

Montecarlo Simulation for Project Management

Monte Carlo Simulation is a powerful analytical tool that utilizes the generation of random samples to find solutions to problems of deterministic nature. By employing probabilistic modeling, it addresses complex systems and processes where analytical solutions may be difficult or impossible to derive directly.

The Process of Monte Carlo Simulation:

1. **Problem Definition:** Begin by mathematically defining the problem, identifying all involved variables, and understanding how these variables interact within the model. This includes defining constraints and relationships among the variables.

In this particular example, we define the mathematical model as the costs sum of the costs of every phase that the project involves

2. **Choosing Probability Distributions:** Select an appropriate probability distribution for each variable. This choice should reflect real-world behavior of the data; for example, task durations might follow a normal distribution, or costs might follow a log-normal distribution due to their positive skew.

In this particular case, we use a Beta-PERT distribution for sample generation. The Beta-PERT distribution is defined as follows:

Density Function

$$f(x) = \begin{cases} \frac{x^{v-1}(1-x)^{w-1}}{B(v,w)} & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Distribution Function

$$F(x) = \begin{cases} \frac{B_x(v,w)}{B(v,w)} & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Montecarlo Simulation for Project Management

We can make use of **scipy** library for **Python** to handle the generation of the distribution and sample directly from it. We only need three values: The **mean**, and shape parameters **v** and **w**

Mean

$$\mu = \frac{x_{min} + x_{max} + \lambda x_{mode}}{(\lambda + 2)}$$

Shape Parameters

$$v = \frac{(\mu - x_{min})(2x_{mode} - x_{min} - x_{max})}{(x_{mode} - \mu)(x_{max} - x_{min})}$$

$$w = \frac{v(x_{max} - \mu)}{(\mu - x_{min})}$$

3. **Sampling:** Generate random samples for each variable from their respective distributions. These samples represent possible values that the variables could realistically assume under actual scenarios.

4. **Computation:** Apply the mathematical model to the sampled values. This step involves computing the outputs or results of the model based on the input samples. In this case, based on the samples generated, we compute the total cost of the project.

