

Monte Carlo Simulation for Construction Project Cost Risk Analysis: A Review of Probabilistic Estimation, Contingency Planning and Risk-Driver Modelling

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Abstract

Construction cost estimates are commonly prepared as deterministic BOQ values, yet actual project expenditure is affected by uncertainty in quantities, market rates, labour productivity, site constraints, design changes, services and finishing specifications. This review synthesises literature on Monte Carlo Simulation (MCS) and related probabilistic methods for construction project cost-risk analysis. It examines how deterministic cost estimation is extended into stochastic forecasting, how probability distributions are assigned to cost items, how percentile outputs such as P50, P80 and P90 support contingency planning, and how item-wise variation can be used to identify risk drivers. The review also integrates insights from fuzzy MCS, correlation-based cost modelling, Bayesian and Markov prediction, schedule-cost integration and predictive analytics. A representative building-project context drawn from the source document indicates the practical relevance of the method: three projects analysed with 10,000 iterations showed mean costs above the base estimate, P90 allowances between about 6.5% and 7.0%, and overrun probabilities close to 80%. Across the reviewed literature, MCS is most useful when the model is transparent, distribution assumptions are defensible, sensitivity or risk-driver outputs are reported, and contingency recommendations are linked to decision confidence. The paper concludes that the next generation of construction cost-risk models should combine BOQ-based simulation with correlation structures, schedule data, live procurement information and project-control dashboards.

Keywords: Monte Carlo Simulation; construction cost risk; probabilistic estimation; BOQ; contingency planning; cost overrun; risk drivers

1. Introduction

Cost certainty is a central requirement in construction project governance. Owners need reliable budgets for sanctioning and funding, consultants need defensible estimates for design decisions, and contractors need realistic cost expectations for procurement and cash-flow planning. However, construction projects are rarely delivered under perfectly fixed conditions. Unit rates change, measured quantities evolve with drawing revisions, site productivity varies, subcontractor performance differs, and finishing or service requirements frequently become clearer only during execution. Consequently, the single number produced by a conventional estimate should be treated as a baseline, not as a full description of the probable final cost.

The limitations of deterministic estimation are especially visible in building projects. A BOQ produced from drawings and schedule rates communicates the expected scope and a traceable rate basis, but it does not state the probability that the final cost will exceed the sanctioned amount. It also does not identify whether a reserve should be 3%, 5%, 8% or another value. Cost risk is therefore not only an accounting issue; it is a decision problem involving confidence levels and uncertainty communication. The construction-management literature has increasingly addressed this issue through quantitative risk analysis, stochastic simulation, cost-driver modelling and dynamic prediction (Chou et al., 2009; Touran, 2003; Bouayed, 2016; Qazi & Simsekler, 2021).

Monte Carlo Simulation has become one of the most widely used probabilistic methods for cost-risk analysis because it is conceptually simple and computationally flexible. Instead of changing one cost item manually, MCS repeatedly samples uncertain inputs and generates thousands of possible total project costs. The resulting distribution supports expected-cost forecasting, standard deviation calculation, percentile-based budgeting and overrun-probability assessment. In practice, this means that a project team can distinguish between a base estimate, a mean cost, a P80 cost and a P90 cost. Such distinction is critical when the client wants a higher level of budget confidence (Sonmez et al., 2007; Bakhshi & Touran, 2014; Ammar et al., 2023).

This review paper is prepared from the supplied project document titled Project Cost Risk Analysis Using Monte Carlo Simulation and expands its literature base into a journal-style review. The source document considered three building projects with low, medium and high budget levels and used SSR 2022-23 rate-based BOQ estimates, triangular uncertainty factors and 10,000 simulation iterations. The present review uses that case context as a practical anchor while synthesising broader research on deterministic estimation, probabilistic simulation, cost contingency, risk-driver ranking, correlated variables, fuzzy uncertainty and data-driven prediction.

