forecasting by incorporating uncertainty factors and probabilistic delay analysis within the Nepalese construction context.

The first objective of the study was to identify the key uncertainty factors affecting project schedule performance in building construction projects. Through literature review and expert validation, fifteen uncertainty factors were retained for analysis. The findings showed that project schedule performance is influenced by a combination of financial, technical, institutional, and external uncertainties. Among these, payment delays, design changes or scope modifications, political uncertainty, material delivery delays or supply chain issues, unreliable suppliers or subcontractors, and land-related disputes emerged as major sources of schedule disruption.

The second objective of the study was to analyse qualitative schedule risk using the 5×5 probability-impact matrix. The matrix-based assessment showed that most of the identified uncertainty factors fell within the low-medium to medium risk categories, while payment delays stood out as the most critical practical risk with a medium-high classification. This indicates that payment-related issues are not only frequent but also significantly disruptive to project schedule performance. The matrix also highlighted that some uncertainty factors, such as legal prosecution or court-issued stay orders, land-related disputes, and political uncertainty, represent low-likelihood but high-consequence risks and remain important due to their substantial impact even at relatively lower occurrence probabilities.

The third objective of the study was to develop a hybrid forecasting model integrating EVM and Monte Carlo Simulation, and to evaluate its performance against traditional deterministic EVM methods. The Earned Value Analysis of the case project confirmed substantial schedule underperformance, as the project had achieved only 72.13% earned progress at the original completion point, with SPI = 0.72 and SPI(t) = 0.74. When analysed at the original completion point as a status date, among the deterministic methods, SPI(t) provided the closest estimate to the revised completion duration. However, when probabilistic delay was integrated through Monte Carlo Simulation, the ESM1-based hybrid forecasts performed better than the other hybrid alternatives in terms of closeness to the revised project duration under the selected base case scenario. The hybrid model produced a P50 completion of 1508.65 days and a P80 completion of 1582.86 days, showing that even after revision of the project schedule, substantial residual schedule risk remained. These findings demonstrate that the hybrid model provides a more realistic and decision-oriented forecast than deterministic EVM alone because it captures both current performance status and future uncertainty.

Overall, the study concludes that integrating EVM and MCS provides a more informative and practical framework for schedule forecasting in building construction projects than conventional deterministic methods alone. The study not only identified the major uncertainty factors affecting schedule performance but also prioritised them qualitatively and incorporated them into a hybrid probabilistic forecasting model to estimate where the project is likely to finish under uncertainty. As such, the proposed framework can serve as a useful decision-support tool for improving schedule forecasting, contingency planning, and proactive risk management in building construction projects.

5.2 Recommendations

Based on the findings of this study, the following recommendations are proposed:

5.2.1 Recommendations for Practice

i. Selection of deterministic forecasting method according to project context

The findings of the case study indicate that SPI(t) provided the closest deterministic estimate to the revised project completion duration among the tested EVM-based methods. This suggests that time-based earned schedule indicators may be more suitable than classical SPI for deterministic duration forecasting in similar building construction projects. However, this implication should be interpreted cautiously and validated through additional case applications.

ii. Selection of hybrid forecasting baseline according to model purpose

The ESM1-based hybrid forecasts were closer to the revised completion duration. This suggests that ESM1 may be a suitable deterministic baseline when the objective is risk-adjusted hybrid forecasting. Since this conclusion is based on a single case project, it should be treated as a case-specific implication rather than a universal rule.

iii. Incorporate probabilistic schedule forecasting into routine project control.

Project managers should move beyond single-point completion forecasts and adopt probabilistic forecasting approaches that provide P50, P80, and P90 completion estimates. This will allow better contingency planning and more realistic communication of schedule expectations.

iv. Strengthen payment and cash flow management.

As payment delays were identified as the most influential factor, project owners, contractors, and financiers should improve billing, certification, and disbursement systems to ensure the timely release of payments during project execution.

v. Improve design finalisation and change control.

Design changes and scope modifications were among the most important delay drivers. Greater emphasis should be placed on early design coordination, design review, and formal change management procedures before and during construction.

vi. Strengthen legal, land, and stakeholder risk management.

Since land-related disputes and political uncertainty contributed significantly to schedule risk, project planning should include early legal due diligence, land clearance verification, stakeholder engagement, and institutional coordination.

vii. Improve procurement and supplier planning.

Material delivery delays and unreliable suppliers were major contributors to schedule overruns. Contractors should adopt stronger procurement planning, supplier prequalification, and material tracking systems to reduce these risks.

5.2.2 Recommendations for Future Research

Building on the findings and limitations of the current study, the following areas are recommended for future research:

i. Apply the hybrid model to multiple case projects.

Since the study is based on a single building project, future studies should test the framework on multiple projects to improve generalisability.

ii. Extend the model to other project types.

Future research should examine whether the same hybrid approach is suitable for road, bridge, hydropower, and infrastructure projects, which may be exposed to different uncertainty patterns.

iii. Incorporate correlated risks and overlapping delay effects.

The present study treats uncertainty factors as independent and uses an additive delay approximation. Future research could use correlation structures and activity-level scheduling logic to better represent real project behaviour.

iv. Collect three-point impact estimates directly from respondents.

Future surveys should collect minimum, most likely, and maximum delay impacts directly so that triangular or PERT distributions can be calibrated more accurately.

v. Use dynamic probabilities across project stages.

The current model assumes a constant probability of occurrence for each factor across the project duration. Future research could model stage-wise or time-varying probabilities to better reflect changing project conditions.

vi. Integrate cost forecasting with schedule forecasting.

Since schedule and cost performance are closely related, future work may extend the model to develop a full schedule-cost risk forecasting framework.

vii. Link the model with CPM/network-based schedule simulation.

Future studies may combine the present hybrid approach with detailed network scheduling techniques so that delay interactions and critical-path effects can be represented more realistically.

REFERENCES

Acebes, F., Pereda, M., Poza, D., Pajares, J., & Galán, J. M. (2015). Stochastic earned value analysis using Monte Carlo simulation and statistical learning techniques. *International Journal of Project Management*, *33*(7), 1597-1609. https://doi.org/10.1016/j.ijproman.2015.06.012

Akadiri, P. O., Olomolaiye, P. O., & Chinyio, E. A. (2013). Multi-criteria evaluation model for the selection of sustainable materials for building projects. *Automation in construction*, *30*, 113-125. https://doi.org/10.1016/j.autcon.2012.10.004

Akhbari, M. (2018). Project time and cost forecasting using Monte Carlo simulation and artificial neural networks. *International Journal of Industrial Engineering & Production Res*earch, *29*(2), 231-239.

Ali, Z., Zhu, F., & Hussain, S. (2018). Identification and assessment of uncertainty factors that influence the transaction cost in public sector construction projects in Pakistan. *Buildings*, *8*(11), 157. https://doi.org/10.3390/buildings8110157

Allahi, F., Cassettari, L., & Mosca, M. (2017). Stochastic risk analysis and cost contingency allocation approach for construction projects applying Monte Carlo simulation. *Proceedings of the World Congress on Engineering* (pp. 385-391).

Babar, S., Thaheem, M. J., & Ayub, B. (2017). Estimated cost at completion: Integrating risk into earned value management. *Journal of Construction Engineering and Management*, *143*(3), 04016104. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001245

Basnet, D. R., & Shrestha, S. K. (2023). Evaluation of Cost Variation in Public Broadcasting Buildings of Nepal: A Case of Nepal Television Building. *Proceedings of 14th IOE Graduate Conference*, *14*, 402–406.

Batselier, J., & Vanhoucke, M. (2015). Empirical evaluation of earned value management forecasting accuracy for time and cost. *Journal of Construction Engineering and Management*, *141*(11), 05015010. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001008

Bhattarai, M. (2023). Causes of delay in construction projects in Nepal. *Saudi Journal of Engineering and Technology*, *8*(06), 108-114. https://doi.org/10.36348/sjet.2023.v08i06.001

Bonate, P. L. (2001). A brief introduction to Monte Carlo simulation. *Clinical pharmacokinetics*, *40*(1), 15-22.

Bonato, F. K., Albuquerque, A. A. d., & Paixão, M. A. S. d. (2019). An application of Earned Value Management (EVM) with Monte Carlo simulation in engineering project management. *Gestão & Produção*, *26*, e4641. https://doi.org/10.1590/0104-530X4641-19

Chitkara, K. (2014). *Construction project management*. Tata McGraw-Hill Education.

Cochran, W. G. (1977). *Sampling techniques*. John Wiley & Sons.

de Andrade, P. A., Martens, A., & Vanhoucke, M. (2019). Using real project schedule data to compare earned schedule and earned duration management project time forecasting capabilities. *Automation in construction*, *99*, 68-78. https://doi.org/10.1016/j.autcon.2018.11.030

Devi, A. C., & Ananthanarayanan, K. (2017). Factors influencing cost over-run in Indian construction projects. MATEC Web of Conferences (Vol. 120, p. 02023). EDP Sciences.

Diamantas, V. K., Kirytopoulos, K. A., & Leopoulos, V. N. (2011). Earned value management under risk. *International Journal of Project Organisation and Management, 3*(3-4), 335-351. https://doi.org/10.1504/IJPOM.2011.042037

Giri, O. P. (2025). Assessment of key risk factors impacting construction project performance. *International Journal of Multidisciplinary Research and Growth Evaluation*, 6(1), 1231–1241. https://doi.org/10.54660/.IJMRGE.2025.6.1.1231-1241

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), Article 012035. https://doi.org/10.1088/1757-899X/528/1/012035

Hillson, D. (2002). Extending the risk process to manage opportunities. *International Journal of Project Management*, *20*(3), 235-240. https://doi.org/10.1016/S0263-7863(01)00074-6

Jangale, S., Jain, A., Pathan, A., Kandekar, P., Sawant, M., & Ghadge, S. (2017). Introduction to cost overrun in residential building: its causes and solutions. *International Journal of Engineering Research & Technology (IJERT)*, *6*(3), 60-62.

Jha, K. N. (2015). *Construction project management: Theory and practice*. Pearson Education India.

Judson, L., & Paul, V. K. (2022). Critical uncertainty factors impacting building construction projects in India. *Civil Engineering and Architecture*, *10*(5), 1854-1863. https://doi.org/10.13189/cea.2022.100512

Khanal, B. P., & Ojha, S. K. (2020). Cause of time and cost overruns in the construction project in Nepal. *Advances in Science, Technology and Engineering Systems*, *5*(4), 192-195.

Kim, B.-C., & Reinschmidt, K. F. (2010). Probabilistic forecasting of project duration using Kalman filter and the earned value method. *Journal of Construction Engineering and Management*, *136*(8), 834-843. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000192

Kish, L. (1965). *Survey sampling*. John Wiley & Sons.

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, 30, 607-610.

Lipke, W. (2014). Introduction to earned schedule. *PM World Journal*, *3*(11), 8-9.

Lipke, W. H. (2020). *Earned schedule plus*. Gatekeeper Press.

Mishra, A. K., & Mallik, K. (2017). Factors and impact of risk management practice on success of construction projects of housing developers, Kathmandu, Nepal. *International Journal of Sciences: Basic and Applied Research (IJSBAR)*, *36*(7), 206-232.

Moradi, N., Mousavi, S. M., & Vahdani, B. (2017). An earned value model with risk analysis for project management under uncertain conditions. *Journal of Intelligent & Fuzzy Systems*, *32*(1), 97-113. https://doi.org/10.3233/JIFS-151139

Mubin, S., Jahan, S., & Gavrishyk, E. (2019). Monte Carlo simulation and modeling of schedule, cost and risks of Dasu hydropower project. *Mehran University Research Journal of Engineering & Technology*, *38*(3), 557-570. https://doi.org/10.22581/muet1982.1903.03

Murali, S., & Kumar, S. (2019). Factors affecting overruns construction time and cost: A case study. *International Journal of Recent Technology and Engineering*, *7*(6C2), 284–288.

Nizam, A., & Elshannaway, A. (2019). Review of earned value management (EVM) methodology, its limitations, and applicable extensions. *Journal of Management & Engineering Integration*, *12*(1), 59-70.

Pradipbhai, O. A., Bharatbhai, P. K., Sureshbhai, G. H., Santoshbhai, C. P., Kailashbhai, N. S., & Patel, J. (2020). Assessment Of Time Delay And Cost Overruns In Indian Construction Industry. *International Research Journal of Engineering and Technology (IRJET)*, *7*(6).

Rauzana, A. (2018). Uncertainty variables on cost estimation in project construction. *IOSR Journal of Business and Management*, *20*(1), 80-86.

Raychaudhuri, S. (2008). Introduction to monte carlo simulation. *Proceedings of the 2008 Winter Simulation Conference* (pp. 91–100). IEEE. https://doi.org/10.1109/WSC.2008.4736059

Rezaie, K., Amalnik, M. S., Gereie, A., Ostadi, B., & Shakhseniaee, M. (2007). Using extended Monte Carlo simulation method for the improvement of risk management: Consideration of relationships between uncertainties. *Applied Mathematics and Computation*, *190*(2), 1492-1501. https://doi.org/10.1016/j.amc.2007.02.038

Sackey, S., Lee, D.-E., & Kim, B.-S. (2020). Duration estimate at completion: Improving earned value management forecasting accuracy. *KSCE journal of civil engineering*, *24*(3), 693-702. https://doi.org/10.1007/s12205-020-0407-5

Sadeghi, N., Fayek, A. R., & Pedrycz, W. (2010). Fuzzy Monte Carlo simulation and risk assessment in construction. *Computer-Aided Civil and Infrastructure Engineering*, *25*(4), 238-252. https://doi.org/10.1111/j.1467-8667.2009.00632.x

Sharma, S., & Goyal, P. K. (2014). Cost overrun factors and project cost risk assessment in construction industry-a state of the art review. *International journal of civil engineering*, *3*(3), 139-154.

Sharma, S., Goyal, P. K., & Chhipa, R. (2020). Forecasting the probability of cost overrun risk of Indian construction projects using fuzzy model. *International Journal of Engineering Research & Technology (IJERT), 11*(1), 10-22.

Sokolowski, J. A. (2010). Monte carlo simulation. *Modelling and Simulation Fundamentals: Theoretical Underpinnings and Practical Domains, Wiley & Sons Inc., New Jersey*, 131-145.

Urgilés, P., Claver, J., & Sebastián, M. A. (2019). Analysis of the earned value management and earned schedule techniques in complex hydroelectric power production projects: Cost and time forecast. *Complexity*, *2019*(1), 3190830. https://doi.org/10.1155/2019/3190830

Vanhoucke, M., & Vandevoorde, S. (2007). A simulation and evaluation of earned value metrics to forecast the project duration. *Journal of the Operational Research Society*, *58*(10), 1361-1374. https://doi.org/10.1057/palgrave.jors.2602296

Vargas, R. V. (2004). Earned value probabilistic forecasting using Monte Carlo simulation. *AACE International Transactions*, CS161.

Wanjari, S. P., & Dobariya, G. (2016). Identifying factors causing cost overrun of the construction projects in India. *Sādhanā*, *41*(6), 679-693. https://doi.org/10.1007/s12046-016-0498-3

APPENDIX I: QUESTIONNAIRE FOR EXPERT VALIDATION

Namaste. I am currently pursuing an MSc in Construction Management at Pulchowk Campus and conducting my master's thesis titled "A Hybrid Forecasting Model Integrating Earned Value Management and Monte Carlo Simulation for Schedule Risk Prediction in Building Construction Projects". This survey aims to validate the relevance of identified uncertainty factors affecting construction project performance in the Nepalese context based on expert judgment. You are kindly requested to rate each factor on a five-point relevance scale (1 = Not relevant, 5 = Highly relevant) according to your professional experience. The information provided will be used solely for academic research purposes, kept confidential, and analyzed in aggregate. Your valuable expertise and time are sincerely appreciated.

By proceeding with this survey, you indicate your informed consent to participate in this academic study. ▢ OK

Q1. Name of Expert: ……………………….

Q2. Organization Type:

▢ Government Organization ▢ Consulting Firm

▢ Contracting Company ▢ Academic Institution

▢ Other (Specify)

Q3. Organization: …………………….

Q4. Professional Role / Designation: …………………….

Q5. Please evaluate the relevance of the following Uncertainty Factors in Nepalese building construction context.

