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MONTE CARLO SIMULATION AS A TOOL FOR TECHNICAL MODELLING AND PROJECT ANALYSIS

by

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Abstract

New sugar industry projects cost many millions of dollars to complete, so it is not surprising that project financiers want both the technical and financial risks to be properly examined. Conventional deterministic methods for "what-if" scenarios or sensitivity analyses can be not only tedious to undertake but presenting the results to decision makers can be challenging. Monte Carlo simulation provides a means to not only overcome the limitations of conventional methods but at the same time add levels of sophistication to the analysis that are not otherwise possible. One such advantage is the ability to use a variety of probability distributions to define each input variable. Monte Carlo simulation involves running thousands of scenarios with a dozen or more variables varying simultaneously, to yield the key outputs as probability plots for ready presentation and interpretation. Modern computers and software tools now make it possible to prepare such models and present the results without the need for PhDs in mathematics, computer science and graphic art. This paper presents the Monte Carlo simulation of a hypothetical sugar industry cogeneration case study. The simulation includes the mass and energy balance for a sugar factory cogeneration plant, to quantify the effects of changing cane quality on power production. The outputs from the technical model are then combined with a discounted cash flow analysis to quantify the financial aspects of the project. The outputs are described and the benefits of the Monte Carlo approach over the more commonly used deterministic sensitivity analysis method are highlighted. The paper concludes with some references for further reading, including a list of potential sources for Monte Carlo simulation tools.

Introduction

The sugar industry, like any other business, uses a variety of tools to assist investment decision making. Given that most of these decisions involve risking many millions of dollars, it is not surprising that project financiers want both the technical and financial risks to be properly examined.

The conventional approach to project evaluation typically includes a technical model combined with a financial model which usually concludes with a discounted cash flow analysis. These models are then manipulated so that a series of "what-if" scenarios or sensitivity analyses are undertaken. For example, the individual may ask the questions: "What happens to project returns if input X increases by 10%"; "What if input X increases by 10% and input Y decreases by 25% ?". Given that a typical project evaluation may involve in excess of a dozen input variables, using discrete (ie. point value) spreadsheet modelling methods to assess the impact of so many variables can be not only tedious, but often presents considerable challenges when communicating the outputs to decision makers.

Savvakis (1994) provided a thorough outline of financial project risk analysis processes based on Monte Carlo analysis. A summary of the key considerations in project evaluation, as outlined by Savvakis is as follows:

- "The evaluation of project risk … depends … on our ability to identify and understand the nature of uncertainty surrounding the key project variables and … having the tools and methodology to process its risk implications on the return of the project"
- Relying on single point values derived from expert opinion or even historical data can create biases in the project evaluation either as a result of the combination of conservative estimates or the unrealistic combination of values in a single scenario (eg. best case outcome for all inputs, or independent manipulation of dependent input variables, resulting in infeasible scenarios).
- Using single point (discrete) values for project inputs in an evaluation, even when best, expected and worst case scenarios are presented, implies that there is a degree of certainty in the forecast project performance that can mislead investment decision makers and certainly leaves them poorly informed about the probability or risk that the end result will be different from the expected result.

The Monte Carlo method / Monte Carlo integration / Monte Carlo analysis

The Wikipedia (Anon, 2006) explains that the name Monte Carlo method is a reference to the famous casino in Monaco, in so much as the method's use of randomness and the repetitive nature of the process are analogous to the activities in a casino.

In essence, Monte Carlo methods involve randomly and simultaneously varying the chosen inputs to a mathematical model (typically represented in a spreadsheet) to yield outputs as a range of possible outcomes, i.e. a set of probability distributions. The key to the method is that, even though the inputs are varied randomly, the set of random values for each input are constrained to fit a user defined probability distribution, which is intended to reflect the real world chance of a given value occurring. For example, many "natural" inputs, such as weather conditions, crop yields etc. can be expected to fit the bell-shaped normal distribution. In contrast, artificial inputs, such as wage rates may have a much narrower and/or uniform (equal probability) distribution. Figure 1 illustrates this input sampling approach for the case where only 100 samples are used versus a much larger number. This highlights the requirement for Monte Carlo methods to be based on thousands of samples/iterations.