2. Review Methodology

The paper follows a structured narrative-review approach. The review is not presented as a formal bibliometric study; rather, it synthesises peer-reviewed and technically relevant literature that directly contributes to construction cost uncertainty, quantitative risk analysis, Monte Carlo Simulation, contingency planning and cost-overrun prediction. Sources were selected when they addressed one or more of the following aspects: stochastic cost estimation, risk quantification, item-based cost simulation, cost contingency, schedule-cost interaction, fuzzy or probabilistic uncertainty, Bayesian or Markov risk prediction, and early-stage cost-driver modelling.

The review period covers foundational contingency and probabilistic-cost studies from 2003 onward and recent studies up to 2025. Older studies are retained because they established key concepts such as probabilistic contingency and item-based simulation; recent studies are included because they demonstrate the shift toward correlated variables, dynamic modelling and decision-support systems. This combination is appropriate for a review paper because the purpose is not only to describe the latest literature, but also to explain the methodological development of MCS-based cost-risk analysis.

The literature was grouped into six themes: deterministic estimation and its limitations; MCS and probabilistic cost distribution; contingency and percentile-based budgeting; item-wise risk-driver identification; hybrid and advanced uncertainty models; and practical implementation in construction decision-making. The synthesis gives priority to studies that report practical outputs such as cost distribution, confidence level, overrun probability, contingency allowance, risk ranking or project-control application.

Table 1. Review scope and selection logic

Element	Adopted approach	Rationale
Review type	Structured narrative review with thematic synthesis	Suitable for integrating quantitative risk methods with practical construction estimation issues.
Core domain	Construction cost estimation, project risk analysis and contingency planning	Directly linked to BOQ-based cost uncertainty and decision-making.
Primary methods reviewed	Monte Carlo Simulation, fuzzy MCS, Bayesian networks, Markov models, predictive analytics and earned-value integration	Covers both classical and emerging probabilistic approaches.
Main output variables	Mean cost, standard deviation, P50, P80, P90, overrun probability and risk-driver ranking	These indicators convert uncertainty into budget and management decisions.
Practical anchor	Low-, medium- and high-budget building-project context from the source document	Ensures that the review is connected to realistic building cost-estimation practice.

3. Deterministic Estimation and the Cost-Risk Problem

A deterministic construction estimate is usually produced by multiplying measured quantities by unit rates and summing the item amounts. In BOQ form, the base cost of item i can be written as $C_i = Q_i \times R_i$, where Q_i is the measured quantity and R_i is the selected rate. The method is transparent, auditable and necessary for tendering or administrative approval. Schedule-of-rate systems such as SSR rates are valuable because they provide a common base-rate reference. However, deterministic estimation implicitly assumes that quantities, rates and execution conditions will remain close to the estimated values.

Research on early cost estimation shows that uncertainty is high when project information is incomplete and that cost drivers should be identified carefully before forecasting final expenditure (Chou et al., 2009; Simić et al., 2023; Castro Miranda et al., 2022). The same problem occurs even when drawings are available: structural quantities may change due to design revision, finishing costs may vary with material selection, external works may expand during execution, and services may be affected by coordination or specification changes. Ali et al. (2018) further showed that managerial and transaction-related uncertainty can create cost effects beyond direct material and labour items.

The main weakness of a single-point estimate is that it cannot answer probability-based management questions. A base estimate does not communicate whether the project has a 30%, 50% or 80% chance of exceeding the budget. It also does not identify the cost level required to achieve a particular confidence. In practice, this often leads to contingency being applied as a flat percentage. While convenient, fixed percentages can be misleading because different projects have different cost structures and risk exposures (Touran, 2003; Sonmez et al., 2007; Ammar et al., 2023).

Quantitative risk analysis addresses this limitation by representing cost as a distribution rather than a single number. The distribution can be constructed using historical data, expert judgement or a combination of both. For many small and medium building projects, complete historical data may not be available for every BOQ item. Therefore, simplified distributions such as triangular distributions remain important because they translate estimator judgement into a formal simulation input (Sadeghi et al., 2010; Moselhi & Roghabadi, 2020).