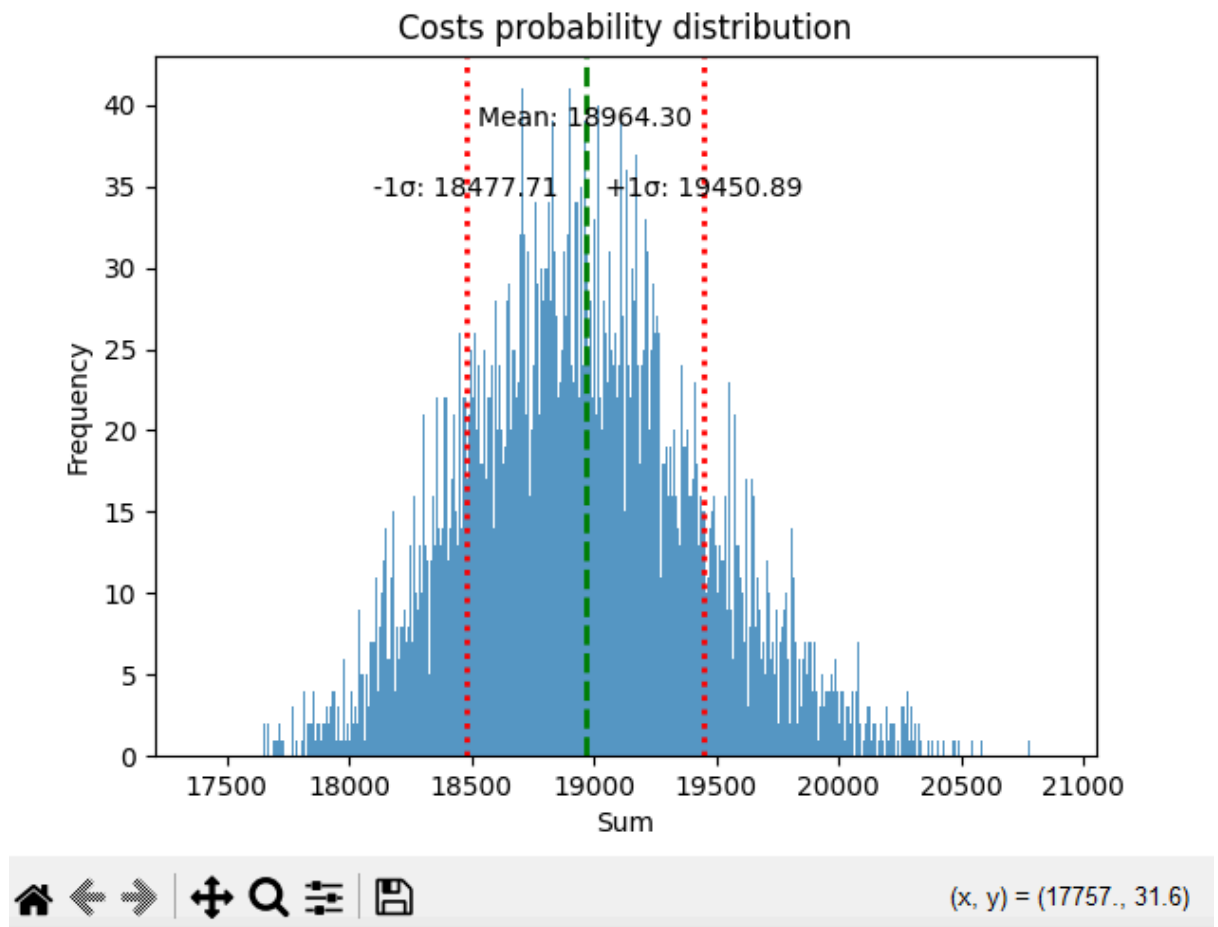
Montecarlo Simulation for Project Management

5. **Analysis of Results:** The outputs generated from these computations form a new distribution of possible outcomes, from which key statistical measures can be derived:
 - **Mean:** Provides an estimate of the expected outcome or central tendency of the results. This is often considered the most likely outcome of the process being modeled.
 - **Standard Deviation:** Offers a measure of variability or uncertainty in the outcomes. It indicates how spread out the results are from the mean, providing insights into the potential risk or volatility of the modeled scenario.

Montecarlo Simulation for Project Management

Phases Costs

Figure 0



Costs output Report

```
=====
Number of simulations:          10000
Mean of distribution:           18964.30
Standard deviation:             486.59
```

