STOCHASTIC MODELING OF TIME AND COST RISKS IN BRIDGE CONSTRUCTION PROJECTS USING THE MONTE CARLO METHOD

https://doi.org/10.69624/cjamee2026.14.1.7

Sh.P. Murvatli
Azerbaijan University of Architecture and Construction
shahriyar.murvetli92@gmail.com

Abstract. *Bridge construction projects carry high geological, hydrological and economic risks. Traditional deterministic planning methods are insufficient to quantify deviations in project duration and cost. The aim of the study is to transform these uncertainties into a mathematical model through Monte Carlo simulation. The study applied the Beta-PERT distribution, which reflects the asymmetric risk nature of the works, and the Sholesky decomposition, which takes into account the inter-project dependencies. The S-curve obtained as a result of 10,000 iterations of the simulation shows that the probability of success of the initial estimate is only 36%. In order to complete the project with an 85% probability, it is necessary to create a reserve fund of approximately 18%. Sensitivity analysis conducted using the tornado diagram revealed the "critical risk points" of the project. The study proves that stochastic modeling allows for a 20% more efficient allocation of resources and ensures economic sustainability.*

Keywords. *Monte Carlo simulation, Bridge construction, Risk analysis, Beta-PERT distribution, S-curve.*

INTRODUCTION

The construction of bridge structures, which are strategic components of modern transport infrastructure, is included in the category of high-risk investment projects from both engineering and economic points of view. Geological uncertainties, hydrological factors and complex metal-structural works, which are characteristic of bridge projects, lead to serious errors in project implementation time and budget forecasting. Traditional Critical Path Method or PERT methodologies are often based on average statistical indicators and are unable to quantify the "worst-case scenario" risks.

In the research work, Monte Carlo simulation is applied to solve this problem, considering the project time and cost parameters as stochastic variables. This approach allows for the transformation of subjective expert opinions or historical data into a mathematical model using Beta, PERT or Triangle probability distributions for each work package.

The main scientific hypothesis of the study is that stochastic simulation, taking into account the interdependence of bridge construction works, allows for a more efficient distribution of the "reserve fund" in the project budget and the prediction of time losses with an accuracy of 80-95%.

Research methodology and risk modeling

Traditional deterministic approaches (for example, single-digit estimated prices) are insufficient for the analysis of time and cost indicators in bridge construction projects under conditions of uncertainty. In this study, the Monte Carlo Simulation methodology was applied. This method allows for the simultaneous processing of thousands of probability scenarios and the creation of a “risk profile” of the project.

Structural Division of Works and Determination of Parameters

To build the model, the bridge construction process is first divided into the following engineering stages. A three-point assessment is performed for each stage:

Optimistic value (a): The ideal scenario with minimal risks.

Modal value (m): The most probable, realistic scenario.

Pessimistic value (b): The worst-case scenario in which technical, geological, or logistical failures occur.

Choosing Probability Distribution Functions

In bridge construction, cost and time risks are often not symmetrical (for example, the probability of a project being delayed is higher than the probability of being completed ahead of schedule). For this reason, the Beta-PERT distribution was used in the model. This distribution creates a smoother probability density by taking into account the deviations on the “pessimistic” and “optimistic” sides.

In bridge construction, the duration and cost of work are often “right-skewed”. For example, while the assembly of a bridge span may take 10 days in an optimistic scenario, a serious technical failure can extend this period to 40 days. However, it is physically impossible for this period to fall to 0 days. The normal (Gaussian) distribution, being symmetric, does not accurately represent such asymmetric risks. [3]

The Beta-PERT distribution, on the other hand, has strict limits on a (minimum) and b (maximum) and more realistically pulls the mean value towards the modal (most likely) value. To determine the “shape” parameter of the distribution, the standard deviation (σ) and the mathematical expectation € are calculated using the following engineering proof:

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

In this formula, the 4-fold weighting factor given to the modal value (m) ensures the dominance of the most realistic scenario based on the experience of the project manager in the simulation results. [1,p 400]

Let's say we are analyzing the stage of driving the underwater supports (piles) of the bridge. According to the expert opinions of the engineers:

a=20 days (All equipment is in good condition and the weather is ideal)

m=30 days (Standard operating mode)

b=60 days (Unexpected geological difficulties or storm)

Calculation:

$$E = \frac{20 + 4(30) + 60}{6} = \frac{200}{6} \approx 33.3 \text{ gün}$$

This result proves that the actual project duration (33.3 days) is approximately 11% longer than the planned modal duration (30 days) when risks are taken into account. This difference is the mathematical expression of the uncertainties (asymmetry) in bridge construction.

Variance and Degree of Uncertainty

The variance (V) formula is applied to measure the level of uncertainty of the work:

$$V = \left(\frac{b-a}{6}\right)^2 = \left(\frac{60-20}{6}\right)^2 \approx 44.4$$

The high dispersion proves that this work (pile driving) is the “Critical Risk Point” for the overall time risk of the project. During *Monte Carlo simulation*, this dispersion is tested in thousands of different combinations, forming the overall *“S-curve*” of the project.