4. Monte Carlo Simulation as a Probabilistic Cost-Risk Method

Monte Carlo Simulation estimates uncertain outcomes through repeated random sampling. In construction cost analysis, every simulation iteration creates one possible project-cost scenario. The base cost of each BOQ item is multiplied by a random factor sampled from a chosen distribution, and the simulated item costs are summed to obtain total project cost. When this process is repeated thousands of times, the results create a probability distribution of total cost. Chou (2011) demonstrated the value of this item-based logic because the total project estimate is understood as the sum of many uncertain work packages rather than a single uncertain total.

The basic equations used in many cost-risk models are straightforward. The base item amount is $C_i = Q_i \times R_i$. If F_i is the sampled uncertainty factor for item i , the simulated item cost is $SC_i = C_i \times F_i$. The simulated total cost in one iteration is $TC = \text{Sum}(SC_i)$. After N iterations, mean cost, standard deviation, minimum, maximum and percentile costs are calculated from the set of TC values. The probability of overrun is estimated as the number of simulated values greater than the base estimate divided by the total number of iterations.

The strength of MCS lies in its ability to convert uncertain inputs into decision-ready outputs. Mean cost indicates the expected cost under uncertainty. Standard deviation describes the spread of outcomes. P50 is the median cost, whereas P80 and P90 represent higher confidence budgets. If the P90 cost is substantially higher than the base estimate, the project team can calculate a P90 allowance as P90 cost minus base cost. This transforms contingency planning from a subjective mark-up into a probabilistic budget decision (Bouayed, 2016; Bakhshi & Touran, 2014).

MCS also supports risk-driver ranking. If simulated standard deviation is computed for individual items, the items with the largest variability or cost contribution can be identified as critical drivers. In building projects, structural work, reinforcement, flooring, joinery, services and external development frequently dominate cost exposure because of their base amounts and sensitivity to market or design changes. This aligns with item-based cost simulation literature and supports targeted procurement and monitoring (Chou, 2011; Simić et al., 2023).

Conceptual Framework for Probabilistic Construction Cost-Risk Review



Figure 1. Conceptual framework for probabilistic construction cost-risk review

Table 2. Deterministic and probabilistic estimation in construction cost control

Dimension	Deterministic estimate BOQ	Probabilistic/MCS estimate	Decision value
Cost representation	Single base value from quantities and rates	Distribution of possible total costs	Shows range and uncertainty instead of only one budget.
Input assumptions	Fixed quantities and fixed rates	Uncertain factors or distributions for selected items	Allows material, labour, productivity and design uncertainty to be represented.
Contingency basis	Often a flat percentage	Difference between P-level cost and base cost	Supports confidence-based contingency selection.
Risk visibility	Limited visibility of item contribution	Item-level standard deviation and sensitivity ranking	Identifies critical work packages requiring control.
Managerial use	Approval and baseline comparison	Forecasting, risk communication, procurement focus and budget governance	Strengthens decision-making before and during execution.

5. Literature Synthesis

The reviewed literature can be understood as a gradual movement from deterministic and qualitative risk thinking toward integrated probabilistic decision support. Early work on contingency emphasised that reserves should be linked to uncertainty rather than imposed as arbitrary percentages (Touran, 2003; Sonmez et al., 2007). Item-based simulation then showed that cost distributions can be generated directly from uncertain work packages (Chou et al., 2009; Chou, 2011). Later studies expanded the method by considering dependence between cost items, fuzzy uncertainty, schedule-cost interaction, earned-value updating, Bayesian classification and Markov-chain prediction (Sadeghi et al., 2010; Firouzi et al., 2016; Deng & Jian, 2022; Ashtari et al., 2022; Leu et al., 2023). Recent research further highlights the need for correlation matrices, time-shifted risks and dependency modelling (Ariza Flores & Zavala Ascaño, 2025; Bara, 2025; Zavala et al., 2025).

A practical synthesis is that MCS is not a substitute for a good estimate; it is an extension of a good estimate. The BOQ, work-breakdown structure and rate basis must first be reliable. The simulation then explores how uncertainty around those inputs affects total cost. Therefore, the quality of a Monte Carlo cost-risk model depends on three layers: the quality of the deterministic estimate, the validity of the uncertainty distributions, and the transparency with which outputs are interpreted for management action.