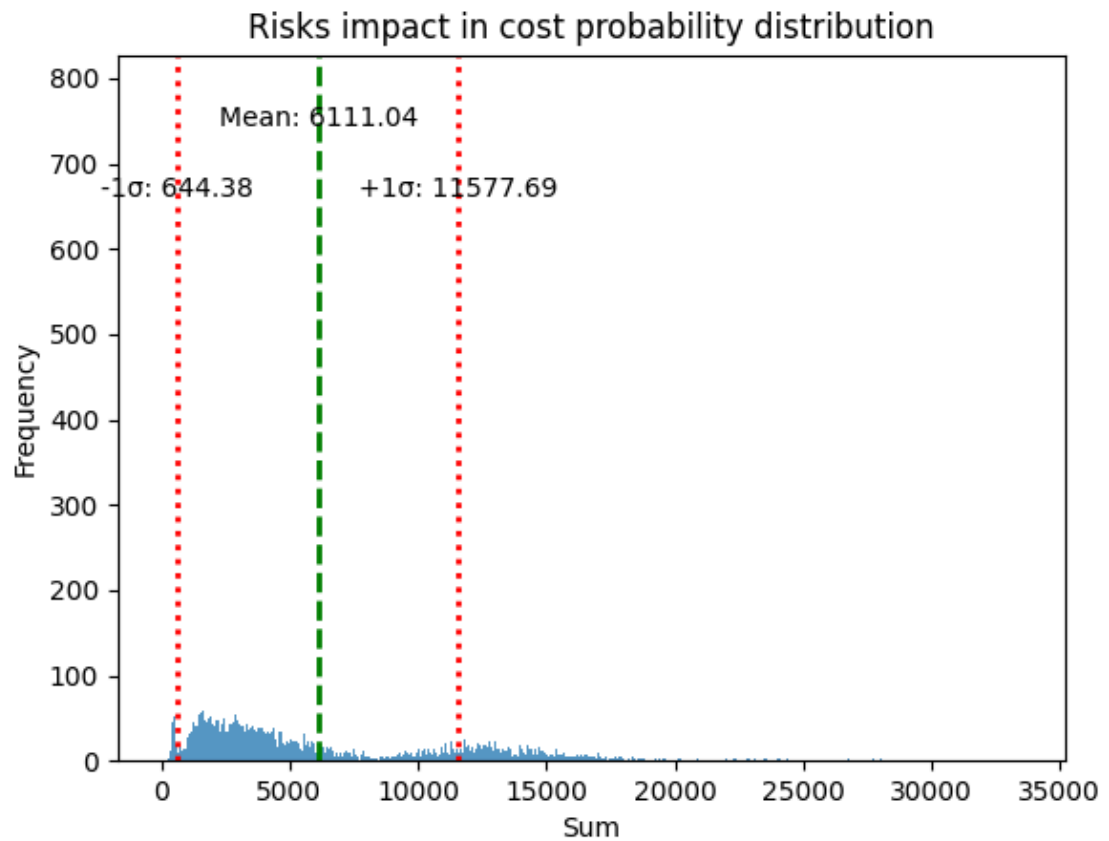
Confidence Intervals for Costs:

```
-----
68% (1 sigma)                  18477.71 - 19450.89
95% (2 sigma)                  17991.11 - 19937.48
99.7% (3 sigma)                17504.52 - 20424.07
=====
```

End of Report

Montecarlo Simulation for Project Management

Risks Impact

**Risks impact in cost output Report**

```
=====
Number of simulations:                10000
Mean of distribution:                 6111.04
Standard deviation:                   5466.66
```

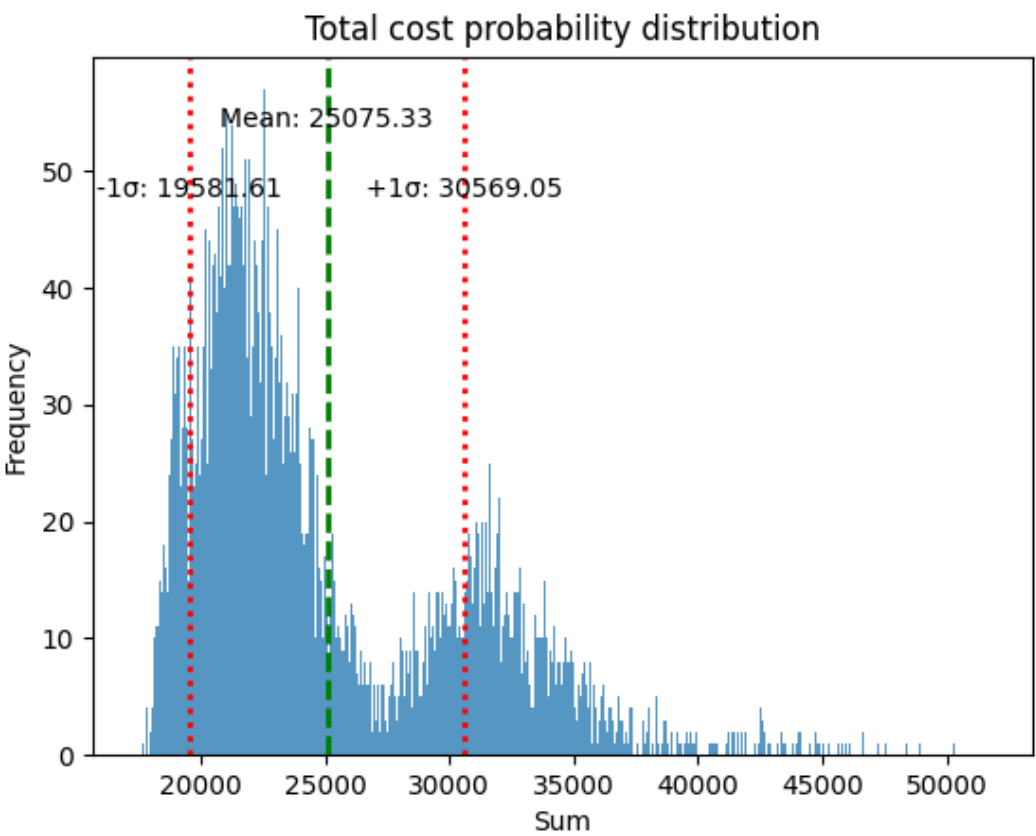
Confidence Intervals for Risks impact in cost:

```
-----
68% (1 sigma)                        644.38 - 11577.69
95% (2 sigma)                        0.00 - 17044.35
99.7% (3 sigma)                      0.00 - 22511.01
=====
```