1 = Not Relevant, 2 = Slightly Relevant, 3 = Moderately Relevant, 4 = Relevant, 5 = Highly Relevant

S.N.	**Uncertainty Factors**	**1**	**2**	**3**	**4**	**5**
1	Material price fluctuation / escalation					
2	Inflation and macroeconomic instability					
3	Exchange rate variability (affecting imported materials)					
4	Change in Material specification					

S.N.	Uncertainty Factors	1	2	3	4	5
5	Labour productivity fluctuation					
6	Labour skill shortages / availability					
7	Labour strikes or union disruptions					
8	Increase in Labour costs					
9	Equipment breakdown or underperformance					
10	Equipment availability issues					
11	Material delivery delays / supply chain issues					
12	Unreliable suppliers or subcontractors					
13	Design errors and omissions					
14	Design changes / scope modifications					
15	Late issuance of drawings / revisions					
16	Incomplete or ambiguous specifications					
17	Unforeseen technical complexities beyond initial plans					
18	Differing/Unforeseen ground conditions (soil variability, buried utilities)					
19	Weather uncertainties (rain, storms affecting concrete curing, masonry, etc.)					
20	Environmental disruptions (landslides, flooding near site)					
21	Permit or approval delays					
22	Regulatory or policy changes during construction					
23	Inspection delays, weak monitoring and supervision					
24	Payment delays					
25	Fluctuations in interest rates					
26	Contract claims and dispute uncertainties					
27	Contractor–subcontractor relationship					

S.N.	Uncertainty Factors	1	2	3	4	5
28	Community or neighbourhood objections					
29	Political uncertainty					
30	Force majeure events (pandemic, earthquake, conflict)					
31	Improper management by Project Management Team					
32	Coordination issues among project stakeholders					
33	Health and safety incidents leading to stoppage					
34	Poor quality of material and equipment					
35	Wastage on Site					
36	Error in construction/Rework					

Q6. If you have any comments on the uncertainty factors identified, please mention.

…………………………………….

Q7. Please mention any other uncertainties you believe significantly affect project performance in Nepalese building construction.

Additional Uncertainty Factor 1: ……………………….

Additional Uncertainty Factor 2: ……………………….

Additional Uncertainty Factor 3: ……………………….

APPENDIX II: RESPONSES FROM EXPERT VALIDATION

A. Expert Details:

Organization	Org Type	Role/Designation	Experience (Years)
Aaramv Studios Pvt. Ltd.	Consulting Firm	Project Manager	7
Rays Consult Pvt. Ltd.	Consulting Firm	Project Manager	16
Engineer's Studio Pvt. Ltd.	Consulting Firm	Project Manager	6
Department of Urban Development and Building Construction	Government Organization	Project Manager	15
Department of Urban Development and Building Construction	Government Organization	Procurement Section Chief/ Senior Divisional Engineer	>20
Department of Urban Development and Building Construction	Government Organization	Senior Divisional Engineer	20
Nawa Kantipur Construction Company Pvt. Ltd.	Contracting Company	Director	17
Batuk Bhairab Construction	Contracting Company	Managing Director	27
Keystone Engineering Advisors Pvt. Ltd.	Contracting Company	Managing Director/Structural Engineer	13

B. Count of Responses and RII for each Uncertainty Factors:

S.N.	Uncertainty Factors	1	2	3	4	5	RII
1	Material price fluctuation / escalation	0	2	0	3	4	0.80
2	Inflation and macroeconomic instability	0	1	1	4	3	0.80

S.N.	Uncertainty Factors	1	2	3	4	5	RII
3	Exchange rate variability (affecting imported materials)	0	2	3	4	0	0.64
4	Change in Material specification	0	2	2	4	1	0.69
5	Labour productivity fluctuation	0	3	4	1	1	0.60
6	Labour skill shortages / availability	0	0	3	3	3	0.80
7	Labour strikes or union disruptions	4	2	0	3	0	0.44
8	Increase in Labour costs	0	2	4	3	0	0.62
9	Equipment breakdown or underperformance	0	4	2	2	1	0.60
10	Equipment availability issues	2	1	4	1	1	0.56
11	Material delivery delays / supply chain issues	0	0	2	4	3	0.82
12	Unreliable suppliers or subcontractors	0	2	0	2	5	0.82
13	Design errors and omissions	0	0	1	5	3	0.84
14	Design changes / scope modifications	0	0	2	2	5	0.87
15	Late issuance of drawings / revisions	0	1	3	5	0	0.69
16	Incomplete or ambiguous specifications	0	1	3	3	2	0.73
17	Unforeseen technical complexities beyond initial plans	0	1	1	7	0	0.73
18	Differing/Unforeseen ground conditions (soil variability, buried utilities)	0	1	3	4	1	0.71
19	Weather uncertainties (rain, storms affecting concrete curing, masonry, etc.)	0	3	2	3	1	0.64
20	Environmental disruptions (landslides, flooding near site)	0	3	4	2	0	0.58
21	Permit or approval delays	0	2	2	3	2	0.71
22	Regulatory or policy changes during construction	0	4	4	1	0	0.53

S.N.	Uncertainty Factors	1	2	3	4	5	RII
23	Inspection delays, weak monitoring and supervision	0	1	1	4	3	0.80
24	Payment delays	0	0	1	1	7	0.93
25	Fluctuations in interest rates	0	1	0	6	2	0.80
26	Contract claims and dispute uncertainties	0	2	4	2	1	0.64
27	Contractor–subcontractor relationship	0	3	2	3	1	0.64
28	Community or neighbourhood objections	0	2	4	3	0	0.62
29	Political uncertainty	0	0	1	5	3	0.84
30	Force majeure events (pandemic, earthquake, conflict)	1	1	1	4	2	0.71
31	Improper management by Project Management Team	0	1	3	5	0	0.69
32	Coordination issues among project stakeholders	0	0	1	5	3	0.84
33	Health and safety incidents leading to stoppage	1	4	3	1	0	0.49
34	Poor quality of material and equipment	0	2	3	4	0	0.64
35	Wastage on Site	0	3	2	4	0	0.62
36	Error in construction/Rework	0	2	1	6	0	0.69

C. Additional Uncertainty Factors Suggested

i. Legal prosecution, court-issued stay orders

ii. Local interference, vandalism and site-level social disturbances

iii. Land-related disputes

APPENDIX III: SURVEY QUESTIONNAIRE

Dear Respondent, I am currently pursuing MSc in Construction Management at Pulchowk Campus and conducting my master's thesis titled "A Hybrid Forecasting Model Integrating Earned Value Management and Monte Carlo Simulation for Schedule Risk Prediction in Building Construction Projects." This survey aims to collect data on uncertainty factors affecting the schedules (time) of building construction projects. You are kindly requested to provide your assessment regarding the schedule impacts of each uncertainty factor. All information provided will be used solely for academic research purposes, kept confidential, and analysed in aggregate. Your time and contribution are greatly appreciated.

Consent to Participate: By proceeding with this survey, you indicate your informed consent to participate in this academic study. ▢ OK

1. Current role

▢ Project Manager	▢ Site Engineer
▢ Contractor	▢ Consultant
▢ Government Official / Client	▢ Other (Specify)

2. Years of experience

▢ <5 Years	▢ 5-10 Years
▢ 10-15 Years	▢ >15 Years

3. Average Project Size involved (NRs.): ……………….

4. Provide your assessment for each of the uncertainty factors listed below: Probability of Occurrence refers to the likelihood that the factor will occur in a typical building project during construction phase.

Minimum Impact refers to the least possible delay (in days), Maximum Impact refers to the worst-case delay (in days) if the factor occurs.

Probability scale (0–1): 0 means never occurs, while 1 means certain to occur. You can input values in decimal.

Uncertainty Factors	Probability of Occurrence (0 to 1)	Minimum Impact (days)	Maximum Impact (days)
Payment delays			
Design errors and omissions			
Design changes / scope modifications			
Political uncertainty			
Coordination issues among project stakeholders			
Material delivery delays / supply chain issues			
Unreliable suppliers or subcontractors			
Labour skill shortages / availability			
Material price fluctuation / escalation			
Inflation and macroeconomic instability			
Inspection delays, weak monitoring and supervision			
Fluctuations in interest rates			
Legal prosecution, court-issued stay orders			
Local interference, vandalism and site-level social disturbances			
Land-related disputes			

APPENDIX IV: DESCRIPTIVE STATISTICS OF PROBABILITY OF OCCURRENCE

Statistics

		Payment delays	Design errors and omissions	Design changes / scope modifications	Political uncertainty	Coordination issues among project stakeholders	Material delivery delays / supply chain issues	Unreliable suppliers or subcontractors	Labor skill shortages / availability	Material price fluctuation / escalation	Inflation and macroeconomic instability	Inspection delays, weak monitoring and supervision	Fluctuations in interest rates	Legal prosecution, court-issued stay orders	Local interference, vandalism and site-level social disturbances	Land-related disputes
N	Valid	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72
	Missing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean		0.4903	0.3254	0.4107	0.3232	0.3422	0.4106	0.3360	0.2978	0.3872	0.2925	0.2864	0.1900	0.2081	0.3396	0.3107
Median		0.5000	0.2000	0.3000	0.2000	0.2000	0.3000	0.2500	0.2000	0.3000	0.2000	0.2000	0.1500	0.1000	0.2500	0.2000
Mode		0.50	0.20	0.30	0.10	0.10	0.20	0.10	0.10	0.30	0.20	.10[a]	.10[a]	0.10	0.20	0.10
Std. Deviation		0.27278	0.26444	0.25506	0.28510	0.29356	0.27619	0.26199	0.26579	0.25037	0.22458	0.26264	0.16293	0.25299	0.26367	0.28143
Skewness		0.480	1.175	0.797	1.033	0.930	0.885	0.844	1.249	1.163	1.781	1.248	1.462	2.011	1.330	1.281
Std. Error of		0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283
Kurtosis		-0.767	0.583	-0.185	0.214	-0.365	-0.178	-0.124	0.812	0.713	3.494	0.626	2.423	3.596	0.918	0.831
Std. Error of		0.559	0.559	0.559	0.559	0.559	0.559	0.559	0.559	0.559	0.559	0.559	0.559	0.559	0.559	0.559
Percentil	25	0.3000	0.1000	0.2000	0.1000	0.1000	0.2000	0.1000	0.1000	0.2000	0.1500	0.1000	0.1000	0.0500	0.2000	0.1000
	50	0.5000	0.2000	0.3000	0.2000	0.2000	0.3000	0.2500	0.2000	0.3000	0.2000	0.2000	0.1500	0.1000	0.2500	0.2000
	75	0.7000	0.5000	0.6000	0.5000	0.6000	0.5000	0.5000	0.4750	0.5000	0.3875	0.3750	0.2000	0.2000	0.4000	0.4000
Inter Quartile Range		0.4000	0.4000	0.4000	0.4000	0.5000	0.3000	0.4000	0.3750	0.3000	0.2375	0.2750	0.1000	0.1500	0.2000	0.3000

a. Multiple modes exist. The smallest value is shown

APPENDIX V: DESCRIPTIVE STATISTICS OF MINIMUM IMPACT RESPONSES

Statistics

		Payment delays	Design errors and omissions	Design changes / scope modifications	Political uncertainty	Coordination issues among project stakeholders	Material delivery delays / supply chain issues	Unreliable suppliers or subcontractors	Labor skill shortages / availability	Material price fluctuation / escalation	Inflation and macroeconomic instability	Inspection delays, weak monitoring and supervision	Fluctuations in interest rates	Legal prosecution, court-issued stay orders	Local interference, vandalism and site-level social disturbances	Land-related disputes
N	Valid	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72
	Missing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean		15.3611	14.3333	15.5833	22.2639	15.1528	10.5972	13.3472	10.5556	12.9444	10.8472	7.8333	7.5833	26.6389	14.9028	25.0694
Median		10.0000	7.0000	11.0000	15.0000	7.0000	7.0000	7.0000	7.0000	7.0000	3.0000	5.0000	3.0000	30.0000	7.0000	15.0000
Mode		15.00	7.00	15.00	30.00	7.00	7.00	7.00	7.00	0.00	0.00	7.00	0.00	30.00	7.00	30.00
Std. Deviation		16.36150	25.11943	15.71198	29.57540	27.51627	13.47471	19.69354	14.60936	25.40815	20.76947	9.81519	13.69975	27.21656	26.26955	30.33723
Skewness		3.482	5.978	2.721	3.666	4.883	4.488	3.482	3.441	5.891	4.689	2.273	3.829	3.034	5.571	3.296
Std. Error of Skewness		0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283
Minimum		1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Percentiles	5	2.0000	0.6500	0.6500	0.0000	0.0000	1.0000	0.6500	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.6500	0.0000
	10	3.0000	1.0000	1.0000	0.0000	0.3000	1.0000	1.3000	1.0000	0.0000	0.0000	1.0000	0.0000	0.3000	1.0000	1.0000
	25	7.0000	5.0000	7.0000	4.0000	2.0000	3.0000	5.0000	2.0000	1.0000	0.0000	1.0000	0.0000	8.5000	5.0000	7.0000
	50	10.0000	7.0000	11.0000	15.0000	7.0000	7.0000	7.0000	7.0000	7.0000	3.0000	5.0000	3.0000	30.0000	7.0000	15.0000
	75	15.0000	15.0000	20.0000	30.0000	18.7500	15.0000	15.0000	10.0000	15.0000	15.0000	9.2500	9.2500	30.0000	15.0000	30.0000

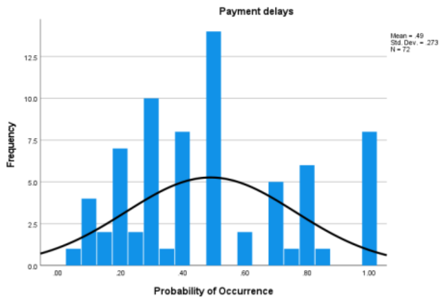
APPENDIX VI: DESCRIPTIVE STATISTICS OF MAXIMUM IMPACT RESPONSES

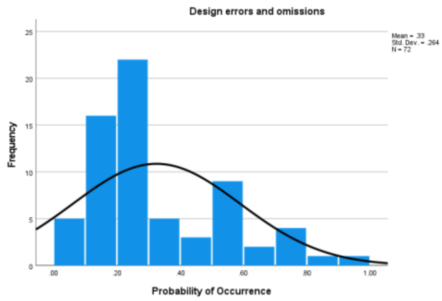
Statistics

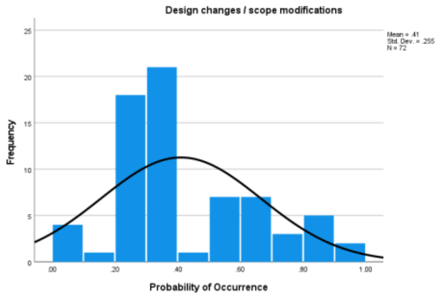
		Payment delays	Design errors and omissions	Design changes / scope modifications	Political uncertainty	Coordination issues among project stakeholders	Material delivery delays / supply chain issues	Unreliable suppliers or subcontractors	Labor skill shortages / availability	Material price fluctuation / escalation	Inflation and macroeconomic instability	Inspection delays, weak monitoring and supervision	Fluctuations in interest rates	Legal prosecution, court-issued stay orders	Local interference, vandalism and site-level social disturbances	Land-related disputes
N	Valid	72	72	72	72	72	72	72	72	72	72	72	72	72	72	72
	Missing	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Mean		65.1528	42.2361	47.0556	71.2778	42.8472	32.7083	42.1111	29.3333	33.9028	30.2500	22.5139	27.2917	93.3333	48.2639	83.0833
Median		32.5000	30.0000	30.0000	50.0000	20.0000	25.0000	30.0000	25.0000	15.0000	15.0000	15.0000	13.5000	90.0000	30.0000	60.0000
Mode		30.00	30.00	30.00	30.00	20.00	30.00	30.00	30.00	7.00[a]	7.00	15.00	0.00	90.00	30.00	60.00
Std. Deviation		76.59325	54.41999	46.84343	82.72238	64.18869	34.90972	53.89336	30.74658	40.96999	38.97408	22.17218	49.25971	75.75907	54.37144	79.80394
Skewness		3.013	3.720	3.357	2.931	3.653	2.615	3.540	3.063	3.004	2.484	2.050	4.994	1.921	4.238	2.191
Std. Error of Skewness		0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283	0.283
Minimum		5.00	0.00	0.00	0.00	0.00	2.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Percentiles	25	30.0000	15.0000	30.0000	17.0000	10.0000	10.0000	15.0000	10.5000	8.5000	7.0000	7.0000	5.2500	48.7500	16.2500	30.0000
	50	32.5000	30.0000	30.0000	50.0000	20.0000	25.0000	30.0000	25.0000	15.0000	15.0000	15.0000	13.5000	90.0000	30.0000	60.0000
	75	90.0000	48.7500	60.0000	97.5000	45.0000	34.2500	45.0000	30.0000	45.0000	35.0000	30.0000	30.0000	107.5000	60.0000	97.5000
	90	120.0000	84.0000	88.5000	120.0000	97.0000	90.0000	90.0000	60.0000	84.0000	78.5000	48.5000	60.0000	180.0000	90.0000	180.0000
	95	244.7500	130.5000	128.0000	235.0000	148.0000	107.0000	180.0000	93.5000	107.0000	120.0000	90.0000	100.0000	257.7500	103.5000	256.0000