For those not familiar with probability frequency distribution diagrams, the x-axis gives the value of the variable and the y-axis is the probability that the variable will have that value within the set of samples or iterations taken. For example, in the desired normal distribution shown in Figure 1, the greatest probability is that the value will be 14% fibre in cane, or more specifically by looking at the area under the curve there is a 90% probability that it will lie between 13.01 and 14.99% fibre. Similarly, there is a smaller than 10% chance that it will be outside this range. Note the desired distribution has been defined as having a mean of 14% fibre in cane with a standard deviation of 0.6 percentage units around this mean and then truncated so values below 10 and above 16.5 do not occur. This method of defining the inputs is relatively common across the various spreadsheet based tools available for Monte Carlo analysis. The more samples that are taken, the smoother the diagram becomes and the more closely it approximates the desired distribution.

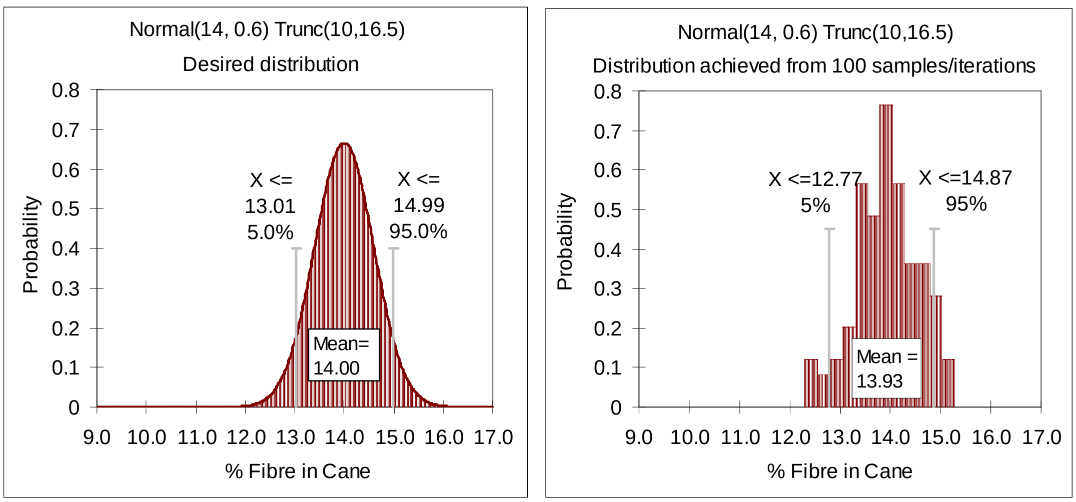

Fig. 1 Example of fibre in cane as a Monte Carlo method input variable presented in probability frequency distribution form. The two plots contrast an ideal distribution with that based on a limited sample size

The requirement for thousands of samples to accurately represent the desired input probability distribution for the inputs is one reason why Monte Carlo methods had not been widely used in project evaluation until the advent of sufficiently low cost computing power. Modern Monte Carlo simulation tools make it possible to run, in a matter of seconds, thousands of scenarios with dozens of variables varying simultaneously, to yield the key outputs as probability plots for ready presentation and interpretation. Similarly, there are now software tools that allow such models to be prepared and the results presented without the need for the user to have PhDs in mathematics, computer science and graphic art.

Figure 2 illustrates the basic structure of a typical spreadsheet based Monte Carlo simulation and as used for the example presented in this paper. The authors have used this technique for models with in excess of 75 inputs, for both pure research / technical modelling, as well as project financial evaluation.

To illustrate one of the many possible applications for Monte Carlo analysis, this paper presents the analysis of a hypothetical sugar industry cogeneration case study. The simulation includes a mass and energy balance for a sugar factory cogeneration plant, to quantify the effects of changing cane quality on power production, which is then combined with a discounted cash flow analysis to quantify the financial aspects of the project.

Techno-financial model

The cogeneration model used in this analysis consisted of six worksheets namely:

- Inputs (24 in total, for both technical and financial parameters. Only 6 of these inputs were varied for the analysis illustrated in this paper, to simplify presentation of the process)
- Fuel balance (for the bagasse and supplementary fuel usage both in and out of the crushing season)
- Cogeneration plant sizing and mass/energy balance (taking into account fuel supply, factory steam/electrical demand and cogeneration plant efficiency)
- Operating/maintenance cost calculations
- Capital cost estimation
- Financials, including discounted cash-flow (DCF) worksheet and internal rate of return (IRR) calculations.