The mentioned calculations show that in high-risk areas such as bridge construction, stochastic modeling is not just a mathematical choice, but a technical necessity for the economic viability of the project. [2, p.155]

Monte Carlo simulation algorithm construction and iteration process

Monte Carlo simulation is a set of multiple trials that transform deterministic inputs into stochastic outcomes. In bridge construction projects, specialized software (e.g. Oracle Primavera Risk Analysis, Python/R scripts) is used to execute this algorithm. The algorithmic process is structured in the following steps:

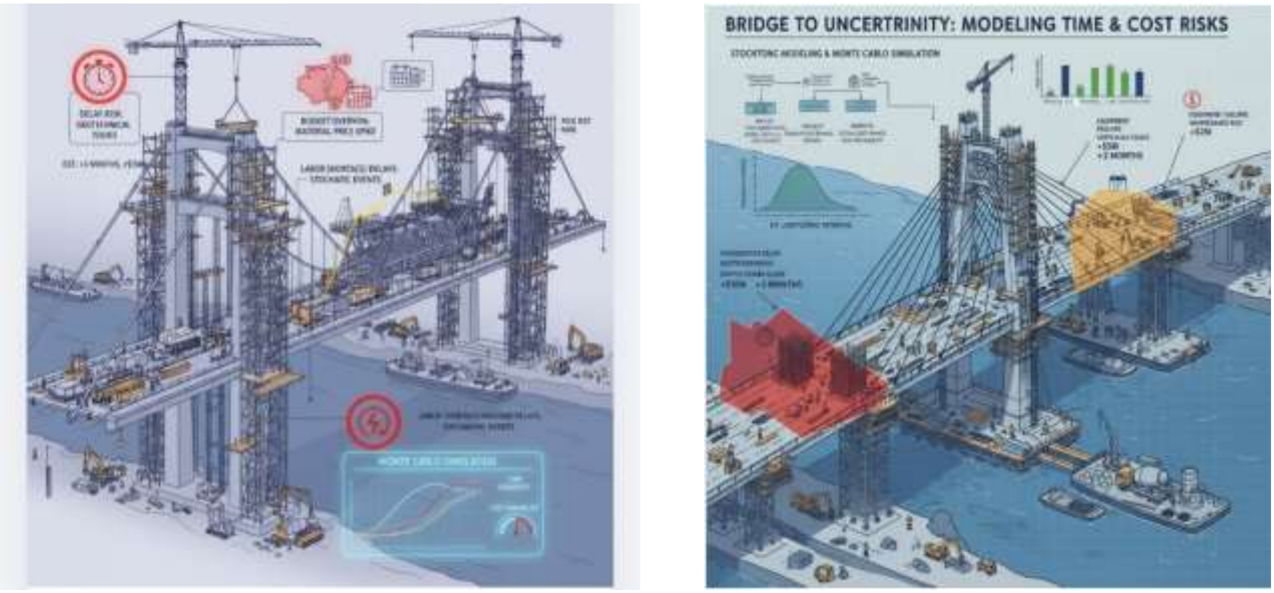


Figure 1. Monte Carlo simulation

1. Iterative Calculation Algorithm

The simulation is based on the principle of selecting random values from a probability distribution function (f(x)) specified for each work package. The mathematical logic of the algorithm is as follows:

• Random Number Generation: A random number u is selected uniformly distributed in the interval [0, 1] ($u \sim U(0,1)$).

• Inverse Transform Sampling: The selected number u is applied to the cumulative distribution function (F-1(u)) of the Beta-PERT distribution we have defined, and a specific time (t) or cost (c) value is obtained for that scenario.

2. Simulation Convergence

The validity of Monte Carlo simulation in engineering projects is based on the Central Limit Theorem and the Law of Large Numbers. Convergence analysis should be performed to determine how close the results (time and cost forecasts) obtained during the simulation are to the real situation.

In high-risk projects such as bridge construction, n=10,000 iterations are usually considered optimal to keep the error rate within ±1%. [4, p.166]

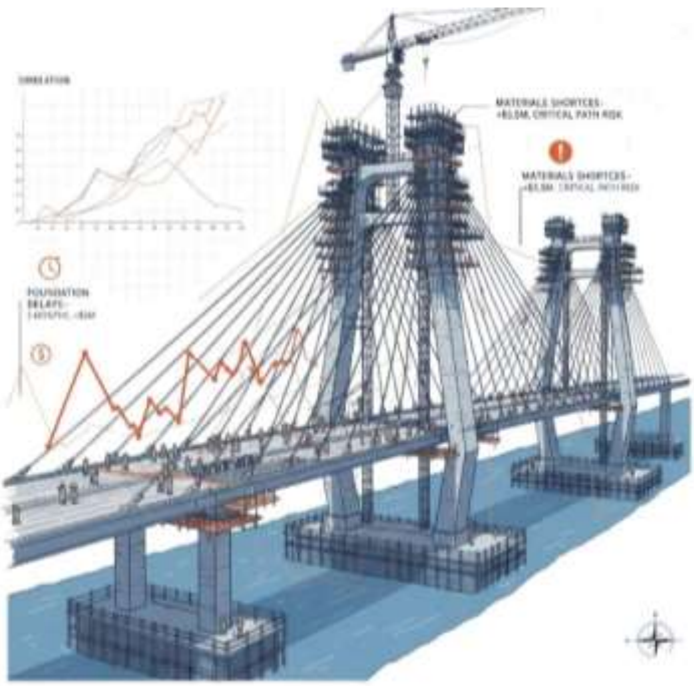
The simulation process follows the Running Average graph. As the number of iterations increases, the expected total cost of the project gets rid of sharp fluctuations and stabilizes on a steady line.