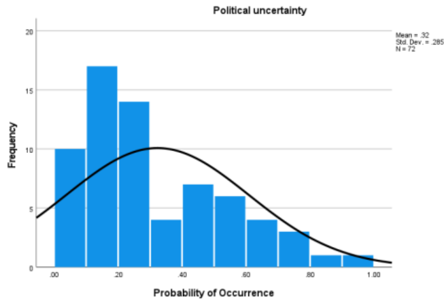
a. Multiple modes exist. The smallest value is shown

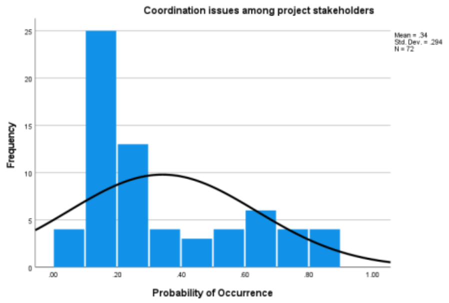
APPENDIX VII: HISTOGRAM OF RESPONSES FOR PROBABILITY OF OCCURRENCES OF VARIOUS UNCERTAINTY FACTORS

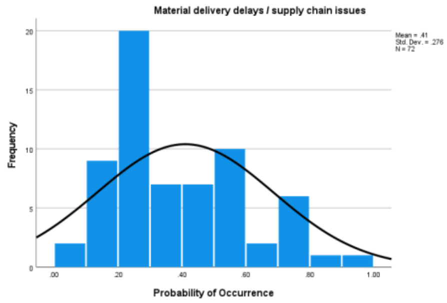


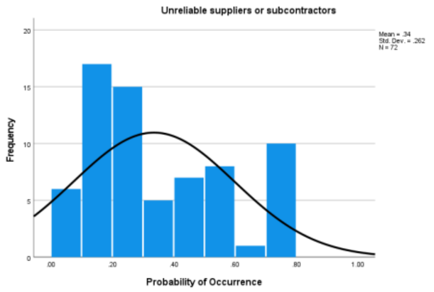


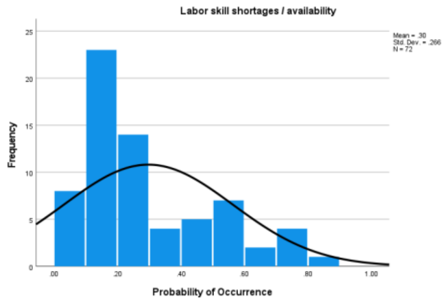


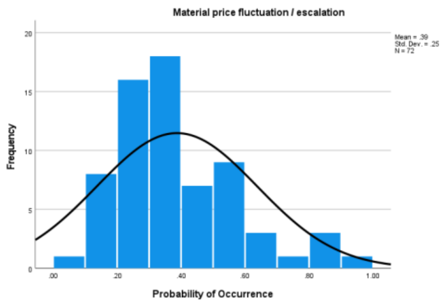


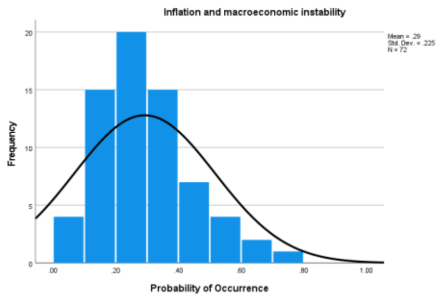


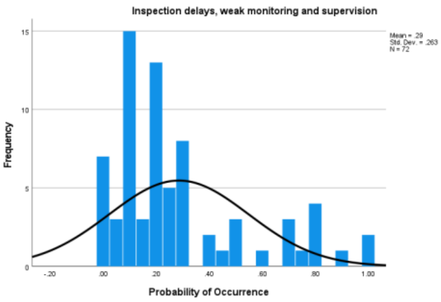


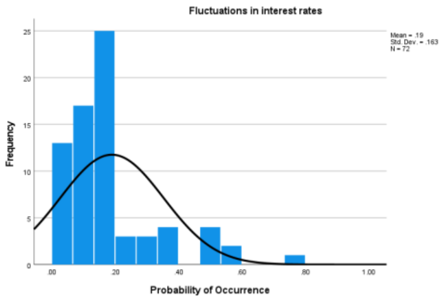


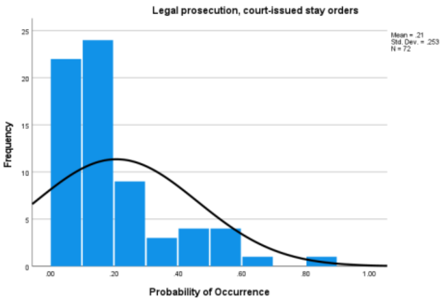


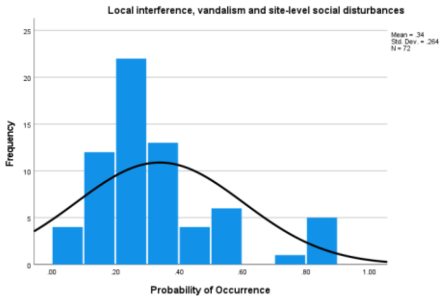


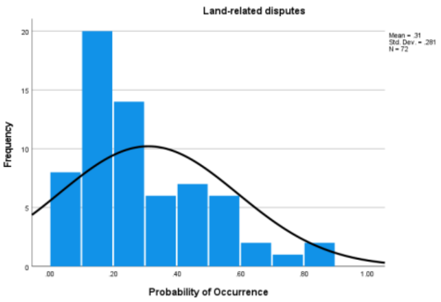



Inspection delays, weak monitoring and supervision
Mean = .29
Std. Dev. = .263
N = 72
Frequency
Probability of Occurrence

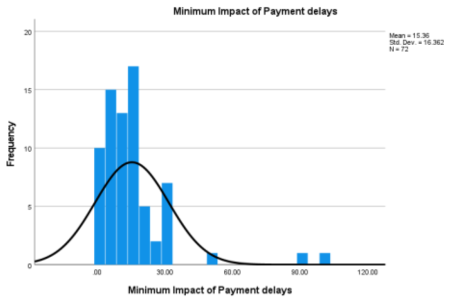

Fluctuations in interest rates
Mean = .19
Std. Dev. = .163
N = 72
Frequency
Probability of Occurrence

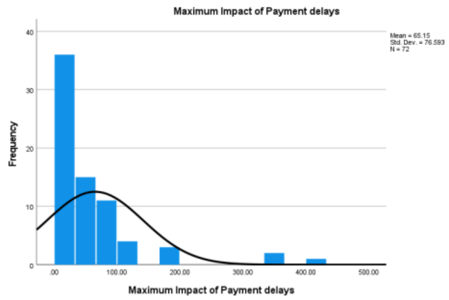

Legal prosecution, court-issued stay orders
Mean = .21
Std. Dev. = .253
N = 72
Frequency
Probability of Occurrence

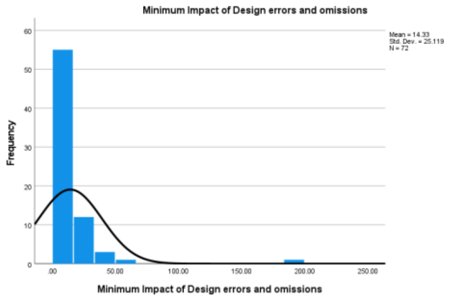

Local interference, vandalism and site-level social disturbances
Mean = .34
Std. Dev. = .264
N = 72
Frequency
Probability of Occurrence

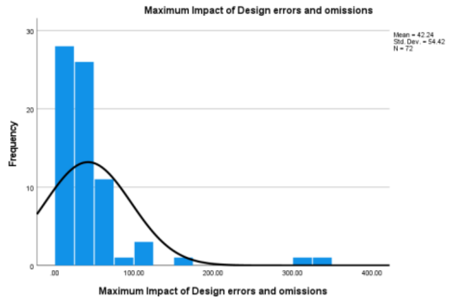

Land-related disputes
Mean = .31
Std. Dev. = .281
N = 72
Frequency
Probability of Occurrence

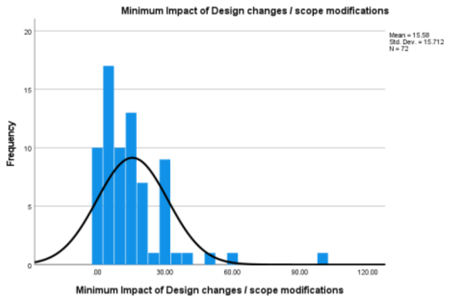
APPENDIX VIII: HISTOGRAM OF RESPONSES FOR MINIMUM AND MAXIMUM IMPACT OF VARIOUS UNCERTAINTY FACTORS

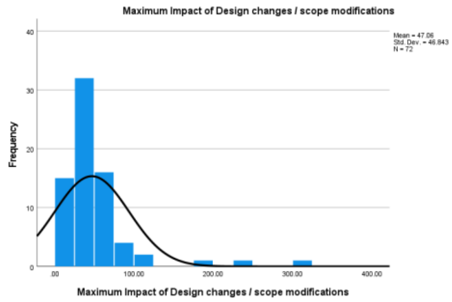


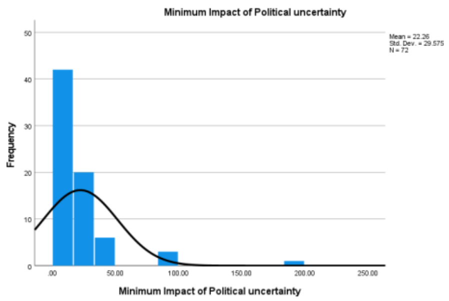


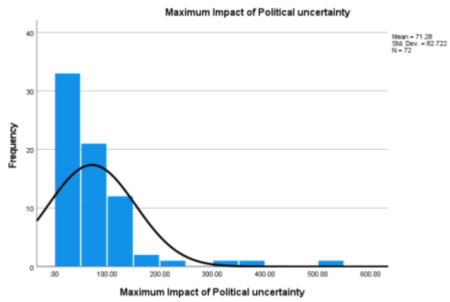


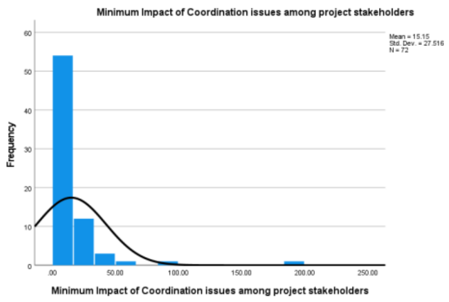


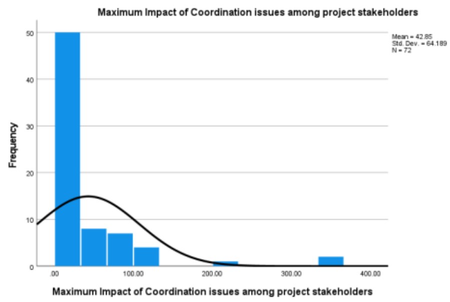


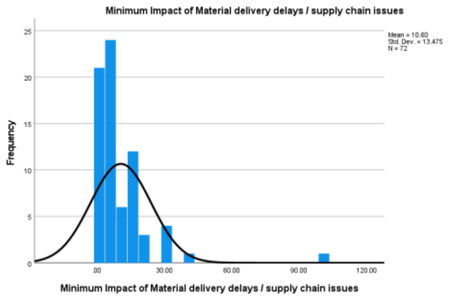


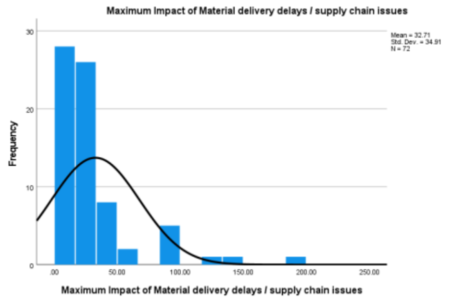


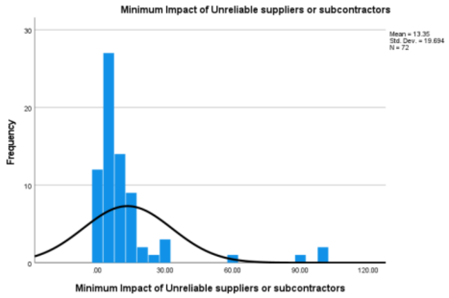


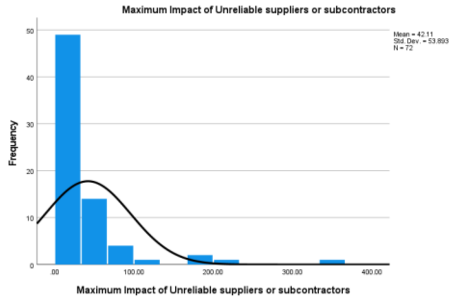


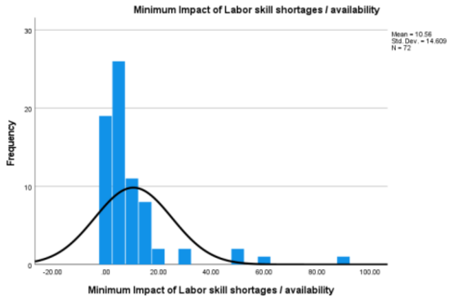


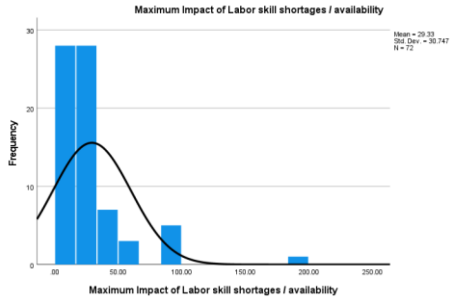

Minimum Impact of Material delivery delays / supply chain issues
Mean = 10.60
Std. Dev. = 13.475
N = 72
Frequency
Minimum Impact of Material delivery delays / supply chain issues

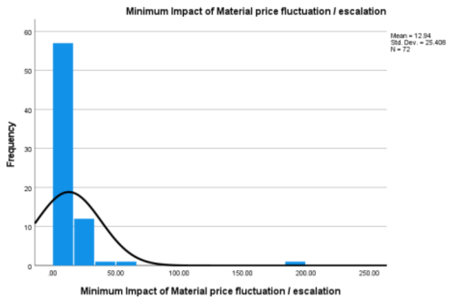

Maximum Impact of Material delivery delays / supply chain issues
Mean = 32.71
Std. Dev. = 34.91
N = 72
Frequency
Maximum Impact of Material delivery delays / supply chain issues

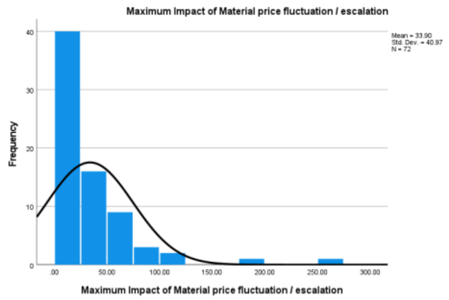

Minimum Impact of Unreliable suppliers or subcontractors
Mean = 13.35
Std. Dev. = 19.694
N = 72
Frequency
Minimum Impact of Unreliable suppliers or subcontractors

