Risk Analysis using Monte Carlo Simulation

When, and where, is a Monte Carlo analysis appropriate? This paper gives an overview of Monte Carlo analysis, and describes the circumstances in which a Monte Carlo analysis can be used to effectively model risk and probability scenarios.

Overview of Monte Carlo Simulation

In any given scenario, such as planning construction time schedules or calculating possible return on a stock portfolio, there are values which cannot be known with certainty. In these cases, it is possible to estimate some probable or likely value for each variable, but that estimate is just a guess – over all the available values, you have to select one.

Imagine a construction schedule that requires 5 tasks to be completed in sequence. Based on professional experience, we can estimate the most likely time to complete each task. The sum of these estimates becomes the estimate for the entire project. We will call this the "most likely" estimate.

	Task 1	Task 2	Task 3	Task 4	Task 5	Total
Most Likely	10	20	30	20	20	100

That estimate, however, is totally reliant on the accuracy of our estimations. If we believe that we can estimate with 100% reliability, then this number should be fine. If not, then the entire schedule is probably incorrect, and we will complete the project either early or late.

Next, we might try to estimate the maximum or minimum time for each task, and then calculate a maximum or minimum time for the entire project. This is useful, because it is now possible to know the absolute bounds of the project – but in a real project, the range of time between absolute minimum and absolute maximum can be very large. We still need some method to determine the range of probable times.

	Task 1	Task 2	Task 3	Task 4	Task 5	Total
Minimum	5	10	25	10	10	60
Most Likely	10	20	30	20	20	100
Maximum	15	30	35	25	25	130

In the real world, the likelihood is that some tasks will be completed early, some will be completed late, and others will be completed on time. The time it takes to complete each individual task can be described as effectively random – it will be some time between the maximum and minimum – and the total schedule time will be the sum of these random variables. More importantly, the time to complete each project is *independent:* each task must be considered separately, and will not be affected by the other tasks.

In this situation, we can apply a Monte Carlo simulation to determine the probability of completion within a specific time frame. The Monte Carlo simulation cannot tell with certainty what the exact completion date will be, but it can describe the probability, or the *risk,* of completing the project within our estimated time frame.

In a Monte Carlo simulation, we use computer software to assign random values to each unknown variable in our model. In the construction case, we assign a random value – based on our estimates of minimum, maximum, and most likely times – to each task. The total time to complete the project is then calculated.

	Task 1	Task 2	Task 3	Task 4	Task 5	Total
Random (T)	11.5	25.9	32.7	23.6	21.5	115.2

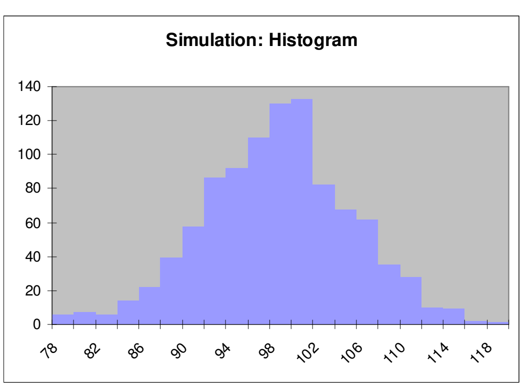
If we calculated just a single set of random variables, the value would be no more reliable than our original estimate. The key to the Monte Carlo simulation is that each variable is assigned a random value – and the total value is calculated – hundreds or even thousands of times during the simulation.

Each time we assign values and calculate the total is referred to as a *trial,* or *iteration,* of the simulation. As the software processes each iteration, the resulting total value is recorded.

Once the simulation is complete, the result is a set of probabilities that the total value – in this case, the total schedule time for the construction project – will fall within certain ranges. For example, if 70% of the iterations of the simulation result in a value lower than our most likely estimate, we can say that there is a 70% chance we will meet that estimate. While this is not a guarantee, it allows us to understand the *risk* that we will not meet our original estimate, and take appropriate precautions. Imagine if the simulation showed only a 30% chance of completion within our most likely estimate – in that case, it might be prudent to revise our schedule or price.

Over 1000 Iterations					Average	96.7
					Min	76.1
					Max	116.8
					Median	96.9
Probability of completion within Most Likely (100)						70%

Also notable is the calculation of minimum and maximum values. In this simulation, with independent values, the observed minimum – that is, the absolute minimum over all iterations of the simulation – is much higher than our original estimated minimum. We can look at the distribution of results via charts, such as a *histogram,* which displays how often the result falls within certain defined ranges (called *bins* in the histogram).



In this example, the *mean* (average) is close to the original most likely estimate of 100, but more values fall below than above the mean – meaning it is more likely we will be under than over the original estimate.

When is a Monte Carlo Simulation Appropriate?

A Monte Carlo simulation can be used in situations where (1) the outcome of some calculation is based on a mathematical relationship among several variables; and (2) those variables are unknown, but can be modeled according to some random distribution.

It is important to note that random variables in a Monte Carlo simulation are assigned independently. As the mathematical relationship between multiple variables becomes more complex, reliable estimates of models can become more and more difficult. If dependent estimates are used – such as using the minimum or maximum value for each variable – the model will become more and more unreliable. Using a Monte Carlo analysis therefore becomes more valuable as the model becomes more complex, because each iteration of the model contains random, independent values for each unknown variable.

The main requirement of using a Monte Carlo simulation to analyze risk is that the unknown variables follow some known random *distribution*. In the example above, the model assumes that we can know the minimum, maximum, and most likely values for each input variable. It further assumes that the value, in any iteration, follows a particular distribution. In the example, the distribution used was the triangular distribution. Different distributions will return different results, and selection of an appropriate distribution is very important when developing a Monte Carlo simulation.

Monte Carlo simulation is described as “Quantitative Risk Analysis”. When used appropriately, a Monte Carlo simulation can quantify and describe the risks associated with a mathematical model based on an independent set of random variables.

The RiskAMP Monte Carlo Add-In for Excel

The RiskAMP Monte Carlo Add-in for Excel provides comprehensive Monte Carlo simulation support within Excel. The Add-In handles inserting random values for variables, provides a large number of random distributions for modeling scenarios, and provides a number of statistical functions for analyzing the simulation.

With the RiskAMP Add-In, any Excel spreadsheet can be modeled using a Monte Carlo simulation. The Add-In uses the Excel calculation engine for each iteration, so any mathematical relationship which can be described in Excel can be part of the simulation. Once the simulation is complete, you can insert results into spreadsheets directly using the Add-In functions, or use a simple Wizard interface to quickly generate charts and statistical results tables.

The RiskAMP Monte Carlo Add-In for Excel is available for trial download at http://www.RiskAMP.com. The RiskAMP Add-In works with Excel 97 and later on Windows 98, NT, 2000 and XP.