End of Report

Montecarlo Simulation for Project Management

Total Costs



Total cost output Report	
=====	
Number of simulations:	10000
Mean of distribution:	25075.33
Standard deviation:	5493.72
Confidence Intervals for Total cost:	

68% (1 sigma)	19581.61 - 30569.05
95% (2 sigma)	14087.90 - 36062.77
99.7% (3 sigma)	8594.18 - 41556.49
=====	
End of Report	

Montecarlo Simulation for Project Management

6. **Confidence Intervals:** A confidence interval is a range of values used to estimate the true value of a parameter based on a statistical sample. In Monte Carlo simulations:
- **Purpose:** Confidence intervals provide a measure of uncertainty around the computed mean of simulation outcomes. They help to understand the precision of the simulation results and how they might vary if the experiment were repeated under the same conditions.
 - **Calculation:** Typically, a confidence interval for the mean is calculated using the sample mean plus or minus a margin of error. The margin of error depends on the standard deviation of the sample and the desired confidence level (commonly 95%). This margin is adjusted by the critical value from the z-distribution (approximately 1.96 for 95% confidence).

Phases Cost

Confidence Intervals for Costs:

68% (1 sigma)	18477.71 - 19450.89
95% (2 sigma)	17991.11 - 19937.48
99.7% (3 sigma)	17504.52 - 20424.07

End of Report

Risks Impact

Confidence Intervals for Risks impact in cost:

68% (1 sigma)	644.38 - 11577.69
95% (2 sigma)	0.00 - 17044.35
99.7% (3 sigma)	0.00 - 22511.01

End of Report

Montecarlo Simulation for Project Management

Total Costs

Confidence Intervals for Total cost:

68% (1 sigma)	19581.61 - 30569.05
95% (2 sigma)	14087.90 - 36062.77
99.7% (3 sigma)	8594.18 - 41556.49

End of Report

7. **Interpretation:** Use the statistical results to make informed decisions or predictions. The mean provides a central value, while the standard deviation informs about the range of outcomes that are likely around the mean. Wider spreads indicate greater uncertainty and risk.

References

RiskAMP. (n.d.). Beta PERT. Retrieved 18/06/2024, from <https://www.riskamp.com/beta-pert>

Guttag, J. (2017, May 19). MIT 6.0002 Introduction to Computational Thinking and Data Science, Monte Carlo Simulation, Fall 2016 [Video]. YouTube. <https://www.youtube.com/watch?v=OgO1gpXSUzU>