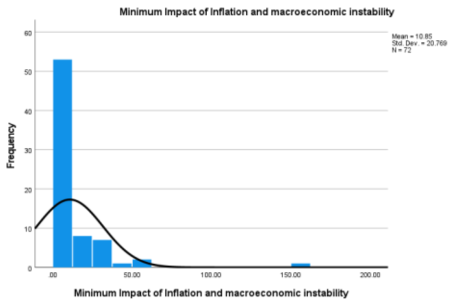

Maximum Impact of Unreliable suppliers or subcontractors
Mean = 42.11
Std. Dev. = 53.893
N = 72
Frequency
Maximum Impact of Unreliable suppliers or subcontractors

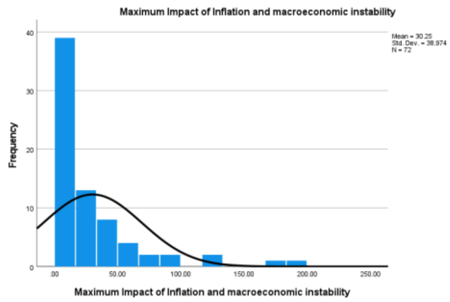

Minimum Impact of Labor skill shortages / availability
Mean = 10.56
Std. Dev. = 14.609
N = 72
Frequency
Minimum Impact of Labor skill shortages / availability

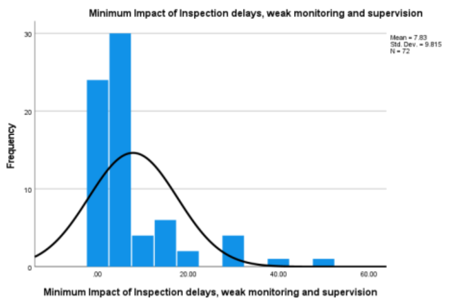

Maximum Impact of Labor skill shortages / availability
Mean = 29.33
Std. Dev. = 30.747
N = 72
Frequency
Maximum Impact of Labor skill shortages / availability

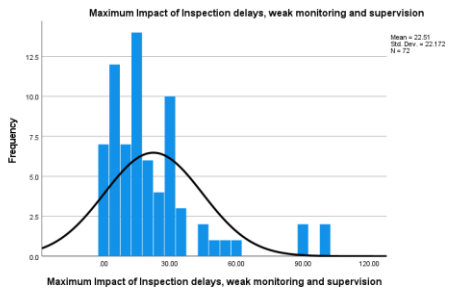

Minimum Impact of Material price fluctuation / escalation
Mean = 12.94
Std. Dev. = 25.408
N = 72
Frequency
Minimum Impact of Material price fluctuation / escalation

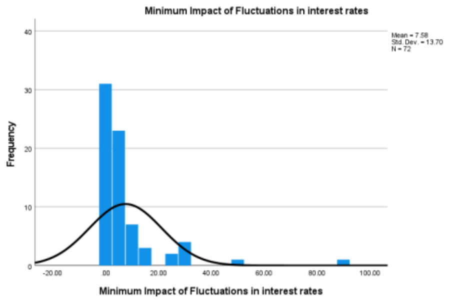

Maximum Impact of Material price fluctuation / escalation
Mean = 33.90
Std. Dev. = 40.87
N = 72
Frequency
Maximum Impact of Material price fluctuation / escalation

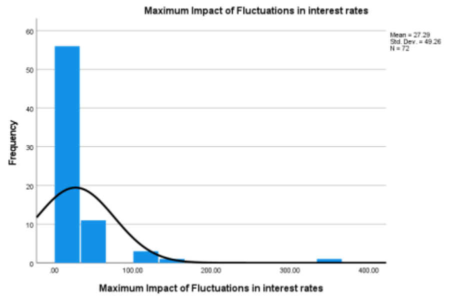

Minimum Impact of Inflation and macroeconomic instability
Mean = 10.85
Std. Dev. = 20.769
N = 72
Frequency
Minimum Impact of Inflation and macroeconomic instability

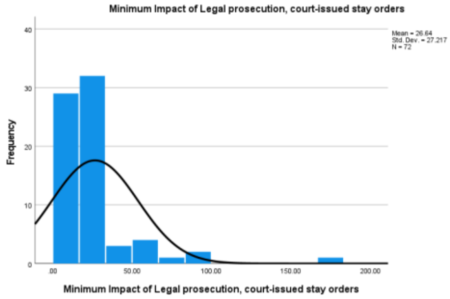

Maximum Impact of Inflation and macroeconomic instability
Mean = 30.25
Std. Dev. = 38.974
N = 72
Frequency
Maximum Impact of Inflation and macroeconomic instability

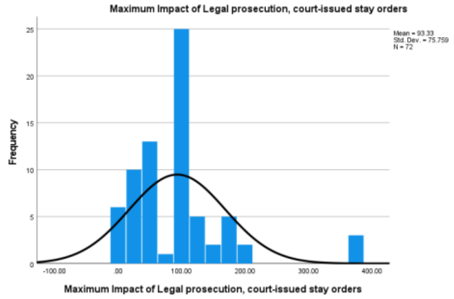

Minimum Impact of Inspection delays, weak monitoring and supervision
Mean = 7.83
Std. Dev. = 9.815
N = 72
Frequency
Minimum Impact of Inspection delays, weak monitoring and supervision

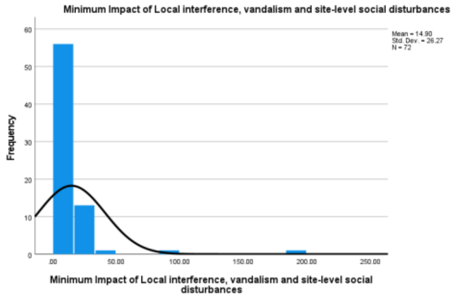

Maximum Impact of Inspection delays, weak monitoring and supervision
Mean = 22.51
Std. Dev. = 22.172
N = 72
Frequency
Maximum Impact of Inspection delays, weak monitoring and supervision

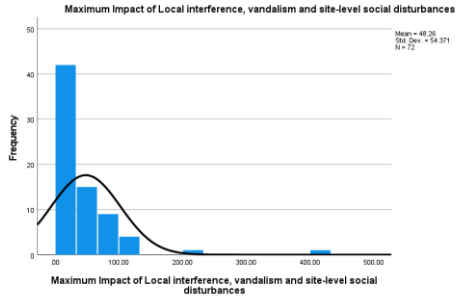

Minimum Impact of Fluctuations in interest rates
Mean = 7.58
Std. Dev. = 13.70
N = 72
Frequency
Minimum Impact of Fluctuations in interest rates

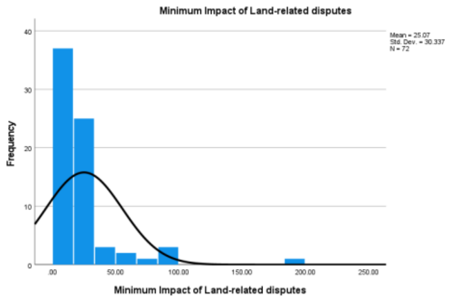

Maximum Impact of Fluctuations in interest rates
Mean = 27.29
Std. Dev. = 49.26
N = 72
Frequency
Maximum Impact of Fluctuations in interest rates

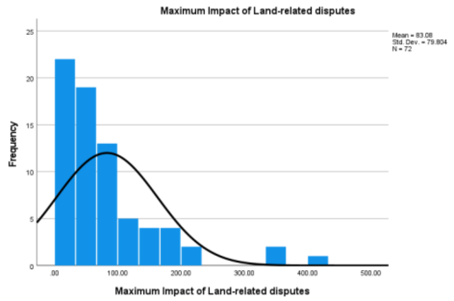

Minimum Impact of Legal prosecution, court-issued stay orders
Mean = 26.64
Std. Dev. = 27.217
N = 72
Frequency
Minimum Impact of Legal prosecution, court-issued stay orders


Maximum Impact of Legal prosecution, court-issued stay orders
Mean = 93.33
Std. Dev. = 75.759
N = 72
Frequency
Maximum Impact of Legal prosecution, court-issued stay orders

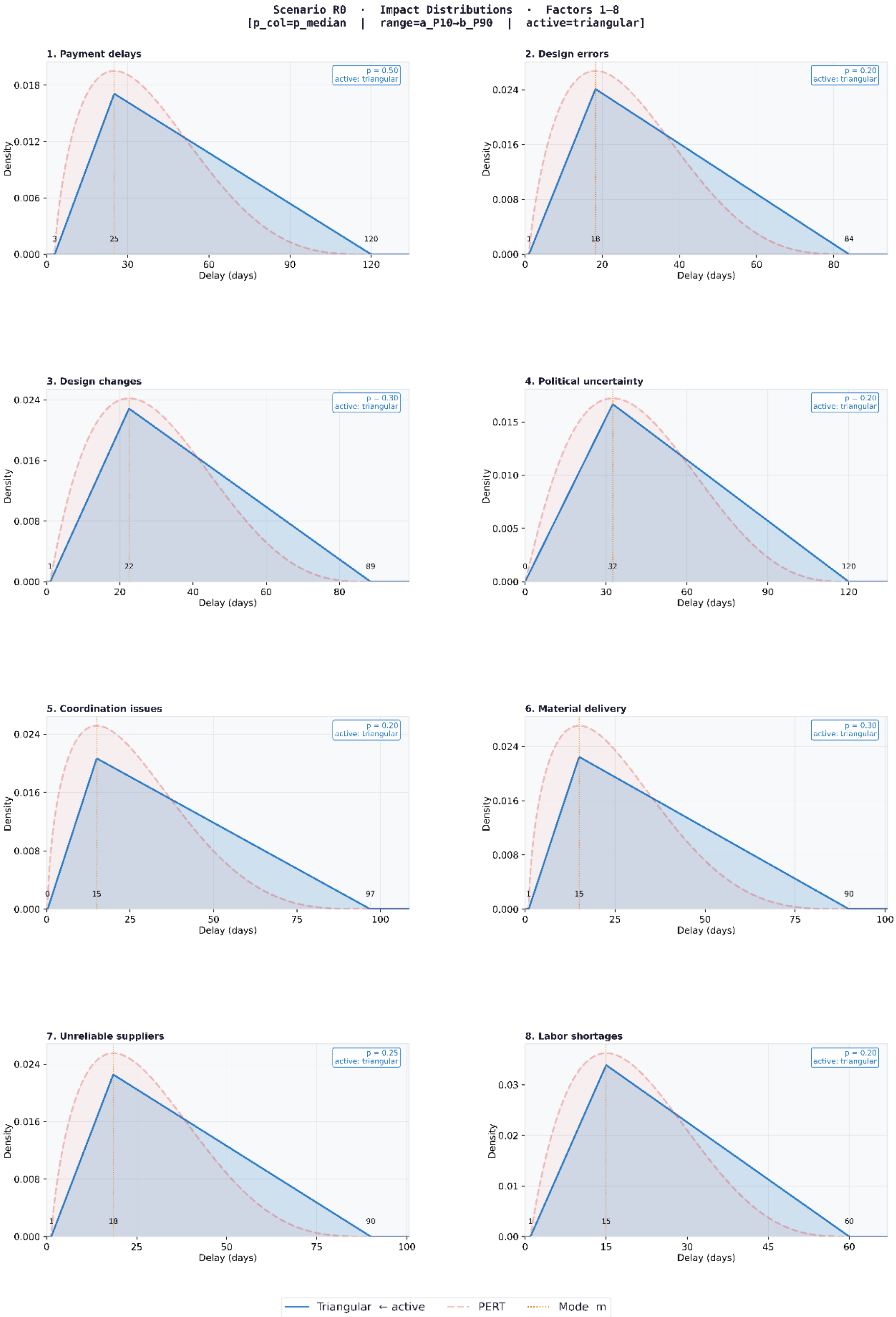

Minimum Impact of Local interference, vandalism and site-level social disturbances
Mean = 14.90
Std. Dev. = 26.27
N = 72
Frequency
Minimum Impact of Local interference, vandalism and site-level social disturbances

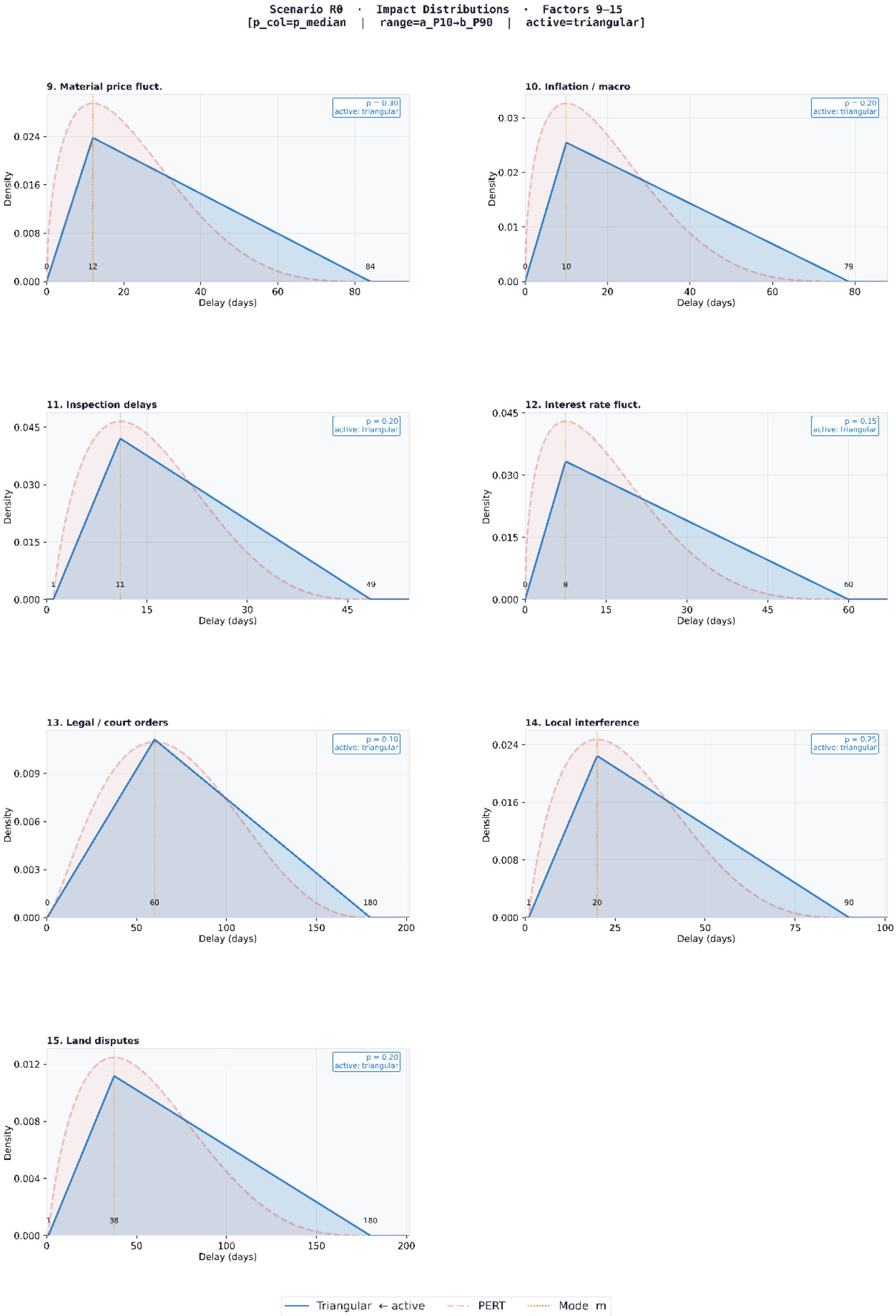

Maximum Impact of Local interference, vandalism and site-level social disturbances
Mean = 48.26
Std. Dev. = 54.371
N = 72
Frequency
Maximum Impact of Local interference, vandalism and site-level social disturbances


Minimum Impact of Land-related disputes
Mean = 25.07
Std. Dev. = 30.337
N = 72
Frequency
Minimum Impact of Land-related disputes


Maximum Impact of Land-related disputes
Mean = 83.08
Std. Dev. = 79.804
N = 72
Frequency
Maximum Impact of Land-related disputes