The data presented by Hodgson and Hocking (2006) was used as a general guide in setting the plant size, bagasse fibre content, supplementary fuel availability, capital cost, operating cost and maintenance cost parameters for the model. The primary departure is that the technical model assumes the entire boiler capacity of the factory is dedicated to cogeneration, which yields a larger net power output than the retrofit arrangement described by Hodgson and Hocking.

The remaining inputs and the probability distributions used in the modelling process are based on the authors' experience for Australian conditions. A hurdle rate of 10% was assumed, i.e. the after tax internal rate of return must be greater than 10% for the project to be considered worthwhile by the equity owners.

The shapes of the technical and financial input probability distributions used in the analysis are illustrated in Figure 2. These include a skewed Weibull type distribution for crop size, a normal distribution for % fibre in cane, a uniform distribution for supplementary fuel availability (in recognition of the arbitrary nature of this variable and to allow direct testing of the influence of this variable on the project outcome), a truncated normal distribution for the capital cost function, and finally uniform distributions for the debt finance ratio and loan interest rate (again in recognition of the arbitrary nature of this variable).

The cogeneration plant net generating efficiency had to be set to a single value, as this is dependent on the forecast capital cost, i.e. it would be unrealistic to allow the plant efficiency to vary to a high value independently of the capital cost of the equipment. Hence, the capital cost distribution was based on a given, i.e. fixed, plant efficiency.