Table 3. Thematic synthesis of key literature streams

Theme	Representative studies	Main methodological contribution	Implication for review paper
Contingency and cost-overflow control	Touran (2003); Sonmez et al. (2007); Bakhshi & Touran (2014); Bouayed (2016); Ammar et al. (2023)	Developed probabilistic or state-of-the-art thinking for contingency determination.	Contingency should be connected to confidence level and risk exposure.
Item-based cost simulation	Chou et al. (2009); Chou (2011)	Modelled total project cost as the sum of uncertain cost items.	BOQ-level simulation is appropriate for building-cost risk analysis.
Fuzzy and judgement-based uncertainty	Sadeghi et al. (2010); Moselhi & Roghabadi (2020)	Integrated expert judgement and fuzzy uncertainty with simulation.	Useful where complete historical data are not available.
Dependence and correlation	Firouzi et al. (2016); Zavala et al. (2025); Bara (2025)	Highlighted dependence among cost items and time-shifted project risks.	Future models should avoid assuming all BOQ items are independent.
Schedule-cost integration	Barraza et al. (2004); Koulinas et al. (2020); Sobieraj & Metelski (2022); Deng & Jian (2022)	Connected probabilistic forecasting with time, earned value and schedule delay.	Cost simulation should eventually be linked to schedule-risk analysis.
Risk prioritisation and decision support	Qazi & Simsekler (2021); Qazi et al. (2021); Starczyk-Koľbyk & Jędras (2025)	Used MCS to improve prioritisation beyond qualitative risk matrices.	Risk ranking should be probability-based and decision-oriented.
Predictive and dynamic risk models	Ashtari et al. (2022); Castro Miranda et al. (2022); Leu et al. (2023)	Applied Bayesian, predictive analytics and Markov concepts for cost-risk prediction.	MCS can be extended into dynamic monitoring and early-warning systems.

Synthesis Map of Construction Cost-Risk Modelling Methods

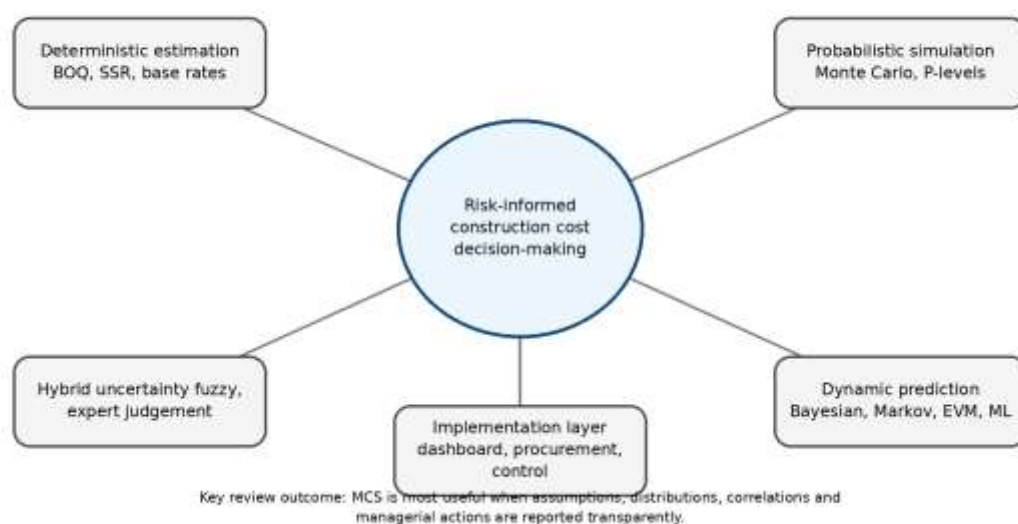


Figure 2. Synthesis map of construction cost-risk modelling methods

6. Input Uncertainty and Distribution Selection

Distribution selection is one of the most important modelling decisions in MCS. If sufficient historical data exist, probability distributions can be fitted using statistical tests. In many construction organisations, however, detailed item-wise histories are unavailable or inconsistent. This is particularly true for small and medium building projects, where estimates may rely on current drawings, standard rates and estimator judgement. In such cases, triangular distribution is often preferred because it uses three intuitive parameters: minimum, most-likely and maximum values.