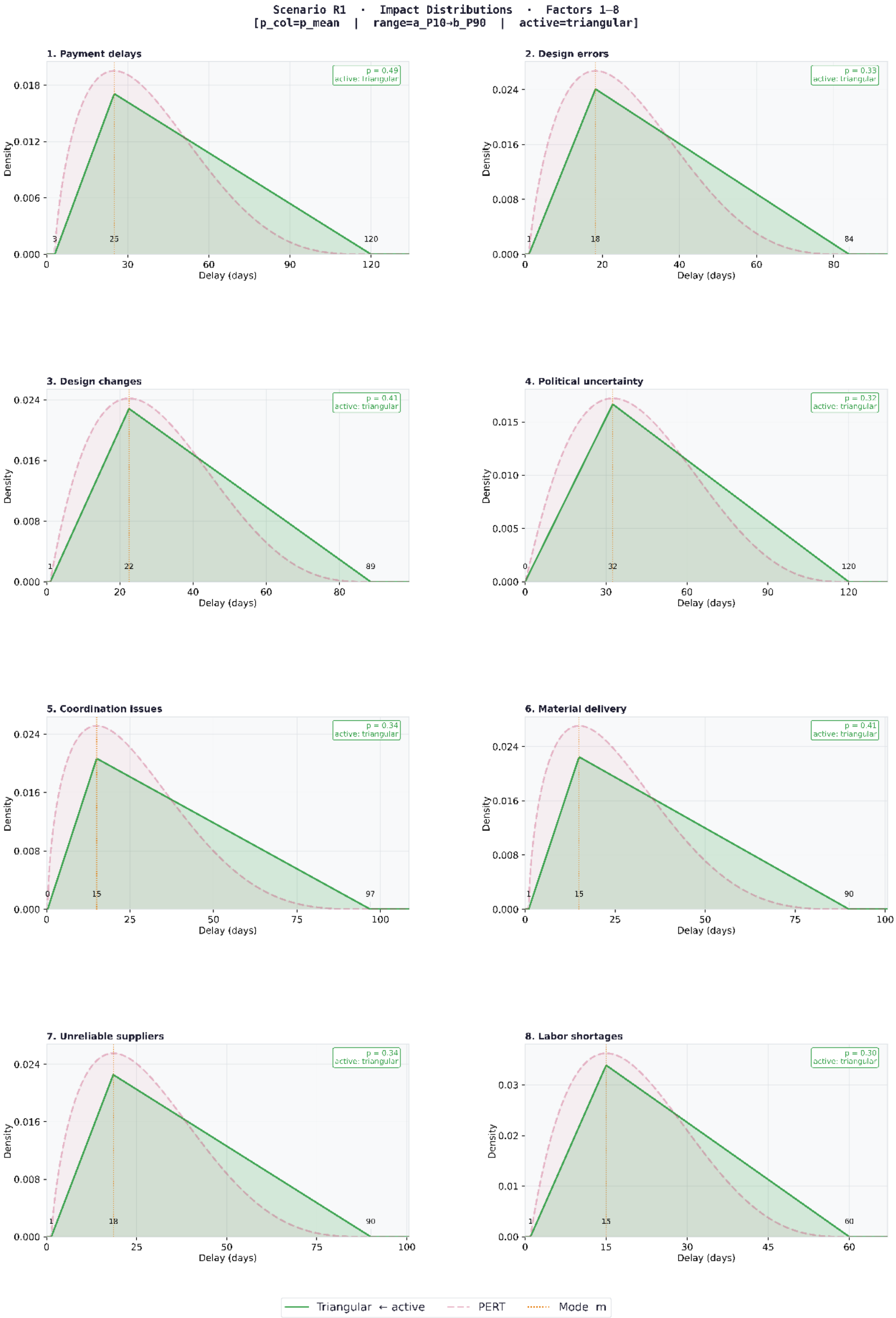
APPENDIX IX: INPUT PROBABILITY DISTRIBUTION FOR RISK SCENARIO R0

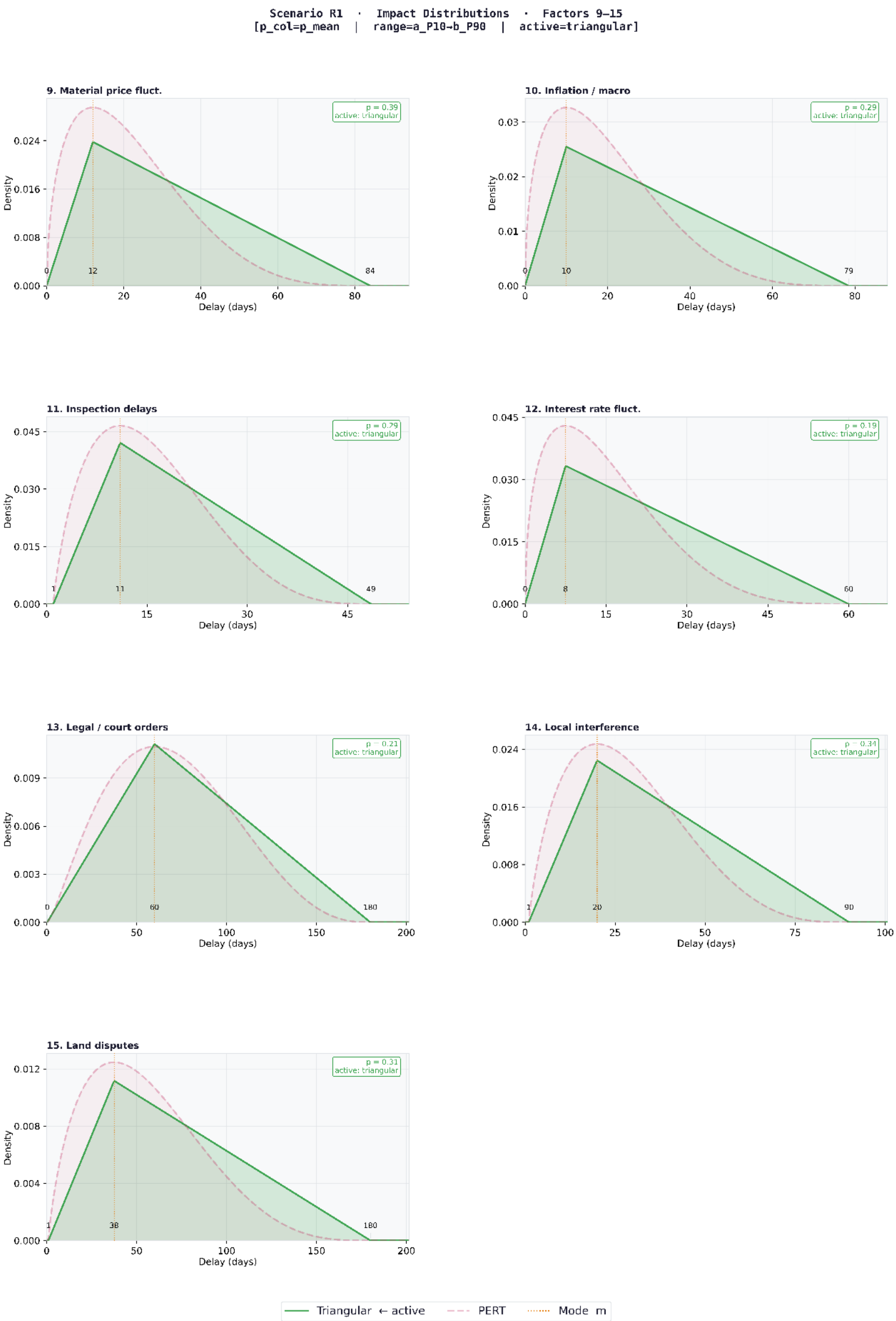




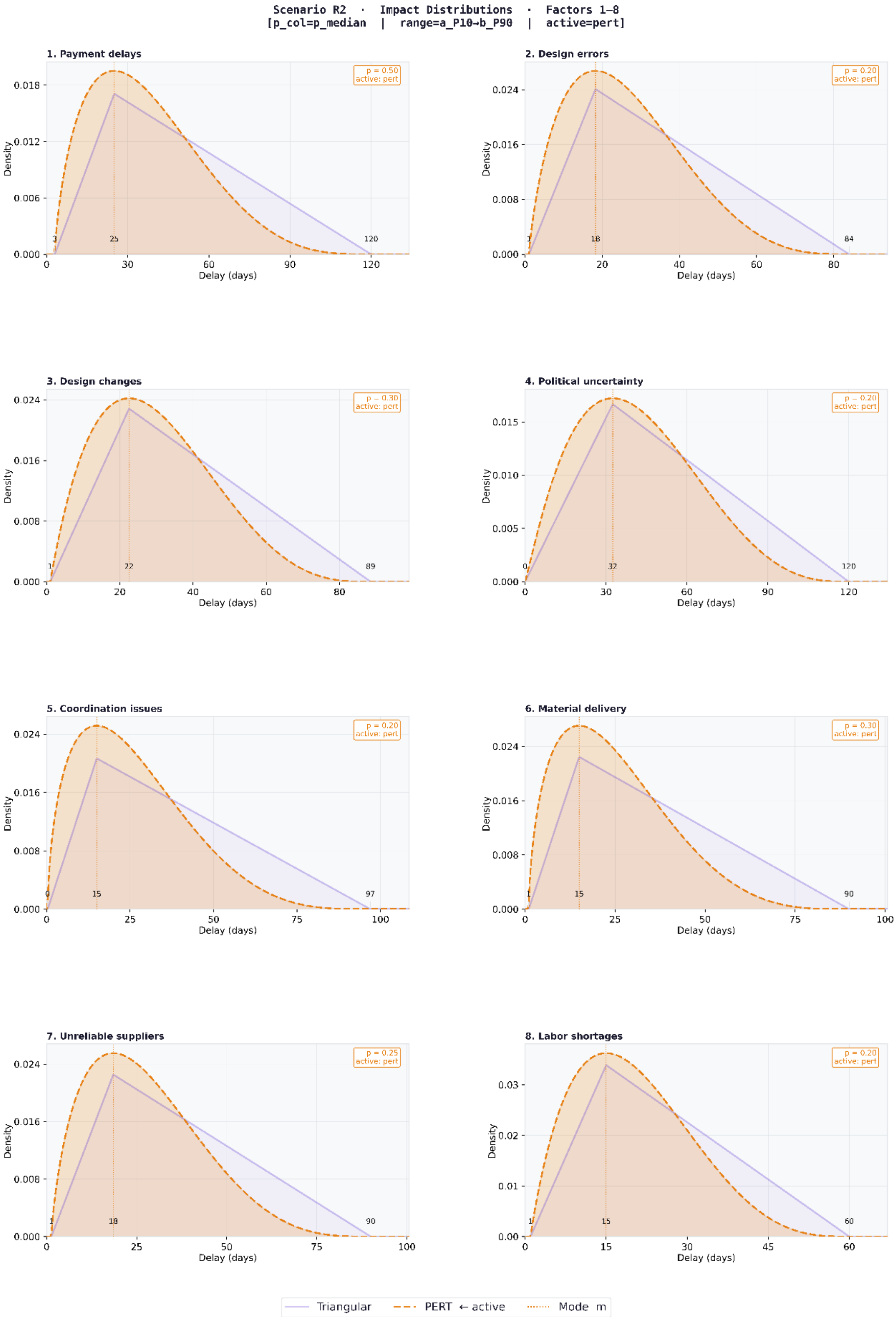
Scenario R0 · Impact Distributions · Factors 9–15
[p_col=p_median | range=a_P10→b_P90 | active=triangular]
9. Material price fluct.
p = 0.30
active: triangular
10. Inflation / macro
p = 0.20
active: triangular
11. Inspection delays
p = 0.20
active: triangular
12. Interest rate fluct.
p = 0.15
active: triangular
13. Legal / court orders
p = 0.10
active: triangular
14. Local interference
p = 0.25
active: triangular
15. Land disputes
p = 0.20
active: triangular
Density
Delay (days)
Triangular ← active
PERT
Mode m

APPENDIX X: INPUT PROBABILITY DISTRIBUTION FOR RISK SCENARIO R1

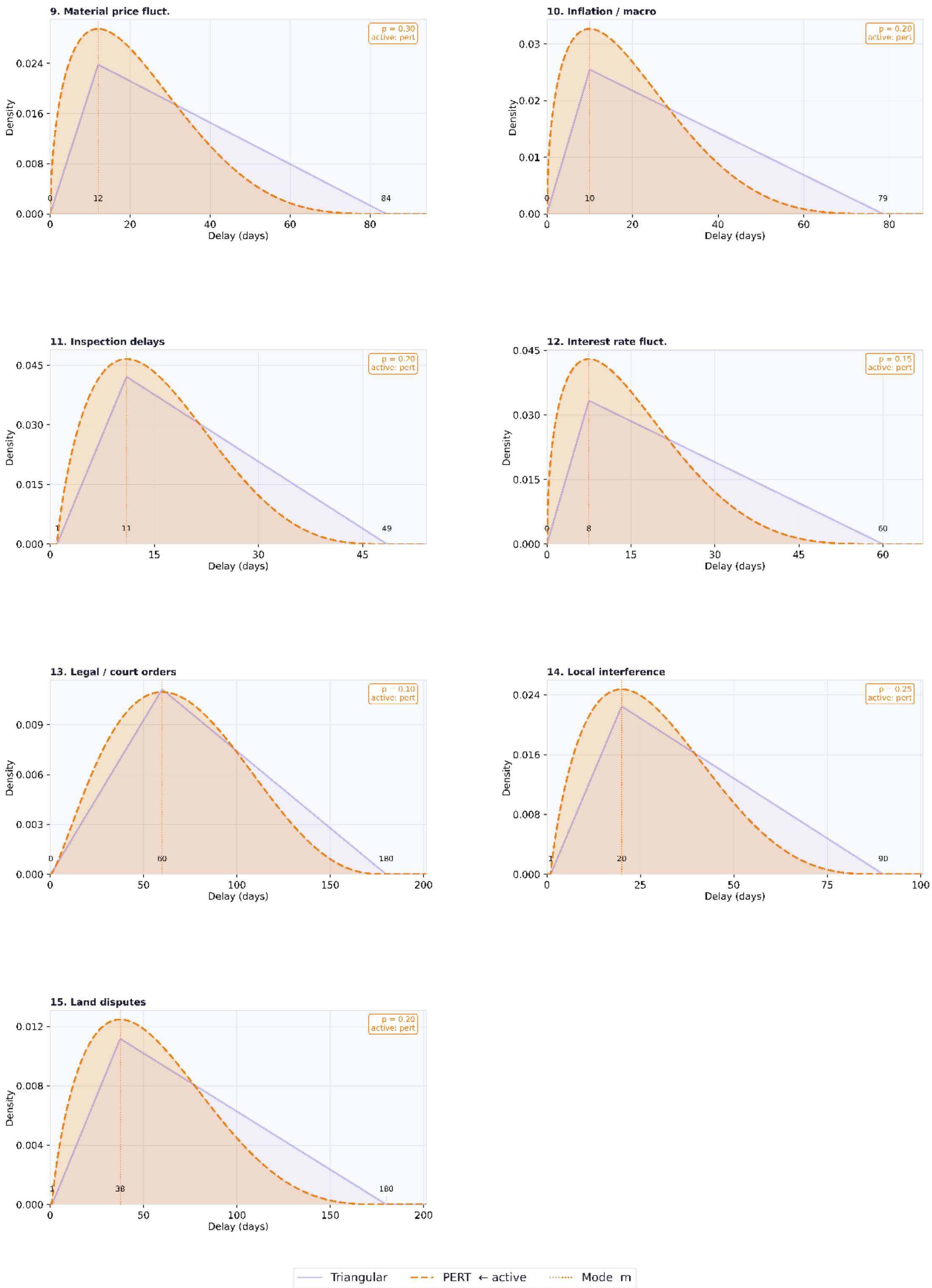



Scenario R1 · Impact Distributions · Factors 9–15
[p_col=p_mean | range=a_P10→b_P90 | active=triangular]
9. Material price fluct.
p = 0.39
active: triangular
10. Inflation / macro
p = 0.29
active: triangular
11. Inspection delays
p = 0.79
active: triangular
12. Interest rate fluct.
p = 0.19
active: triangular
13. Legal / court orders
p = 0.21
active: triangular
14. Local interference
p = 0.34
active: triangular
15. Land disputes
p = 0.31
active: triangular
Density
Delay (days)
Triangular ← active
PERT
Mode m

