What is Monte Carlo Simulation?

Monte Carlo simulation, or probability simulation, is a technique used to understand the impact of risk and uncertainty in financial, project management, cost, and other forecasting models.

Uncertainty in Forecasting Models

When you develop a forecasting model – any model that plans ahead for the future – you make certain assumptions. These might be assumptions about the investment return on a portfolio, the cost of a construction project, or how long it will take to complete a certain task. Because these are projections into the future, the best you can do is estimate the expected value.

You can't know with certainty what the actual value will be, but based on historical data, or expertise in the field, or past experience, you can draw an estimate. While this estimate is useful for developing a model, it contains some inherent uncertainty and risk, because it's an estimate of an unknown value.

Estimating Ranges of Values

In some cases, it's possible to estimate a range of values. In a construction project, you might estimate the time it will take to complete a particular job; based on some expert knowledge, you can also estimate the absolute maximum time it might take, in the worst possible case, and the absolute minimum time, in the best possible case. The same could be done for project costs. In a financial market, you might know the distribution of possible values through the *mean* and *standard deviation* of returns.

By using a range of possible values, instead of a single guess, you can create a more realistic picture of what might happen in the future. When a model is based on ranges of estimates, the output of the model will also be a range.

This is different from a normal forecasting model, in which you start with some fixed estimates – say the time it will take to complete each of three parts of a project – and end up with another value – the total time for the project. If the same model were based on ranges of estimates for each of the three parts of the project, the result would be a range of times it might take to complete the project. When each part has a minimum and maximum estimate, we can use those values to estimate the total minimum and maximum time for the project.

What Monte Carlo Simulation can Tell You

When you have a range of values as a result, you are beginning to understand the risk and uncertainty in the model. The key feature of a Monte Carlo simulation is that it can tell you – based on how you create the ranges of estimates – how *likely* the resulting outcomes are.

How It Works

In a Monte Carlo simulation, a random value is selected for each of the tasks, based on the range of estimates. The model is calculated based on this random value. The result of the model is recorded, and the process is repeated. A typical Monte Carlo simulation calculates the model hundreds or thousands of times, each time using different randomly-selected values.

When the simulation is complete, we have a large number of results from the model, each based on random input values. These results are used to describe the likelihood, or probability, of reaching various results in the model.

For Example

For example, consider the model described above: we are estimating the total time it will take to complete a particular project. In this case, it's a construction project, with three parts. The parts have to be done one after the other, so the total time for the project will be the sum of the three parts. All the times are in months.

Task	Time Estimate			
Job 1	5 Months			
Job 2	4 Months			
Job 3	5 Months			
Total	14 Months			

Table 1: Basic Forecasting Model

In the simplest case, we create a single estimate for each of the three parts of the project. This model gives us a result for the total time: 14 months. But this value is based on three estimates, each of which is an unknown value. It might be a good estimate, but this model can't tell us anything about risk. How likely is it that the project will be completed on time?

To create a model we can use in a Monte Carlo simulation, we create three estimates for each part of the project. For each task, we estimate the minimum and maximum expected time (based on our experience, or expertise, or historical information). We use these with the “most likely” estimate, the one that we used above:

Task	Minimum	Most Likely	Maximum	
Job 1	4 Months	5 Months	7 Months	
Job 2	3 Months	4 Months	6 Months	
Job 3	4 Months	5 Months	6 Months	
Total	11 Months	14 Months	19 Months	

Table 2: Forecasting Model Using Range Estimates

This model contains a bit more information. Now there is a range of possible outcomes. The project might be completed in as little as 11 months, or as long as 19 months.

In the Monte Carlo simulation, we will randomly generate values for each of the tasks, then calculate the total time to completion[1]. The simulation will be run 500 times. Based on the results of the simulation, we will be able to describe some of the characteristics of the risk in the model.

To test the likelihood of a particular result, we count how many times the model returned that result in the simulation. In this case, we want to know how many times the result was less than or equal to a particular number of months.