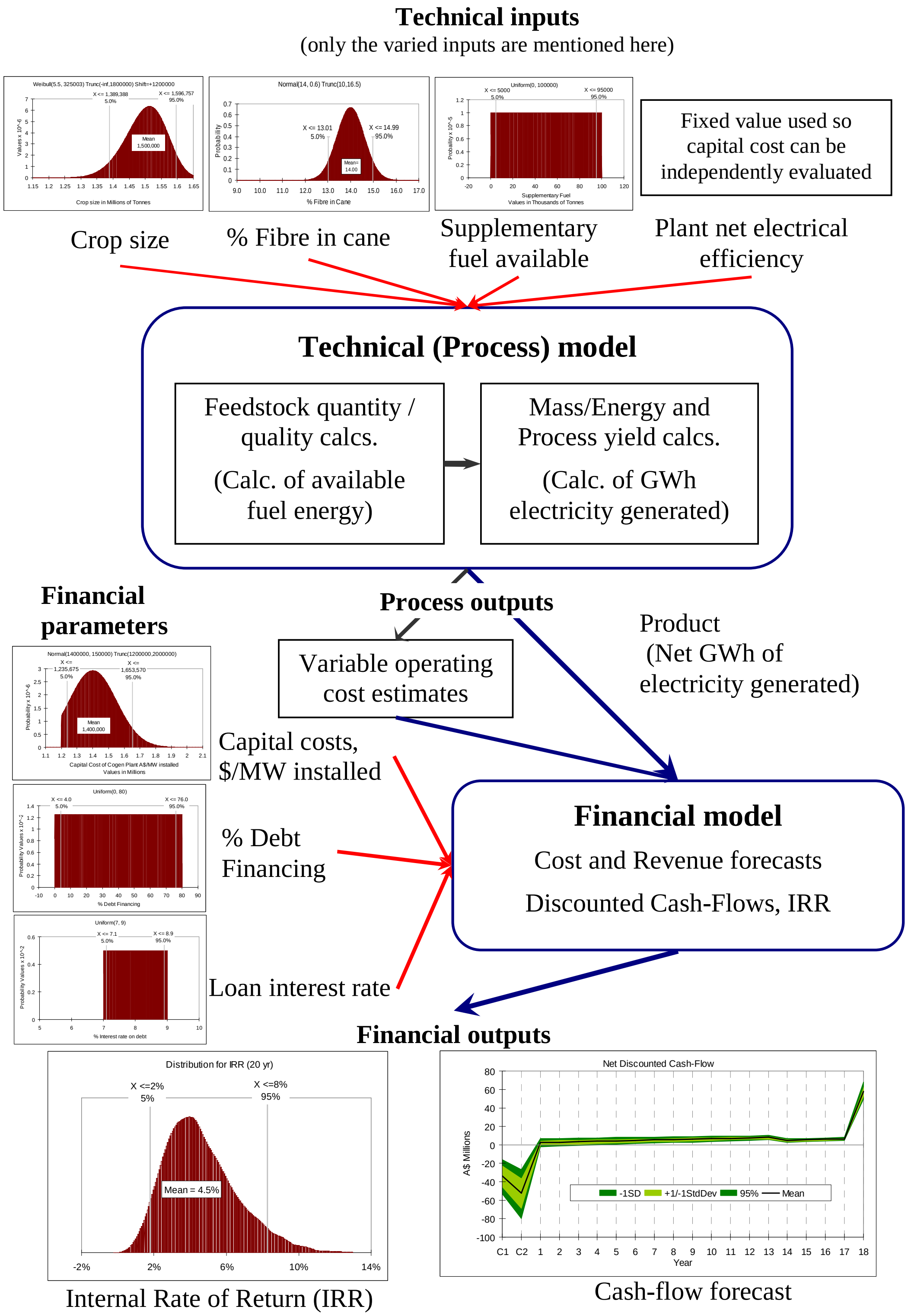

Fig. 2 – Outline of the Monte Carlo Procedure

Results and Discussion

The cogeneration model took approximately two days to prepare and debug. The subsequent Monte Carlo analysis took under four hours to implement, with a 10 000 step simulation taking under a minute to run on a standard laptop PC.

The results of the analysis are presented in Figures 3, 4 and 5.

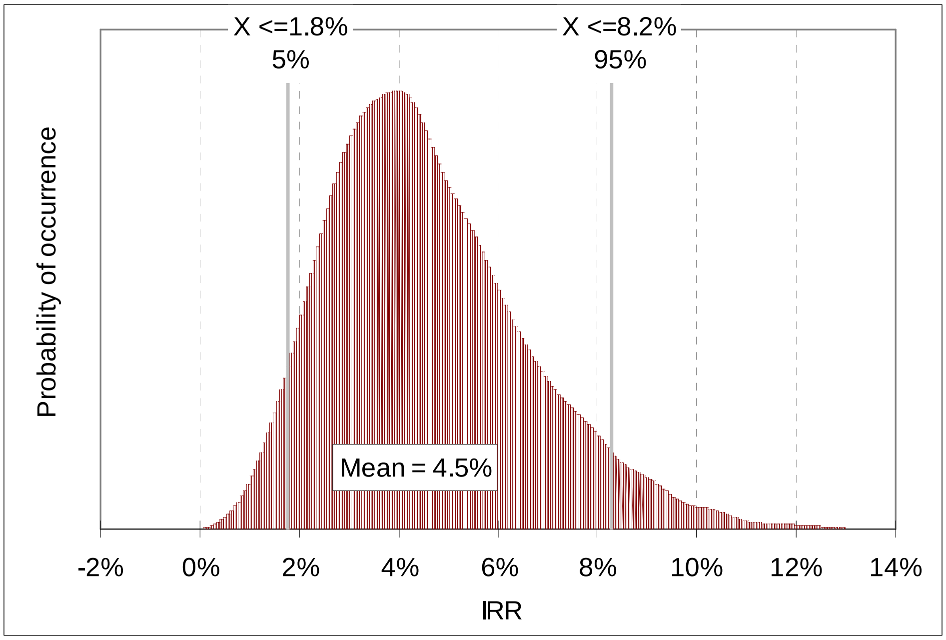

Fig. 3 – Forecast Rate of Return

Based on the results illustrated in Figure 3 the forecast internal rate of return (IRR) shows a 90% confidence interval of 1.8%-8.2% and an expected outcome of 4.5%. Similarly, negative returns appear unlikely and returns up to 10% are possible. The probability distribution shows a skew away from the higher possible returns, which indicates that ideal performance of the investment is not easily achieved. Overall the predicted returns are less than the 10% hurdle rate used for the project, so it is clear that further work is required to address the deficiency in the expected performance.