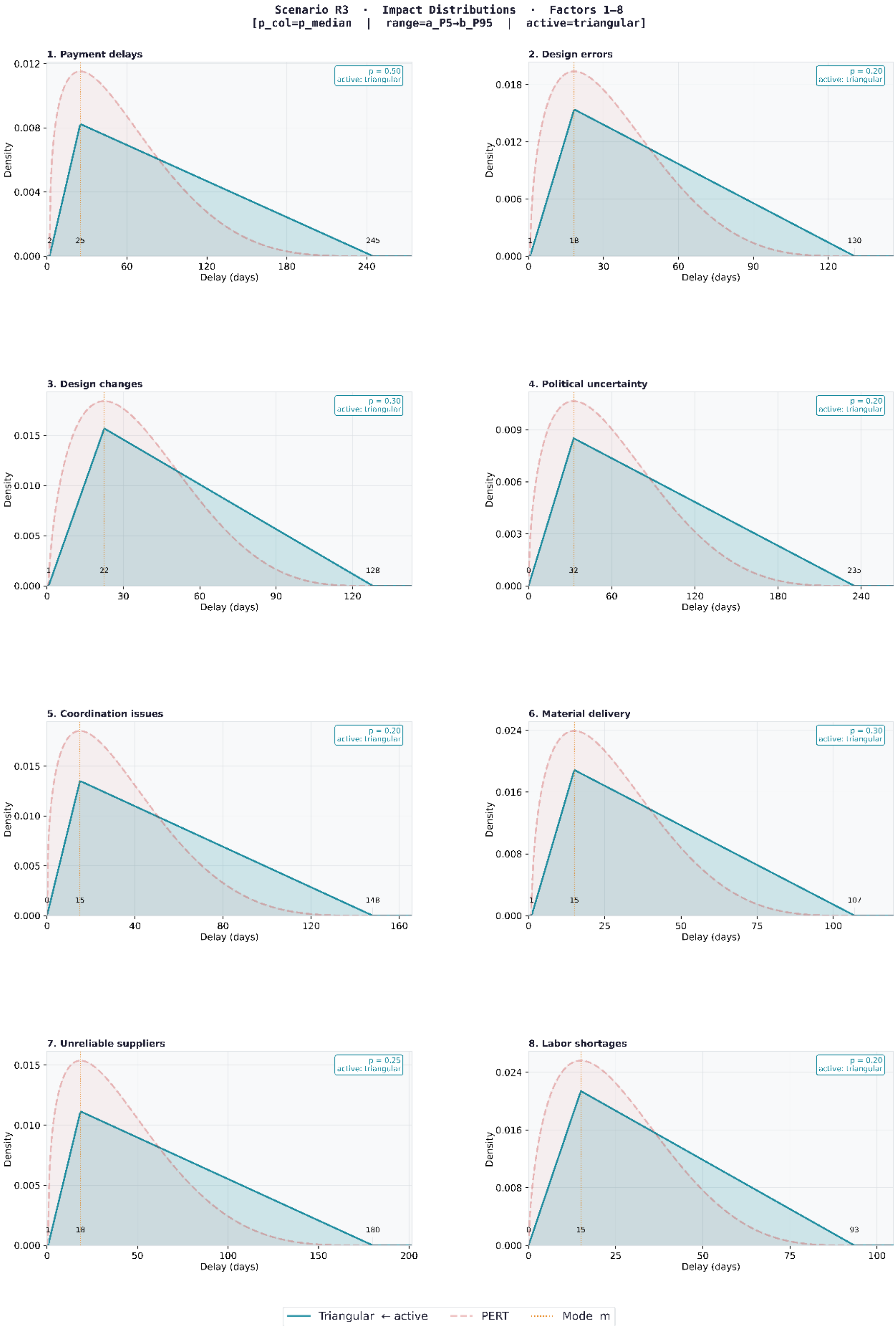
APPENDIX XI: INPUT PROBABILITY DISTRIBUTION FOR RISK SCENARIO R2

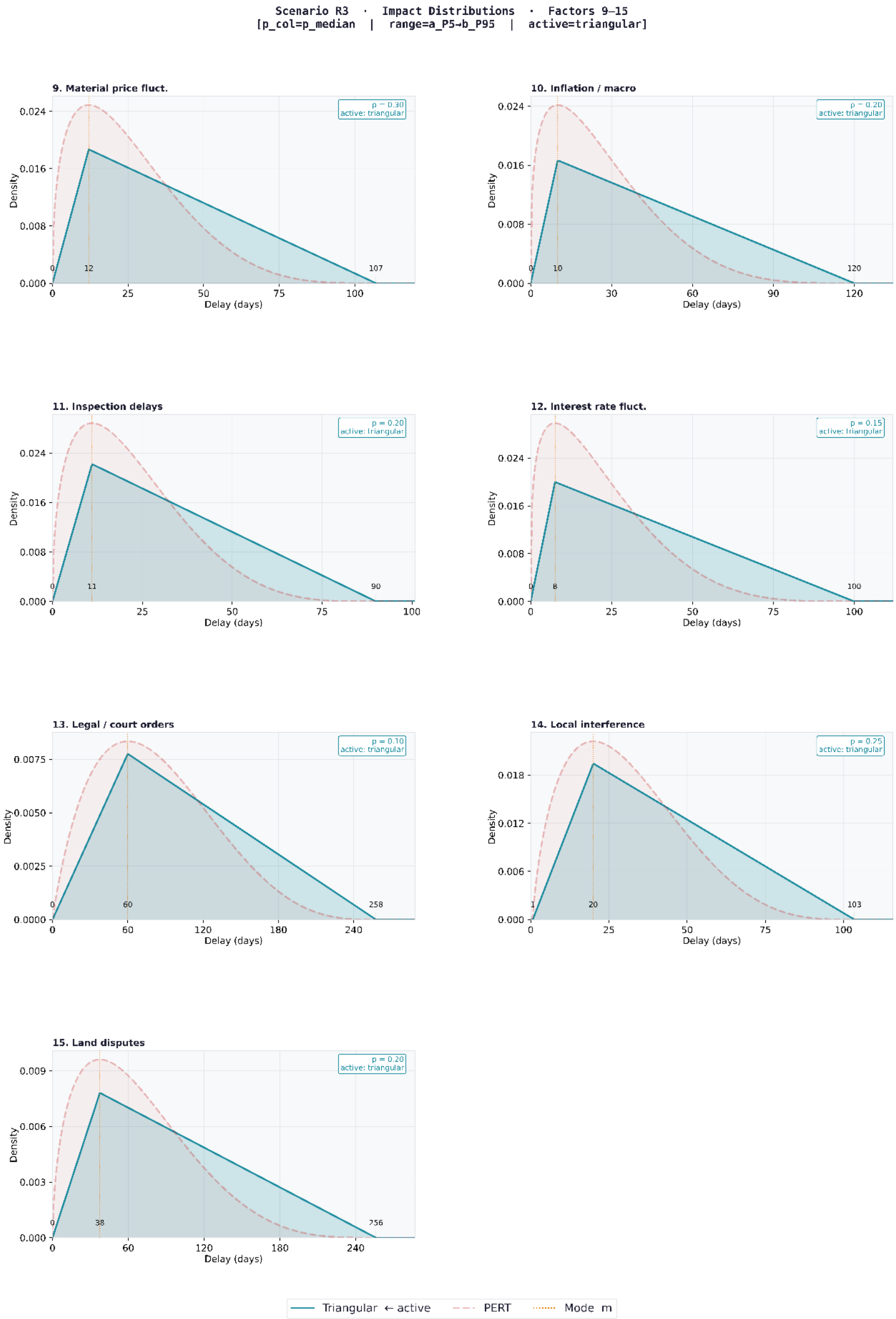


Scenario R2 · Impact Distributions · Factors 9–15
[p_col=p_median | range=a_P10→b_P90 | active=pert]

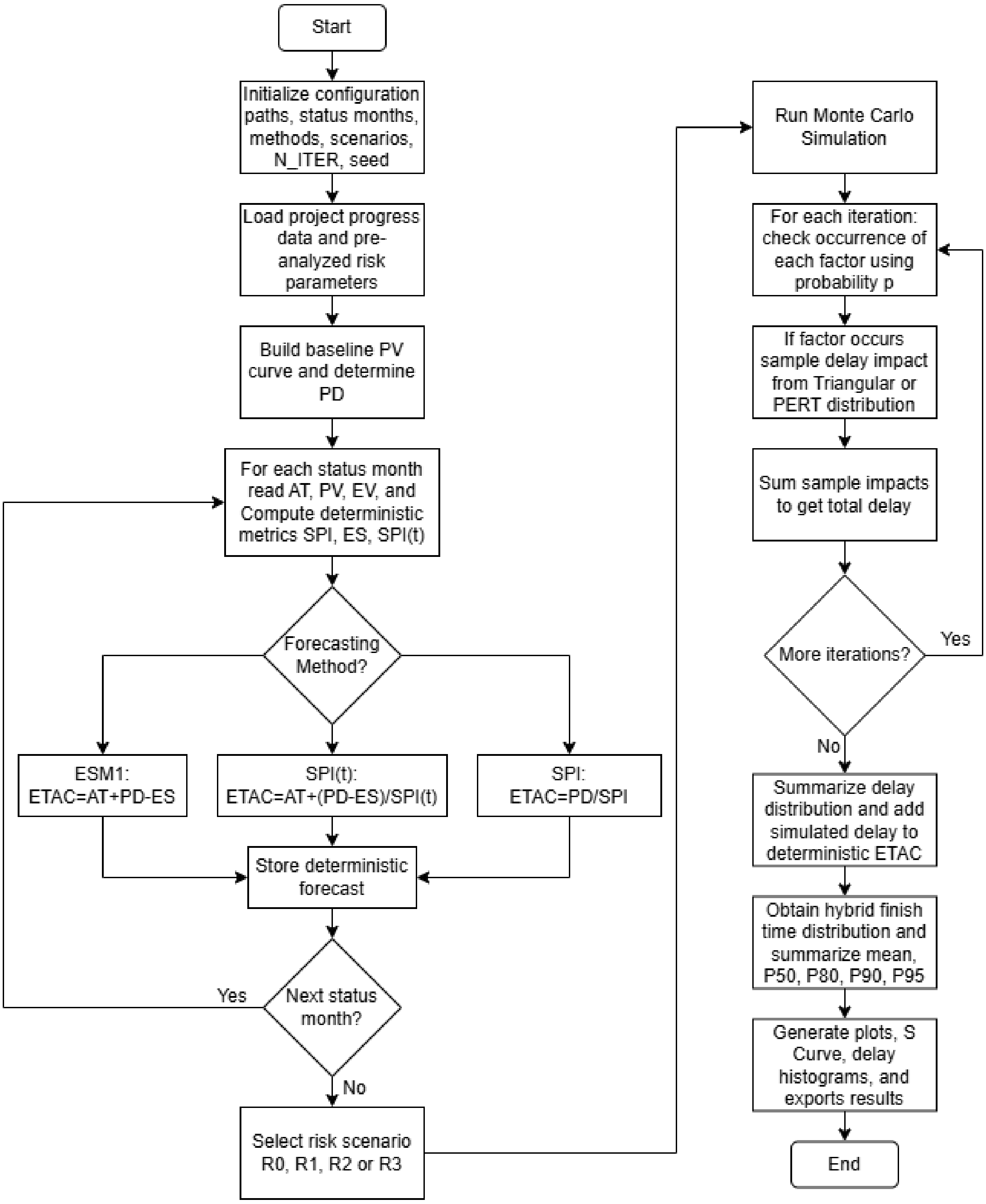


APPENDIX XII: INPUT PROBABILITY DISTRIBUTION FOR RISK SCENARIO R3




Scenario R3 · Impact Distributions · Factors 9–15
[p_col=p_median | range=a_P5→b_P95 | active=triangular]
9. Material price fluct.
p = 0.30
active: triangular
10. Inflation / macro
p = 0.20
active: triangular
11. Inspection delays
p = 0.20
active: triangular
12. Interest rate fluct.
p = 0.15
active: triangular
13. Legal / court orders
p = 0.10
active: triangular
14. Local interference
p = 0.25
active: triangular
15. Land disputes
p = 0.20
active: triangular
Density
Delay (days)
Triangular ← active
PERT
Mode m