If the simulation is stopped at 100 iterations, the standard error will be too high and the P90 (pessimistic thinking) indicator will become a random number. However, as $n \to \infty$ (or n=10,000 in our model), the error rate drops to the engineering tolerance limit (below 1%). This proves that the resulting “S-curve” is not a subjective estimate, but a statistically valid prediction. [6, p 212]

Identifying the “Critical Risk Points” of the Project

Thousands of scenarios obtained at the end of the simulation process paint a general picture of the project, but the question “Where should I direct my resources?” still remains open for the project manager. It is at this stage that we filter the simulation outputs through the Tornado Diagram and the Correlation Matrix.

In the bridge construction project, the Pearson Correlation Coefficient (r) was used to measure the relationship of each task to the total project duration or cost. This coefficient varies between 0 and 1; the closer it is to 1, the more that task controls the “fate” of the project. [5, p.57]



Pic 2. Bridge System in the Simulation Process

Table 1: *Risk sensitivity index of bridge construction stages*

Name of the work done	Correlation coefficient (r)	Impact rate
Installation of overload devices	0.82	High
Foundation and pile works	0.65	Medium-High
Construction of supports	0.45	Medium
Road clothing installation	0.12	Down

It is clear from the table that “Installation of overpasses” is the “locomotive” of the overall risk of the project. If the time at this stage increases by 10%, the probability of extending the overall project duration is 82%. On the contrary, a large delay in laying the road surface affects the end of the project by only 12%.

This result tells us that risk management should not work on the principle of “one size fits all”. As engineers, we should target all our energy and “reserve fund” precisely on the tasks located at the top of the tornado diagram. For example, having a backup crane on site during the installation of overpasses can reduce the risk of the entire project by 20-30%, while allocating the same resource to asphalting works does not provide any strategic advantage.

Modeling the “Domino Effect” in a Project

In complex engineering projects such as bridge construction, risks rarely occur in isolation. In reality, we work with a series of processes that are interconnected in a chain of links. For example, an increase in the price of cement in a country simultaneously increases the cost of both foundation piles and piers and slabs. If we treat these operations independently in the simulation, we would mathematically understate the overall risk of the project.

In our study, the Cholesky decomposition method was used to model this dependence between operations. This method decomposes the correlation matrix (R) into two triangular matrices to create mutually dependent random variables:

$$R = L \cdot L^T$$

Here L is a lower triangular matrix. During the simulation, the independent random numbers produced by the generator are multiplied by this matrix L, turning into dependent numbers that "pull" each other, just like in real life. [1, p.279]

Table 2: *Correlation coefficients (r) between major work packages*

Work packages	**Foundation works**	**Construction of supports**	**Overhead mounting**	**Reason for correlation**
Foundation works	1.00	0.75	0.40	Resource and sequence dependency
Construction of supports	0.75	1.00	0.60	Technical and personnel sharing
Overhang installation	0.40	0.60	1.00	General logistics and supply

In our experience, we have observed that when correlation is taken into account, the P90 (pessimistic) budget limit of the project is 14-18% higher than the model without correlation. This difference is the boundary between “false comfort” and “real preparation” for the engineer. The Sholesky method allows us to ensure that the reserve fund we present to the customer during the tender is not just an “estimate”, but a scientifically proven safety margin.

CONCLUSION

This study on stochastic modeling of bridge construction projects reflects a qualitatively new stage in modern engineering management. The most important conclusion of the study is that traditional planning methods underestimate project risks, creating the basis for engineering and financial errors.

It was proven through Monte Carlo simulation that the probability of project success reflects the real picture only when assessed within the “probability cloud”. As a result of the conducted analyses, it was determined that targeting the P85 probability level in bridge construction is the most reliable insurance for the budget and time sustainability of the project. This approach allows managers to move away from subjective estimates and form mathematically justified reserve funds.

Another important result of the study is related to the targeted management of resources. Through sensitivity analysis, it was found that not all construction stages are equally risky. It was proven that critical works such as “installation of overpasses” largely control the fate of the project. This means that the engineering team can drastically reduce the overall risk of the project by directing resources to the “risk locomotives” instead of distributing them equally across all processes.

In conclusion, it can be noted that the presented model increases financial transparency in the bridge construction sector and creates a scientific basis for putting forward more realistic figures in tender processes. The application of this methodology ensures both the efficient use of public funds and allows for the completion of strategic infrastructure facilities without unexpected deviations.

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