The triangular model is not perfect. It may oversimplify extreme market events, does not automatically represent correlation, and depends on the judgement used to select the range. Nevertheless, it is transparent and easy to explain to practitioners. The estimator can specify a favourable case, a most probable case and an adverse case for each cost item. When used consistently across a BOQ, the method produces a reasonable first-level risk distribution that is more informative than a fixed contingency.

Advanced literature suggests several ways to improve input modelling. Firouzi et al. (2016) and Zavala et al. (2025) emphasise dependence among cost items. Sadeghi et al. (2010) and Moselhi and Roghabadi (2020) show that fuzzy representations can handle vague expert knowledge. Bara (2025) further argues that risks should be considered with timing and dependency relationships rather than as isolated independent events. These developments do not invalidate the triangular approach; instead, they indicate how it can be upgraded when data availability and project complexity justify a more advanced model.

7. Percentile-Based Contingency Planning

Contingency is the financial reserve required to absorb uncertainty. Traditional practice often treats contingency as a standard percentage of project cost, but the reviewed literature shows that a more rigorous method is to select contingency based on a cost distribution. If the client accepts moderate risk, a P80 budget may be considered. If the client wants a higher confidence level, a P90 or higher budget may be required. The formula $\text{Contingency_Pk} = \text{Pk cost} - \text{base cost}$ connects reserve directly to the desired confidence level.

Percentile-based contingency also improves communication. Instead of stating that a project needs a 5% contingency without explanation, the estimator can state that the P90 cost is a defined amount and that only 10% of simulated outcomes exceed it. This helps owners, consultants and contractors understand the trade-off between budget reserve and overrun risk. It also allows comparison across project categories. A similar percentage allowance can represent very different absolute cash reserves in low-budget and high-budget projects.

This confidence-level interpretation is consistent with contingency research and recent risk-analysis frameworks. Touran (2003) established the need for probabilistic contingency models; Bakhshi and Touran (2014) reviewed contingency methods; Ammar et al. (2023) discussed state-of-the-art contingency determination; and Ariza Flores and Zavala Ascaño (2025) showed the value of quantitative risk analysis for cost and time estimation. Together, these studies support the argument that P-level outputs are more defensible than arbitrary mark-ups.

8. Risk-Driver Modelling and Managerial Interpretation

A cost-risk model is useful only if it guides action. Therefore, risk-driver ranking is an essential output. If RCC, reinforcement, flooring, doors/windows, external development or MEP services dominate uncertainty, the project team can focus on detailed quantity checking, early procurement, rate locking, design coordination, vendor comparison and strict measurement control. This shifts MCS from a passive forecasting tool to an active management instrument.

The reviewed literature supports this management orientation. Chou (2011) demonstrates the value of item-level cost simulation; Qazi and Simsekler (2021) show that risk prioritisation becomes stronger when uncertainty in risk ratings is represented; Qazi et al. (2021) combine risk matrices with MCS for more robust ranking; and Starczyk-Kołybyk and Jędras (2025) compare qualitative and quantitative methods in a building-contract context. The shared conclusion is that qualitative identification is useful but insufficient when decisions require financial magnitude and probability.

Risk-driver interpretation should also consider project scale. In a small residential project, the absolute risk amount may be limited but can still affect project viability because margins are narrow. In a large commercial project, the percentage variation may appear moderate, but the absolute amount can be very high. Therefore, both percentage

indicators and monetary values should be reported. A good cost-risk report should state the base estimate, mean cost, P80/P90 costs, overrun probability, contingency requirement and leading risk drivers together.