APPENDIX XIII: ALGORITHM FOR PYTHON CODE



APPENDIX XIV: SIMULATION CODE

```
"""

Hybrid Forecasting Model Integrating Earned Value Management and
Monte Carlo Simulation for Schedule Risk Prediction in Building
Construction Projects
"""

import math
from dataclasses import dataclass
from pathlib import Path
from typing import Dict, List, Tuple

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd


# ------------------------------------------------------------------
# 0) CONFIGURATION
# ------------------------------------------------------------------

BASE_DIR        = Path(r"[INSERT DATA FOLDER PATH]")
RESULTS_DIR     = Path(r"[INSERT RESULTS FOLDER PATH]")

PROGRESS_XLSX   = BASE_DIR / "progress_report.xlsx"
RISK_PARAMS_XLSX = BASE_DIR / "risk_parameters.xlsx"

MONTH_COL            = "Month"
TIME_COL             = "Cumulative Days"
EV_COL               = "Actual Progress"
PV_COL               = "Planned Progress"
PLANNED_FINISH_LABEL = "18 Shrawan, 2082"

STATUS_MONTHS = [
    "Magh, 2079",
    "Shrawan, 2080",
    "Magh, 2080",
    "Shrawan, 2081",
    "Magh, 2081",
    "18 Shrawan, 2082",
]

DET_METHODS = ["ES_ESM1", "ES_SPI(t)", "SPI_classic"]

FACTOR_NAMES = [
    "Payment delays",
    "Design errors and omissions",
    "Design changes / scope modifications",
    "Political uncertainty",
    "Coordination issues among project stakeholders",
    "Material delivery delays / supply chain issues",
    "Unreliable suppliers or subcontractors",
    "Labor skill shortages / availability",
    "Material price fluctuation / escalation",
    "Inflation and macroeconomic instability",
```

```
    "Inspection delays, weak monitoring and supervision",
    "Fluctuations in interest rates",
    "Legal prosecution, court-issued stay orders",
    "Local interference, vandalism and site-level social
disturbances",
    "Land-related disputes",
]
N_FACTORS = 15

RISK_SCENARIOS = [
    ("R0", dict(p_col="p_median", impact_dist="triangular",
a_col="a_P10", b_col="b_P90")),
    ("R1", dict(p_col="p_mean",   impact_dist="triangular",
a_col="a_P10", b_col="b_P90")),
    ("R2", dict(p_col="p_median", impact_dist="pert",
a_col="a_P10", b_col="b_P90")),
    ("R3", dict(p_col="p_median", impact_dist="triangular",
a_col="a_P5",  b_col="b_P95")),
]

N_ITER       = 5000
SEED         = 2026
OUTPUT_XLSX  = RESULTS_DIR / "simulation_outputs.xlsx"
COMPLETE_TOL = 0.999999


# -----------------------------------------------------------------
# 1) UTILITIES
# -----------------------------------------------------------------

def normalize_label(x: object) -> str:
    s = str(x).strip().lower().replace(",", " ")
    return " ".join(s.split())


def coerce_numeric(s: pd.Series) -> pd.Series:
    return pd.to_numeric(s, errors="coerce")


def standardize_percent_to_fraction(series: pd.Series) ->
pd.Series:
    s  = coerce_numeric(series)
    mx = s.max(skipna=True)
    if pd.notna(mx) and mx > 1.0:
        s = s / 100.0
    return s.clip(lower=0.0, upper=1.0)


def summarize_distribution(x: np.ndarray) -> Dict[str, float]:
    x = np.asarray(x, dtype=float)
    x = x[np.isfinite(x)]
    if x.size == 0:
        return {k: float("nan") for k in ["mean", "std", "p50",
"p80", "p90", "p95"]}
    return {
        "mean": float(np.mean(x)),
        "std":  float(np.std(x, ddof=1)) if x.size > 1 else 0.0,
        "p50":  float(np.quantile(x, 0.50)),
```

```
        "p80":  float(np.quantile(x, 0.80)),
        "p90":  float(np.quantile(x, 0.90)),
        "p95":  float(np.quantile(x, 0.95)),
    }


def find_row_index(df: pd.DataFrame, label: str) -> int:
    idx = df.index[df[MONTH_COL].map(normalize_label) ==
normalize_label(label)]
    if len(idx) == 0:
        raise ValueError(f"Label '{label}' not found in progress
data.")
    return int(idx[0])


# -----------------------------------------------------------------
# 2) LOAD PRE-ANALYZED RISK PARAMETERS
# -----------------------------------------------------------------

def load_risk_parameters(xlsx_path: Path) -> pd.DataFrame:
    df = pd.read_excel(xlsx_path)
    required_cols = [
        "Factor", "p_median", "p_mean",
        "m_median", "a_P5", "a_P10", "b_P90", "b_P95"
    ]
    missing = [c for c in required_cols if c not in df.columns]
    if missing:
        raise ValueError(f"Missing columns in
risk_parameters.xlsx: {missing}")
    df =
df.set_index("Factor").reindex(FACTOR_NAMES).reset_index()
    return df


# -----------------------------------------------------------------
# 3) EARNED SCHEDULE COMPUTATION
# -----------------------------------------------------------------

@dataclass
class ESResult:
    ES: float
    t0: float
    t1: float
    PV0: float
    PV1: float
    EV: float
    lam: float


@dataclass
class DeterministicForecast:
    status_month:   str
    det_method:     str
    AT_days:        float
    PD_days:        float
    PV_pct:         float
    EV_pct:         float
    SPI:            float
```

```
    ES_days:        float
    SPI_t:          float
    EAC_days:       float
    remaining_days: float
    completed_flag: int
    ES_t0:          float
    ES_t1:          float
    ES_PV0:         float
    ES_PV1:         float
    ES_lam:         float


def build_baseline_curve(df_prog: pd.DataFrame) ->
Tuple[pd.DataFrame, float]:
    finish_idx = find_row_index(df_prog, PLANNED_FINISH_LABEL)
    df_cut     = df_prog.iloc[:finish_idx + 1].copy()
    df_cut[TIME_COL] = coerce_numeric(df_cut[TIME_COL])
    df_cut["PV"]     =
standardize_percent_to_fraction(df_cut[PV_COL])
    baseline = df_cut[[TIME_COL,
"PV"]].dropna().sort_values(TIME_COL)
    baseline = baseline.drop_duplicates(subset=[TIME_COL],
keep="last")
    if float(baseline.iloc[0][TIME_COL]) > 0.0:
        baseline = pd.concat(
            [pd.DataFrame({TIME_COL: [0.0], "PV": [0.0]}),
baseline],
            ignore_index=True
        )
    baseline["PV"] =
np.maximum.accumulate(baseline["PV"].to_numpy(dtype=float))
    pd_days = float(df_cut.iloc[-1][TIME_COL])
    return baseline.reset_index(drop=True), pd_days


def compute_earned_schedule(
    baseline_time: np.ndarray,
    baseline_pv:   np.ndarray,
    ev_fraction:   float,
) -> ESResult:
    EV = float(ev_fraction)
    t  = np.asarray(baseline_time, dtype=float)
    pv = np.maximum.accumulate(np.asarray(baseline_pv,
dtype=float))

    if math.isnan(EV):
        return ESResult(float("nan"), float("nan"), float("nan"),
                        float("nan"), float("nan"), EV,
float("nan"))
    if EV <= pv[0]:
        t1  = float(t[1])  if len(t) > 1 else float(t[0])
        pv1 = float(pv[1]) if len(t) > 1 else float(pv[0])
        return ESResult(0.0, 0.0, t1, 0.0, pv1, EV, 0.0)
    if EV >= pv[-1]:
        t0  = float(t[-2])  if len(t) > 1 else 0.0
        pv0 = float(pv[-2]) if len(t) > 1 else 0.0
        return ESResult(float(t[-1]), t0, float(t[-1]), pv0,
float(pv[-1]), EV, 1.0)
```

```
    for i in range(1, len(t)):
        if pv[i] >= EV:
            t0, t1   = float(t[i - 1]), float(t[i])
            PV0, PV1 = float(pv[i - 1]), float(pv[i])
            if PV1 == PV0:
                return ESResult(t1, t0, t1, PV0, PV1, EV, 1.0)
            lam = max(0.0, min(1.0, (EV - PV0) / (PV1 - PV0)))
            ES  = t0 + lam * (t1 - t0)
            return ESResult(float(ES), t0, t1, PV0, PV1, EV,
float(lam))

    return ESResult(float("nan"), float("nan"), float("nan"),
                    float("nan"), float("nan"), EV, float("nan"))


def compute_deterministic_forecast(
    df_prog:        pd.DataFrame,
    baseline_curve: pd.DataFrame,
    pd_days:        float,
    status_month:   str,
    det_method:     str,
) -> DeterministicForecast:
    row_idx = find_row_index(df_prog, status_month)
    row     = df_prog.iloc[row_idx]
    AT      =
float(coerce_numeric(pd.Series([row[TIME_COL]])).iloc[0])
    PV_s    =
float(standardize_percent_to_fraction(pd.Series([row[PV_COL]])).i
loc[0])
    EV_s    =
float(standardize_percent_to_fraction(pd.Series([row[EV_COL]])).i
loc[0])
    AT      = min(AT, pd_days)

    t_arr  = baseline_curve[TIME_COL].to_numpy(dtype=float)
    pv_arr = baseline_curve["PV"].to_numpy(dtype=float)

    SPI   = float(EV_s / PV_s) if (pd.notna(PV_s) and PV_s > 0
and pd.notna(EV_s)) else float("nan")
    esr   = compute_earned_schedule(t_arr, pv_arr, EV_s)
    ES    = esr.ES
    SPI_t = float(ES / AT) if (AT > 0 and pd.notna(ES)) else
float("nan")

    completed = int(pd.notna(EV_s) and EV_s >= COMPLETE_TOL)

    if completed:
        EAC_t     = AT
        remaining = 0.0
    else:
        rem_planned = max(0.0, pd_days - ES) if pd.notna(ES) else
float("nan")
        if det_method == "ES_ESM1":
            EAC_t = AT + rem_planned if pd.notna(rem_planned)
else float("nan")
        elif det_method == "ES_SPI(t)":
            EAC_t = (AT + rem_planned / SPI_t
```

```
                     if (pd.notna(rem_planned) and
pd.notna(SPI_t) and SPI_t > 0)
                     else float("nan"))
        elif det_method == "SPI_classic":
            EAC_t = pd_days / SPI if (pd.notna(SPI) and SPI > 0)
else float("nan")
        else:
            raise ValueError(f"Unknown det_method: {det_method}")
        remaining = max(0.0, EAC_t - AT) if pd.notna(EAC_t) else
float("nan")

    return DeterministicForecast(
        status_month   = status_month,
        det_method     = det_method,
        AT_days        = AT,
        PD_days        = pd_days,
        PV_pct         = PV_s * 100.0,
        EV_pct         = EV_s * 100.0,
        SPI            = SPI,
        ES_days        = ES,
        SPI_t          = SPI_t,
        EAC_days       = EAC_t,
        remaining_days = remaining,
        completed_flag = completed,
        ES_t0          = esr.t0,
        ES_t1          = esr.t1,
        ES_PV0         = esr.PV0 * 100.0,
        ES_PV1         = esr.PV1 * 100.0,
        ES_lam         = esr.lam,
    )


# ----------------------------------------------------------------
# 4) MONTE CARLO SIMULATION
# ----------------------------------------------------------------

def sample_pert(a: float, m: float, b: float, rng:
np.random.Generator,
                lam: float = 4.0) -> float:
    if b <= a or any(math.isnan(v) for v in [a, m, b]):
        return float("nan")
    m     = min(max(m, a), b)
    alpha = 1.0 + lam * (m - a) / (b - a)
    beta  = 1.0 + lam * (b - m) / (b - a)
    return float(a + rng.beta(alpha, beta) * (b - a))


def run_monte_carlo(
    df_params:   pd.DataFrame,
    p_col:       str,
    a_col:       str,
    b_col:       str,
    impact_dist: str,
    n_iter:      int,
    seed:        int,
) -> Tuple[np.ndarray, pd.DataFrame]:
    rng     = np.random.default_rng(seed)
    delays  = np.zeros(n_iter, dtype=float)
```

```
    contrib = np.zeros((n_iter, N_FACTORS), dtype=float)

    p_arr = pd.to_numeric(df_params[p_col],
errors="coerce").to_numpy(dtype=float)
    a_arr = pd.to_numeric(df_params[a_col],
errors="coerce").to_numpy(dtype=float)
    m_arr = pd.to_numeric(df_params["m_median"],
errors="coerce").to_numpy(dtype=float)
    b_arr = pd.to_numeric(df_params[b_col],
errors="coerce").to_numpy(dtype=float)

    for k in range(n_iter):
        total = 0.0
        for i in range(N_FACTORS):
            p = p_arr[i]
            if math.isnan(p):
                continue
            if rng.random() < max(0.0, min(1.0, p)):
                a, m, b = a_arr[i], m_arr[i], b_arr[i]
                if any(math.isnan(v) for v in [a, m, b]) or b <
a:
                    continue
                m = min(max(m, a), b)
                if impact_dist == "triangular":
                    imp = float(rng.triangular(a, m, b))
                elif impact_dist == "pert":
                    imp = sample_pert(a, m, b, rng)
                else:
                    raise ValueError("impact_dist must be
'triangular' or 'pert'")
                if not math.isnan(imp):
                    contrib[k, i] += imp
                    total         += imp
        delays[k] = total

    contrib_table = pd.DataFrame({
        "Factor": FACTOR_NAMES,
        "Mean delay contribution (days)": contrib.mean(axis=0),
    }).sort_values("Mean delay contribution (days)",
ascending=False).reset_index(drop=True)

    return delays, contrib_table


# ----------------------------------------------------------------
# 5) HYBRID MODEL
# ----------------------------------------------------------------

def compute_hybrid_finish(det: DeterministicForecast, delays:
np.ndarray) -> np.ndarray:
    if det.completed_flag == 1 or not np.isfinite(det.EAC_days)
or det.remaining_days <= 0:
        return np.full(len(delays), fill_value=det.AT_days,
dtype=float)
    return det.EAC_days + delays


# ----------------------------------------------------------------
```

```
# 6) PLOTTING
# ---------------------------------------------------------------

def plot_scurve(df_prog_cut: pd.DataFrame, out_png: Path) ->
None:
    pv = standardize_percent_to_fraction(df_prog_cut[PV_COL]) *
100.0
    ev = standardize_percent_to_fraction(df_prog_cut[EV_COL]) *
100.0
    x  = coerce_numeric(df_prog_cut[TIME_COL])
    plt.figure(figsize=(10, 5))
    plt.plot(x, pv, label="Planned Value (PV)", marker="o",
markersize=3)
    plt.plot(x, ev, label="Earned Value (EV)",  marker="s",
markersize=3)
    plt.xlabel("Cumulative Days")
    plt.ylabel("Cumulative Progress (%)")
    plt.title("S-Curve: Planned Value vs Earned Value")
    plt.legend()
    plt.tight_layout()
    plt.savefig(out_png, dpi=200)
    plt.close()


def plot_delay_histogram(delays: np.ndarray, scenario_id: str,
out_png: Path) -> None:
    plt.figure(figsize=(8, 5))
    plt.hist(delays, bins=50, edgecolor="white", linewidth=0.3)
    plt.xlabel("Total Simulated Delay (days)")
    plt.ylabel("Frequency")
    plt.title(f"Simulated Delay Distribution: {scenario_id}")
    plt.tight_layout()
    plt.savefig(out_png, dpi=180)
    plt.close()


# ---------------------------------------------------------------
# 7) MAIN
# ---------------------------------------------------------------

def main() -> None:
    RESULTS_DIR.mkdir(parents=True, exist_ok=True)

    df_prog   = pd.read_excel(PROGRESS_XLSX)
    df_params = load_risk_parameters(RISK_PARAMS_XLSX)

    baseline_curve, pd_days = build_baseline_curve(df_prog)
    finish_idx  = find_row_index(df_prog, PLANNED_FINISH_LABEL)
    df_prog_cut = df_prog.iloc[:finish_idx + 1].copy()

    plot_scurve(df_prog_cut, out_png=RESULTS_DIR /
"scurve_PV_EV.png")

    det_rows:    List[dict] = []
    det_objects: Dict[Tuple[str, str], DeterministicForecast] =
{}

    for status_month in STATUS_MONTHS:
```

```
        for det_method in DET_METHODS:
            det = compute_deterministic_forecast(
                df_prog        = df_prog_cut,
                baseline_curve = baseline_curve,
                pd_days        = pd_days,
                status_month   = status_month,
                det_method     = det_method,
            )
            det_objects[(status_month, det_method)] = det
            det_rows.append({
                "Status_month"  : det.status_month,
                "Det_method"    : det.det_method,
                "AT_days"       : det.AT_days,
                "PD_days"       : det.PD_days,
                "PV_pct"        : det.PV_pct,
                "EV_pct"        : det.EV_pct,
                "SPI"           : det.SPI,
                "ES_days"       : det.ES_days,
                "SPI(t)"        : det.SPI_t,
                "EAC_days"      : det.EAC_days,
                "Remaining_days": det.remaining_days,
            })

    det_table = pd.DataFrame(det_rows)

    risk_summary_rows: List[dict] = []
    hybrid_rows:       List[dict] = []
    contrib_tables:    Dict[str, pd.DataFrame] = {}

    for scenario_id, cfg in RISK_SCENARIOS:
        delays, contrib_table = run_monte_carlo(
            df_params   = df_params,
            p_col       = cfg["p_col"],
            a_col       = cfg["a_col"],
            b_col       = cfg["b_col"],
            impact_dist = cfg["impact_dist"],
            n_iter      = N_ITER,
            seed        = SEED,
        )
        contrib_tables[scenario_id] = contrib_table

        plot_delay_histogram(
            delays,
            scenario_id = scenario_id,
            out_png     = RESULTS_DIR /
f"delay_hist_{scenario_id}.png",
        )

        summ = summarize_distribution(delays)
        risk_summary_rows.append({"RiskScenario": scenario_id,
**summ})

        for status_month in STATUS_MONTHS:
            for det_method in DET_METHODS:
                det         = det_objects[(status_month,
det_method)]
                finish_days = compute_hybrid_finish(det, delays)
                hs          = summarize_distribution(finish_days)
```

```
                hybrid_rows.append({
                    "Status_month"    : status_month,
                    "Det_method"      : det_method,
                    "RiskScenario"    : scenario_id,
                    "AT_days"         : det.AT_days,
                    "PD_days"         : det.PD_days,
                    "Det_EAC_days"    : det.EAC_days,
                    "Finish_mean_days": hs["mean"],
                    "Finish_P50_days" : hs["p50"],
                    "Finish_P80_days" : hs["p80"],
                    "Finish_P90_days" : hs["p90"],
                    "Finish_P95_days" : hs["p95"],
                })

    risk_summary_table = pd.DataFrame(risk_summary_rows)
    hybrid_table       = pd.DataFrame(hybrid_rows)

    with pd.ExcelWriter(OUTPUT_XLSX, engine="openpyxl") as
writer:
        det_table.to_excel(          writer,
sheet_name="EVM_ES_Deterministic", index=False)
        risk_summary_table.to_excel( writer,
sheet_name="MCS_Delay_Summary",    index=False)
        hybrid_table.to_excel(       writer,
sheet_name="Hybrid_Results",        index=False)
        df_params.to_excel(          writer,
sheet_name="Risk_Parameters_Used",  index=False)
        for sid, ct in contrib_tables.items():
            ct.to_excel(writer, sheet_name=f"Contrib_{sid}",
index=False)


if __name__ == "__main__":
    main()
```