Figure 4, a Tornado plot generated by a multiple regression analysis of IRR against the input variables, helps to highlight which of the key inputs are influencing the IRR of the project and thus which aspects deserve attention if the project is to be given the go-ahead. In Figure 4 the bars with positive values indicate a positive rate of change of IRR with that specific input. Similarly, negative values indicate a negative correlation between IRR and those inputs (ie. Steam plant capital costs and finance interest rate). The magnitude of the bars represents the relative influence of the inputs on IRR. This form of plot is generated by all of the commonly used commercial Monte Carlo analysis tools.

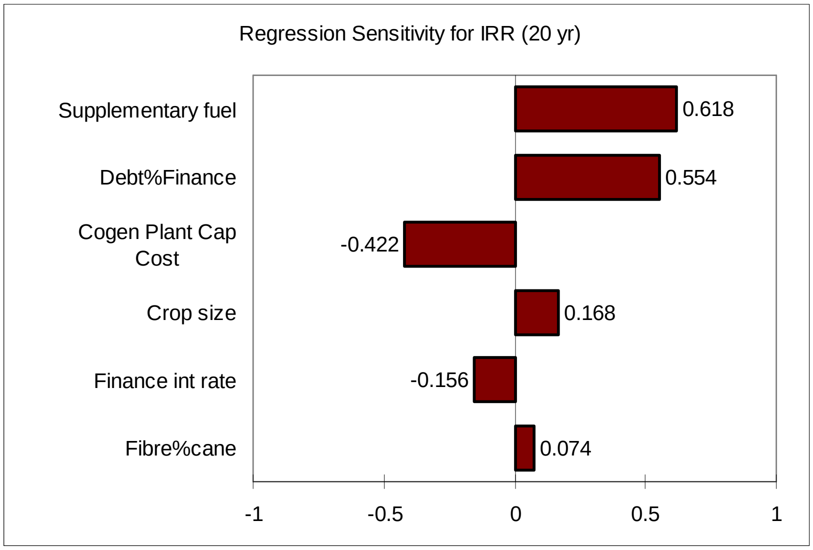

Fig. 4 – Sensitivity analysis (Tornado plot)

Figure 5 gives a time series probability plot for net cash flow. This indicates that the cash flow of the project is expected to rise above zero in the first year of operation of the plant. However, there is a 5% chance that it will be very close to zero for the first four or five years. In addition, Figure 5 shows that the owner's equity (ie. funds outlaid during the two construction years) is very variable, as expected because this results from the varying of the debt financing ratio. Obviously, debt financing reduces exposure of the equity owners during the initial period of the project, and interestingly the narrowness of the curve in the later years suggests that debt financing appears to have little long-term influence on the net cash flow. Thus one can conclude that maximising the debt financing ratio is one way to minimise the risk to the equity owners for relatively little impact on their return. In the Australian context, where lending institution interest rates are lower than equity market expected returns, this is a common finding. However, this may not be the case in other economies.