Table 4. Generic Monte Carlo workflow for BOQ-based cost-risk analysis

Step	Action	Output	Quality check
1	Prepare item-wise BOQ with quantities and base rates.	Deterministic base estimate.	Check drawings, SSR/rate source, units and arithmetic.
2	Select uncertain cost heads and assign distribution parameters.	Minimum, most-likely and maximum factors or fitted distributions.	Document basis of assumptions and exclude fixed items if appropriate.
3	Run simulation for sufficient iterations.	Set of total simulated costs.	Check convergence of mean and percentiles.
4	Calculate distribution outputs.	Mean, standard deviation, minimum, maximum, P50, P80, P90.	Confirm units and consistency with base estimate.
5	Compute overrun probability and contingency.	Probability of TC > base cost and P-level allowance.	Link selected contingency to client risk tolerance.
6	Rank cost-risk drivers.	Critical BOQ items by standard deviation or sensitivity.	Convert findings into procurement and monitoring actions.

9. Application Context Derived from the Source Document

The source project document provides a useful practical context for the review because it applies the reviewed concepts to three building categories. The projects are a low-budget residential row house, a medium-budget G+4 residential building and a high-budget commercial building. The reported model used SSR 2022-23 rates as the deterministic base, applied triangular uncertainty factors and performed 10,000 iterations for each project. The results show why the review topic is practically important: all three projects produced simulated mean costs above the base estimate and high probabilities of exceeding the deterministic budget.

The same source document also identifies typical building cost-risk drivers. RCC work was the dominant risk driver across the three projects, while flooring, doors/windows, plastering and external development were also important. This pattern supports the review conclusion that item-level simulation is more useful than total-cost mark-up because it identifies where management attention should be concentrated.

Table 5. Illustrative project evidence from the source document

Project	Base estimate	Mean simulated cost	P90 cost	Overrun probability	Main risk drivers
P01 - Row House Manoj Punwal/Punnal	INR 10.00 lakh	INR 10.27 lakh	INR 10.70 lakh	78.08%	RCC, flooring, doors/windows, plastering, excavation
P02 - Cool Homes	INR 57.50 lakh	INR 58.97 lakh	INR 61.25 lakh	79.54%	RCC, flooring/tiling, doors/windows, external development, plastering
P03 - 18 Latitude	INR 11.50 crore	INR 11.79 crore	INR 12.25 crore	79.72%	RCC, doors/windows, flooring/tiling, external development, plastering

10. Advanced Extensions of Monte Carlo Cost-Risk Models

Although BOQ-based triangular MCS is practical, the literature shows that more advanced models may be required for complex projects. Dependence between cost items is one extension. Concrete, reinforcement, shuttering and labour productivity may be linked; finishing and service changes may also occur together. If these relationships are ignored, the simulation may understate or distort the total cost range. Correlation matrices or copula-based approaches can be used when data are available (Firouzi et al., 2016; Zavala et al., 2025). Schedule-cost integration is another major extension. Delays can increase labour, overhead, equipment, financing and escalation costs. Therefore, cost-risk analysis should not remain isolated from schedule-risk analysis. Research on stochastic S-curves, simulation-based delay risk, Time-at-Risk and earned-value MCS indicates that project duration and cost-at-completion forecasting can be combined (Barraza et al., 2004; Koulinas et al., 2020; Sobieraj & Metelski, 2022; Deng & Jian, 2022). Predictive and dynamic models are also emerging. Bayesian networks can classify projects by cost-overrun risk, Markov-chain models can represent movement between risk states, and predictive analytics can improve early-stage cost estimation by learning from historical project data (Ashtari et al., 2022; Leu et al., 2023; Castro Miranda et al., 2022). These tools are data-intensive, but they are promising for organisations that maintain structured project-cost databases.

11. Research Gaps

The review identifies several gaps. First, many studies focus on infrastructure, megaprojects or high-rise cases, while small and medium building projects receive less attention. Second, practical BOQ-based examples are still limited, even though most construction estimates are prepared in BOQ format. Third, many MCS studies report total distribution outputs but do not translate them into specific procurement, design or monitoring actions. Fourth, dependence among BOQ items is often recognised theoretically but not implemented in simple spreadsheet models. Fifth, schedule-cost interaction remains underdeveloped in routine building estimates.

Another important gap is model updating. A pre-execution simulation is useful, but cost risk changes during procurement and construction. Once actual quantities, market quotations and progress data are available, distributions should be updated. Earned-value management, procurement dashboards and Bayesian updating can help convert MCS from a one-time planning exercise into a live cost-control system. This is a strong future direction for academic research and construction practice.