Time	Number of Times (Out of 500)	Percent of Total (Rounded)	
12 Months	1	0%	
13 Months	31	6%	
14 Months	171	34%	
15 Months	394	79%	
16 Months	482	96%	
17 Months	499	100%	
18 Months	500	100%	

Table 3: Results of a Monte Carlo Simulation

The original estimate for the “most likely”, or expected case, was 14 months. From the Monte Carlo simulation, however, we can see that out of 500 trials using random values, the total time was 14 months or less in only 34% of the cases.

Put another way, in the simulation there is only a 34% chance – about 1 out of 3 – that any individual trial will result in a total time of 14 months or less. On the other hand, there is a 79% chance that the project will be completed within 15 months. Further, the model demonstrates that it is extremely unlikely, in the simulation, that we will ever fall at the absolute minimum or maximum total values.

This demonstrates the risk in the model. Based on this information, we might make different choices when planning the project. In construction, for example, this information might have an impact on our financing, insurance, permits, and hiring needs. Having more information about risk at the beginning means we can make a better plan for going forward.

1 In this example, we use the beta-PERT distribution to generate random values based on a minimum, most likely, and maximum value. The PERT distribution is often used to model estimates of expert data. For more information on this and other probability distributions, see the documentation on our website.

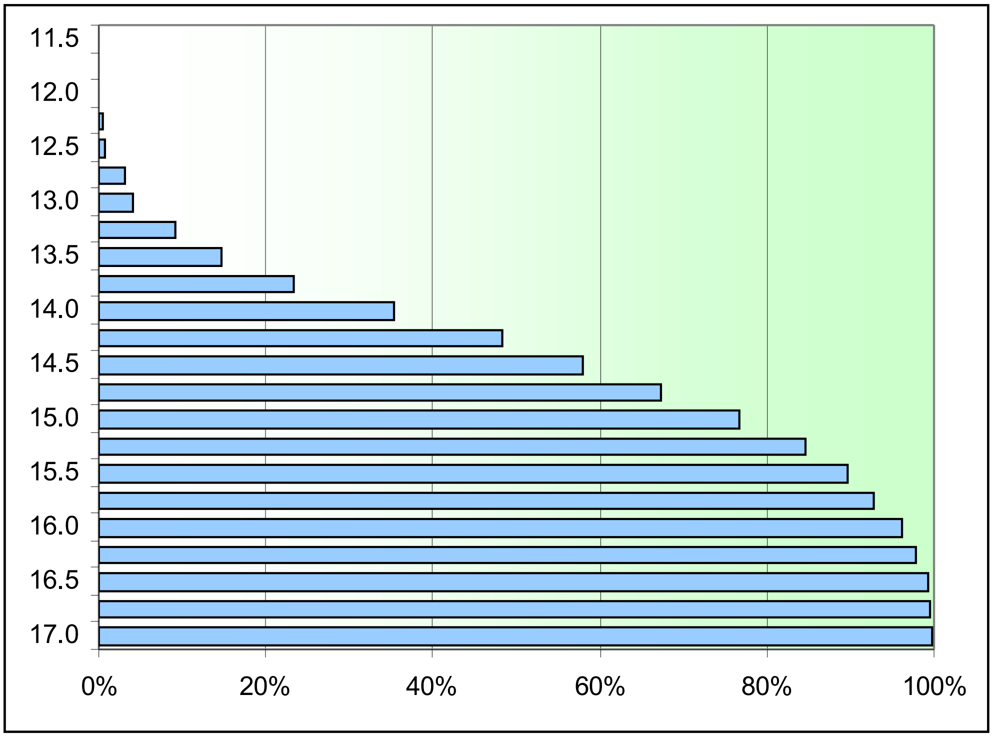

Figure 1: Probability of Completion Within Specified Time (Months)

How Reliable Is It?

Like any forecasting model, the simulation will only be as good as the estimates you make. It's important to remember that the simulation only represents probabilities and not certainty. Nevertheless, Monte Carlo simulation can be a valuable tool when forecasting an unknown future.

About RiskAMP

RiskAMP is a Monte Carlo simulation engine that works with Microsoft Excel®. The RiskAMP Add-in adds comprehensive probability simulation to spreadsheet models and Excel® applications. The Add-in includes 22 random distributions, 17 statistical analysis functions, a wizard for creating charts and graphs, and VBA® support – all for a fraction of the price of competing packages.

For more information, visit our website at http://www.riskAMP.com.