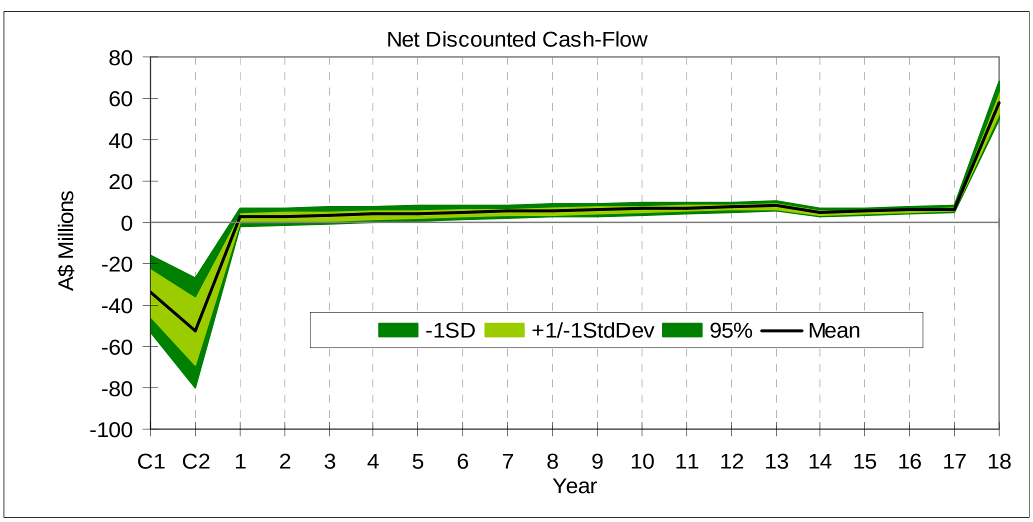

Fig. 5 – Forecast Net Discounted Cash Flow

Conclusions

For the worked example, it is evident that the project is most strongly influenced by the amount of supplementary fuel made available to the cogeneration plant, followed by the debt financing ratio and the capital cost of the cogeneration plant itself. The significance of other factors such as power selling price or operating/maintenance costs was not included in the analysis. In essence, these were assumed to have little inherent uncertainty/variability and/or there is little scope for the project proponents to influence these variables.

The importance of the fuel supply to cogeneration project economics has been found time and again by the authors to be one of the keys to project economics. This highlights the need for such projects to secure as much fuel as possible (be it bagasse or supplementary fuels) and to ensure that this fuel supply can be guaranteed. At least one sugar cogeneration project in Australia has failed financially because the supplementary fuel supply was not adequately secured.

Similarly, the key role played by up-front capital costs in overall project performance is a feature of most large projects.

Finally, the influence of debt financing, in this instance, is directly as a result of the cost of debt capital being less than the cost of equity (ie. the equity owners have higher expectations for financial return on funds invested than the lending institutions).

The Monte Carlo analysis method outlined here has illustrated the ease with which a spreadsheet model can be used to rapidly analyse and present the outcomes of a project evaluation. The example was a cogeneration project. However, the method could equally well be applied to by-product plant investments such as ethanol, stockfeeds or speciality chemicals. Similarly, the authors have found Monte Carlo methods and the associated sensitivity analysis outputs very useful for purely technical modelling, such as mass, energy and chemical species balances in complex advanced power generation cycles.

Recommendations for further reading on Monte Carlo analysis

For further reading on the application of Monte Carlo techniques the following resources are recommended:

Introduction to Monte Carlo simulation. This reference is provided by Microsoft Corporation and has specific instructions on how to use Monte Carlo methods in MS-Excel®. http://office.microsoft.com/en-au/excel/HA011118931033.aspx

Savvakis Savvides, Risk Analysis in Investment Appraisal, Project Appraisal Journal, Vol. 9, No. 1, March 1994. Available at SSRN: http://ssrn.com/abstract=265905 or DOI: 10.2139/ssrn.265905

The resources supplied by Monte Carlo Simulation software providers are also very useful. A selection of the commonly used Monte Carlo simulation software tools is as follows:

- @Risk by Palisade Asia-Pacific Pty Limited. A suite of fully featured Monte Carlo Simulation and decision support packages for Microsoft Excel®. See www.palisade.com.au .
- CrystalBall by Decisioneering Inc. A suite of fully featured Monte Carlo Simulation and decision support packages for Microsoft Excel®. See www.decisioneering.com .
- GoldSim by GoldSim Technology Group. One of very few non-spreadsheet based modelling and Monte Carlo analysis software packages. Not recommended for first time or casual users of Monte Carlo methods. See www.goldsim.com .
- Lumenaut by Lumenaut Ltd. An intermediate cost Monte Carlo simulation add-in for Microsoft Excel®. See www.lumenaut.com .
- Riskamp by Structured Data, LLC. A low cost but well featured Monte Carlo simulation add-in for Microsoft Excel®. Approximately one tenth the licence cost of the fully specified decision support packages such as @Risk or Crystal Ball but well suited to standard Monte Carlo analysis. See www.riskamp.com .
- RiskEase by Master Solutions Ltd. An intermediate cost Monte Carlo simulation add-in for Microsoft Excel®. See www.riskease.com .
- w3mcsim – An online Monte Carlo simulation tool for scientists provided by the University of California. The authors do not recommend this tool as spreadsheet based tools will suit most users best. Located at www.biocyb.cs.ucla.edu/montecarlo/montecarlo.html

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