Table 6. Research gaps and future research agenda

Gap	Why it matters	Recommended future direction
Limited BOQ-based evidence for small and medium building projects	Many contractors and consultants work with BOQ estimates and schedule rates rather than advanced databases.	Develop spreadsheet-compatible MCS frameworks validated on residential and commercial building projects.
Weak treatment of correlation between cost items	Linked cost movements can alter total risk exposure.	Use correlation matrices, copulas or scenario-based dependence mapping for major cost heads.
Limited integration of schedule and cost uncertainty	Delays can increase cost through overheads, labour, equipment and escalation.	Combine BOQ cost simulation with activity-duration simulation and earned-value data.
Insufficient updating during execution	A pre-project model becomes stale when market rates and quantities change.	Create dashboards that update distributions using procurement quotations, actual quantities and progress data.
Risk outputs not always converted into action	Percentiles are useful only if they influence decisions.	Link risk-driver rankings to procurement strategy, rate locking, design finalisation and quality control.

12. Practical Recommendations for Construction Estimators

For practical implementation, construction estimators should begin by preparing a clean deterministic BOQ and separating fixed, low-risk and high-risk items. Major work heads should then receive documented uncertainty ranges. Where historical data are not available, the basis for minimum, most-likely and maximum values should be recorded through expert judgement, market inquiry or previous project experience. The simulation should report mean, standard deviation, P50, P80, P90 and overrun probability, not only a single final number.

The selected contingency level should reflect risk tolerance. A client with limited financial flexibility may prefer a P90 budget, while a client willing to accept moderate risk may use P80. The estimator should also explain the difference between percentage and absolute allowance. For large projects, a small percentage variation can represent a large monetary reserve. Finally, the risk-driver table should be converted into action: verify structural quantities, lock critical material rates early, finalise finishing specifications, coordinate services before execution, and monitor external development scope carefully.

Table 7. Application-ready checklist for a Scopus-level MCS cost-risk study

Checklist item	Minimum expectation	Purpose
Transparent case description	Project type, scope, base estimate and rate source are stated.	Allows readers to understand the estimation context.
Documented distribution assumptions	Minimum, most-likely and maximum factors or fitted distributions are justified.	Improves reproducibility and credibility.
Adequate simulation iterations	Iterations are sufficient for stable percentile estimates.	Reduces random sampling instability.
Complete output reporting	Mean, standard deviation, P50, P80, P90, overrun probability and allowance are reported.	Supports budget decision-making.
Risk-driver ranking	Critical BOQ items are ranked and interpreted.	Turns simulation into management action.
Limitations and future scope	Independence, data quality and schedule-cost limitations are acknowledged.	Prevents overclaiming and strengthens academic quality.

13. Conclusion

This review examined Monte Carlo Simulation and related probabilistic methods for construction project cost-risk analysis. The synthesis shows that deterministic BOQ estimates remain essential but are incomplete as decision tools because they do not communicate cost range, overrun probability or confidence-based contingency. MCS addresses this weakness by transforming item-level uncertainty into a total cost distribution from which mean cost, standard deviation, P50, P80, P90 and risk allowances can be calculated.

The literature confirms that MCS is practical for construction because it can be implemented using existing BOQ structures and understandable distribution assumptions. Triangular distributions are particularly useful when historical data are limited, although their assumptions should be documented carefully. For advanced applications, cost-risk models should incorporate dependence between cost items, schedule-cost interaction, fuzzy or expert uncertainty, and dynamic updating through earned-value or procurement data.

The source document reinforces the practical importance of this review. Its three building-project simulations showed high overrun probabilities and the repeated dominance of RCC and finishing-related items as cost-risk drivers. This supports the central conclusion that cost contingency should not be treated as a fixed percentage only; it should be selected from probability-based outputs and supported by item-wise risk-driver control. Future research should therefore focus on integrated, data-updated and decision-oriented cost-risk models that are simple enough for routine construction practice but rigorous enough for academic and professional acceptance.

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