APPENDIX XV: SIMULATION RESULTS

Status_month	Det_method	Risk Scenario	AT_days	PD_days	Det_EAC_days	Finish_mean_days	Finish_P50_days	Finish_P80_days	Finish_P90_days	Finish_P95_days
Magh, 2079	ES_ESM1	R0	193	1096	1075.675	1216.768	1207.058	1281.268	1322.833	1360.261
Magh, 2079	ES_SPI(t)	R0	193	1096	991.5742	1132.667	1122.958	1197.168	1238.732	1276.16
Magh, 2079	SPI_classic	R0	193	1096	826.4146	967.5078	957.7983	1032.008	1073.573	1111.001
Shrawan, 2080	ES_ESM1	R0	379	1096	1147	1288.093	1278.384	1352.593	1394.158	1431.586
Shrawan, 2080	ES_SPI(t)	R0	379	1096	1266.415	1407.508	1397.798	1472.008	1513.573	1551.001
Shrawan, 2080	SPI_classic	R0	379	1096	1330.188	1471.281	1461.572	1535.782	1577.346	1614.774
Magh, 2080	ES_ESM1	R0	558	1096	1211.353	1352.446	1342.737	1416.946	1458.511	1495.939
Magh, 2080	ES_SPI(t)	R0	558	1096	1381.615	1522.709	1512.999	1587.209	1628.774	1666.201
Magh, 2080	SPI_classic	R0	558	1096	1409.143	1550.236	1540.527	1614.736	1656.301	1693.729
Shrawan, 2081	ES_ESM1	R0	744	1096	1231.13	1372.224	1362.514	1436.724	1478.289	1515.716
Shrawan, 2081	ES_SPI(t)	R0	744	1096	1339.243	1480.336	1470.626	1544.836	1586.401	1623.829
Shrawan, 2081	SPI_classic	R0	744	1096	1462.852	1603.946	1594.236	1668.446	1710.011	1747.438
Magh, 2081	ES_ESM1	R0	924	1096	1316.956	1458.049	1448.339	1522.549	1564.114	1601.542
Magh, 2081	ES_SPI(t)	R0	924	1096	1440.455	1581.548	1571.839	1646.049	1687.613	1725.041
Magh, 2081	SPI_classic	R0	924	1096	1618.081	1759.174	1749.465	1823.675	1865.239	1902.667
18 Shrawan, 2082	ES_ESM1	R0	1096	1096	1377.268	1518.361	1508.652	1582.862	1624.426	1661.854
18 Shrawan, 2082	ES_SPI(t)	R0	1096	1096	1474.37	1615.463	1605.754	1679.964	1721.528	1758.956
18 Shrawan, 2082	SPI_classic	R0	1096	1096	1519.479	1660.572	1650.862	1725.072	1766.637	1804.065
Magh, 2079	ES_ESM1	R1	193	1096	1075.675	1274.79	1267.082	1347.384	1396.146	1435.934
Magh, 2079	ES_SPI(t)	R1	193	1096	991.5742	1190.69	1182.982	1263.284	1312.045	1351.833
Magh, 2079	SPI_classic	R1	193	1096	826.4146	1025.53	1017.822	1098.124	1146.886	1186.674
Shrawan, 2080	ES_ESM1	R1	379	1096	1147	1346.116	1338.408	1418.71	1467.471	1507.259
Shrawan, 2080	ES_SPI(t)	R1	379	1096	1266.415	1465.53	1457.822	1538.124	1586.886	1626.674
Shrawan, 2080	SPI_classic	R1	379	1096	1330.188	1529.304	1521.596	1601.898	1650.659	1690.447
Magh, 2080	ES_ESM1	R1	558	1096	1211.353	1410.469	1402.761	1483.063	1531.824	1571.612

Status_month	Det_method	Risk Scenario	AT_days	PD_days	Det_EAC_days	Finish_mean_days	Finish_P50_days	Finish_P80_days	Finish_P90_days	Finish_P95_days
Magh, 2080	ES_SPI(t)	R1	558	1096	1381.615	1580.731	1573.023	1653.325	1702.086	1741.875
Magh, 2080	SPI_classic	R1	558	1096	1409.143	1608.259	1600.551	1680.853	1729.614	1769.402
Shrawan, 2081	ES_ESM1	R1	744	1096	1231.13	1430.246	1422.538	1502.84	1551.602	1591.39
Shrawan, 2081	ES_SPI(t)	R1	744	1096	1339.243	1538.358	1530.65	1610.952	1659.714	1699.502
Shrawan, 2081	SPI_classic	R1	744	1096	1462.852	1661.968	1654.26	1734.562	1783.323	1823.112
Magh, 2081	ES_ESM1	R1	924	1096	1316.956	1516.071	1508.363	1588.665	1637.427	1677.215
Magh, 2081	ES_SPI(t)	R1	924	1096	1440.455	1639.571	1631.863	1712.165	1760.926	1800.714
Magh, 2081	SPI_classic	R1	924	1096	1618.081	1817.197	1809.489	1889.791	1938.552	1978.34
18 Shrawan, 2082	ES_ESM1	R1	1096	1096	1377.268	1576.384	1568.676	1648.978	1697.739	1737.528
18 Shrawan, 2082	ES_SPI(t)	R1	1096	1096	1474.37	1673.486	1665.778	1746.08	1794.841	1834.629
18 Shrawan, 2082	SPI_classic	R1	1096	1096	1519.479	1718.594	1710.886	1791.189	1839.95	1879.738
Magh, 2079	ES_ESM1	R2	193	1096	1075.675	1181.817	1174.275	1230.3	1264.534	1296.797
Magh, 2079	ES_SPI(t)	R2	193	1096	991.5742	1097.717	1090.175	1146.2	1180.434	1212.697
Magh, 2079	SPI_classic	R2	193	1096	826.4146	932.5575	925.015	981.0403	1015.274	1047.537
Shrawan, 2080	ES_ESM1	R2	379	1096	1147	1253.143	1245.6	1301.626	1335.859	1368.123
Shrawan, 2080	ES_SPI(t)	R2	379	1096	1266.415	1372.558	1365.015	1421.04	1455.274	1487.537
Shrawan, 2080	SPI_classic	R2	379	1096	1330.188	1436.331	1428.788	1484.814	1519.047	1551.311
Magh, 2080	ES_ESM1	R2	558	1096	1211.353	1317.496	1309.953	1365.979	1400.212	1432.476
Magh, 2080	ES_SPI(t)	R2	558	1096	1381.615	1487.758	1480.216	1536.241	1570.475	1602.738
Magh, 2080	SPI_classic	R2	558	1096	1409.143	1515.286	1507.743	1563.769	1598.002	1630.266
Shrawan, 2081	ES_ESM1	R2	744	1096	1231.13	1337.273	1329.731	1385.756	1419.99	1452.253
Shrawan, 2081	ES_SPI(t)	R2	744	1096	1339.243	1445.385	1437.843	1493.868	1528.102	1560.365
Shrawan, 2081	SPI_classic	R2	744	1096	1462.852	1568.995	1561.453	1617.478	1651.712	1683.975
Magh, 2081	ES_ESM1	R2	924	1096	1316.956	1423.098	1415.556	1471.581	1505.815	1538.078
Magh, 2081	ES_SPI(t)	R2	924	1096	1440.455	1546.598	1539.056	1595.081	1629.315	1661.578
Magh, 2081	SPI_classic	R2	924	1096	1618.081	1724.224	1716.681	1772.707	1806.94	1839.204

Status_month	**Det_method**	**Risk Scenario**	**AT_days**	**PD_days**	**Det_EAC_days**	**Finish_mean_days**	**Finish_P50_days**	**Finish_P80_days**	**Finish_P90_days**	**Finish_P95_days**
18 Shrawan, 2082	ES_ESM1	R2	1096	1096	1377.268	1483.411	1475.869	1531.894	1566.128	1598.391
18 Shrawan, 2082	ES_SPI(t)	R2	1096	1096	1474.37	1580.513	1572.97	1628.996	1663.229	1695.493
18 Shrawan, 2082	SPI_classic	R2	1096	1096	1519.479	1625.622	1618.079	1674.104	1708.338	1740.601
Magh, 2079	ES_ESM1	R3	193	1096	1075.675	1285.557	1269.319	1385.082	1450.208	1507.295
Magh, 2079	ES_SPI(t)	R3	193	1096	991.5742	1201.457	1185.218	1300.982	1366.108	1423.195
Magh, 2079	SPI_classic	R3	193	1096	826.4146	1036.297	1020.059	1135.822	1200.948	1258.035
Shrawan, 2080	ES_ESM1	R3	379	1096	1147	1356.883	1340.644	1456.408	1521.534	1578.62
Shrawan, 2080	ES_SPI(t)	R3	379	1096	1266.415	1476.297	1460.059	1575.822	1640.948	1698.035
Shrawan, 2080	SPI_classic	R3	379	1096	1330.188	1540.071	1523.832	1639.596	1704.722	1761.808
Magh, 2080	ES_ESM1	R3	558	1096	1211.353	1421.236	1404.997	1520.761	1585.887	1642.973
Magh, 2080	ES_SPI(t)	R3	558	1096	1381.615	1591.498	1575.26	1691.023	1756.149	1813.236
Magh, 2080	SPI_classic	R3	558	1096	1409.143	1619.026	1602.787	1718.551	1783.676	1840.763
Shrawan, 2081	ES_ESM1	R3	744	1096	1231.13	1441.013	1424.775	1540.538	1605.664	1662.751
Shrawan, 2081	ES_SPI(t)	R3	744	1096	1339.243	1549.125	1532.887	1648.65	1713.776	1770.863
Shrawan, 2081	SPI_classic	R3	744	1096	1462.852	1672.735	1656.496	1772.26	1837.386	1894.473
Magh, 2081	ES_ESM1	R3	924	1096	1316.956	1526.838	1510.6	1626.363	1691.489	1748.576
Magh, 2081	ES_SPI(t)	R3	924	1096	1440.455	1650.338	1634.099	1749.863	1814.989	1872.076
Magh, 2081	SPI_classic	R3	924	1096	1618.081	1827.964	1811.725	1927.489	1992.615	2049.701
18 Shrawan, 2082	ES_ESM1	R3	1096	1096	1377.268	1587.151	1570.912	1686.676	1751.802	1808.889
18 Shrawan, 2082	ES_SPI(t)	R3	1096	1096	1474.37	1684.253	1668.014	1783.778	1848.904	1905.99
18 Shrawan, 2082	SPI_classic	R3	1096	1096	1519.479	1729.361	1713.123	1828.886	1894.012	1951.099

APPENDIX XVI: OFFICIAL LETTER FOR ACCESS TO CASE PROJECT PROGRESS RECORDS

नेपाल सरकार
शहरी विकास मन्त्रालय
शहरी विकास तथा भवन निर्माण विभाग
संघीय शहरी विकास तथा भवन निर्माण कार्यालय
बबरमहल, काठमाडौं

प.सं. २०८२/०८३
चलानी नम्बर: १०९६

मिति-२०८२/१२/३०
नेपाल सम्बत् ११४६

विषय:- अध्ययन कार्यका लागि समन्वय गरिएको सम्बन्धमा। ।

श्री जयन श्रेष्ठ।

प्रस्तुत विषयमा श्री त्रिभुवन विश्वविद्यालय, इ.अ.सं., पुल्चोक क्याम्पसको मिति २०८२-११-२६ गतेको प्राप्त पत्र तथा निजबाट प्राप्त विवरणहरूको पूर्णरूपमा अध्ययन प्रयोजनका लागि मात्र प्रयोग हुने प्रतिवद्धता पत्र बमोजिम यस कार्यालयबाट स्वीकृत वा कार्यान्वयनमा रहेको कुनै एक भवन निर्माण आयोजनाको प्रगति सम्बन्धी कागजात वा विवरणहरू माग भएकोमा यस कार्यालयबाट स्वीकृत एक संयुक्त आवास भवनको मासिक प्रगति प्रतिवेदनमा पेश भए बमोजिमका विवरणहरूको डिजिटल प्रति उपलब्ध गराइएको व्यहोरा अनुरोध छ। साथै उपलब्ध गराइएको विवरण अध्ययन बाहेक अन्य कार्यमा प्रयोग भएको खण्डमा यस कार्यालय उत्तरदायी नहुने समेत व्यहोरा जानकारी गराइन्छ।

(ई. रमेश थपलिया)
कार्यालय प्रमुख
कार्यालय प्रमुख

बोधार्थ:
श्री त्रि. वि., इ.अ.सं., पुल्चोक क्याम्पस,
पुल्चोक, लालितपुर।

फोन नं.: ०१-५३६२४०८, ५३५१०७१, ५३५१०७२, इमेल: dudbc.piu3@gmail.com, fudbc.ktm@dudbc.gov.np

APPENDIX XVII: SUBMISSION ACCEPTANCE CONFIRMATION – 18TH IOE GRADUATE CONFERENCE

From:	<ioegc17@gmail.com>
To:	<jayan.stha.35@gmail.com>, <subashkbhattarai@gmail.com>
Date:	Apr 28, 2026, 9:33 AM
Subject:	[IOEGC18] Editor Decision

[IOEGC18] Editor Decision Inbox ×

Dr. Pradeep Shrestha Tue, Apr 28, 9:33 AM (2 days ago)
to me, Subash

Jayan Shrestha, Subash Kumar Bhattarai:

We have reached a decision regarding your submission to 18th IOE Graduate Conference, "Identification of Key Uncertainty Factors Affecting Schedule Performance in Building Construction Projects in Nepal".

Our decision is to: Accept Submission

With Warm Regards,
IOEGC-18 Editorial Team

APPENDIX XVIII: ORIGINALITY REPORT

iThenticate **Similarity Report ID:** oid:3117:584568124

PAPER NAME	AUTHOR
Hybrid Forecasting Model Integrating Earned Value Management and Monte Carlo Simulation for Schedule Risk Prediction in Building Construction Projects	**Jayan Shrestha**
WORD COUNT	CHARACTER COUNT
16368 Words	**94968 Characters**
PAGE COUNT	FILE SIZE
63 Pages	**1.3MB**
SUBMISSION DATE	REPORT DATE
Apr 29, 2026 10:13 PM GMT+5:45	**Apr 29, 2026 10:14 PM GMT+5:45**

● 4% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

- 4% Internet database
- 2% Publications database
- Crossref database
- Crossref Posted Content database
- 0% Submitted Works database

● Excluded from Similarity Report

- Bibliographic material
- Quoted material
- Cited material
- Small Matches (Less then 10 words)

Summary

iThenticate **Similarity Report ID:** oid:3117:584568124

4% Overall Similarity

Top sources found in the following databases:

- 4% Internet database
- 2% Publications database
- Crossref database
- Crossref Posted Content database
- 0% Submitted Works database

TOP SOURCES

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	coursehero.com Internet	<1%
2	fastercapital.com Internet	<1%
3	mdpi.com Internet	<1%
4	fastercapital.com Internet	<1%
5	elibrary.tucl.edu.np:8080 Internet	<1%
6	brightideas.houstontx.gov Internet	<1%
7	ascelibrary.org Internet	<1%
8	suaire.sua.ac.tz Internet	<1%

Sources overview

9	Omri-David Soffer, Lori R. Newman, Mary Brennan, David N. Williams, C... Crossref	<1%
10	etd.aau.edu.et Internet	<1%
11	projectmanagementpathways.com Internet	<1%
12	dspace.univ-ghardaia.dz Internet	<1%
13	cris.brighton.ac.uk Internet	<1%
14	hugepdf.com Internet	<1%
15	pingpdf.com Internet	<1%
16	colorado.edu Internet	<1%
17	jfm.edu.vn Internet	<1%
18	preprints.jmir.org Internet	<1%
19	repository.pauwes-cop.net Internet	<1%
20	Hasan Bakırcı, Ayşe Zeynep Sözen. "Causes of Employer-Induced Disr... Crossref	<1%

21	d2k0ddhflgrk1i.cloudfront.net Internet	<1%
22	spectrum.library.concordia.ca Internet	<1%
23	Anuj Kumar Singh, D.A. Patel, V.H. Lad. "Hybrid linear–nonlinear regres... Crossref	<1%
24	Dhafer Ali Alqahtani, Mohd Ahmed, Javed Mallick, Muhammad D. S. Al ... Crossref	<1%
25	elibrary.tucl.edu.np Internet	<1%
26	ir.kdu.ac.lk Internet	<1%
27	sweetstudy.com Internet	<1%
28	Mario Vanhoucke. "Measuring Time", Springer Science and Business M... Crossref	<1%
29	engineersblog.net Internet	<1%
30	i-jmst.vimaru.edu.vn Internet	<1%
31	ir.library.nitw.ac.in:8080 Internet	<1%
32	repository.ju.edu.et Internet	<1%

33	sajie.journals.ac.za Internet	<1%