Article

EXPLORING MONTE CARLO SIMULATION APPLICATIONS FOR PROJECT MANAGEMENT

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Abstract

Monte Carlo simulation is a useful technique for modeling and analyzing real-world systems and situations. This paper is a conceptual paper that explores the applications of Monte Carlo simulation for managing project risks and uncertainties. The benefits of Monte Carlo simulation are using quantified data, allowing project managers to better justify and communicate their arguments when senior management is pushing for unrealistic project expectations. Proper risk management education, training, and advancements in computing technology combined with Monte Carlo simulation software allow project managers to implement the method easily. In the field of project management, Monte Carlo simulation can quantify the effects of risk and uncertainty in project schedules and budgets, giving the project manager a statistical indicator of project performance such as target project completion date and budget.

Keywords

Monte Carlo simulation, project management, risk analysis and management, exploratory study

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Introduction

The area of risk management has received significant recognition in the field of project management in recent years (Kwak and Stoddard, 2004). Project managers and their superiors discovered that the process of identification, analysis, and assessment of possible project risks benefits them greatly in developing risk mitigation and contingency plans for complex project (Charette, 1996). This planning, in turn, helps the project manager better handle the difficult situations that invariably occur during projects, and therefore allows for more successful project completion.

One method used by some project managers during the risk analysis process is Monte Carlo simulation applications. This activity has been widely used for decades to simulate various mathematical and scientific situations, and it is mentioned often in project management curricula and standards, such as *A Guide to the Project Management Body of Knowledge* (Project Management Institute, 2004). Monte Carlo simulation has not yet, however, found a strong footing in the actual practice of project management in the "real world".

This paper reviews the applications of Monte Carlo simulation and its relevance to risk management and analysis in project management. It also outlines the uses of Monte Carlo simulation in other disciplines and in the field of project management. Finally, it discusses the pros and cons of Monte Carlo simulation applications in project management environment, some examples of proposed improvements or alternatives to Monte Carlo simulation, and concludes with a recommendation that more project managers should take advantage of this simple and useful tool in managing project risks and uncertainties.

Overview of Monte Carlo simulation

Brief history of Monte Carlo simulation

The Monte Carlo simulation encompasses "any technique of statistical sampling employed to approximate solutions to quantitative problems" (Monte Carlo Method, 2005). A model or a real-life system or situation is developed, and this model contains certain variables. These variables have different possible values, represented by a probability distribution function of the values for each variable. The Monte Carlo method simulates the full system many times (hundreds or even thousands of times), each time randomly choosing a value for each variable from its probability distribution. The outcome is a probability distribution of the overall value of the system calculated through the iterations of the model.

The invention of this method, especially the use of computers in making the calculations, has been credited to Stanislaw Ulam, a mathematician working on the US' Manhattan Project during World War II (Eckhardt, 1987). His work with Jon von Neuman and Nicholas Metropolis transformed statistical sampling "from a mathematical curiosity to a formal methodology applicable to a wide variety of problems" (Monte Carlo Method, 2005). Metropolis is actually credited with naming the methodology after the casinos of Monte Carlo, and Ulam and Metropolis published their first paper on the method in 1949 (Metropolis and Ulam, 1949).

Limited applications to project management

With regards to project management, Monte Carlo simulation is

> "a technique that computes or iterates the project cost or schedule many times using input values selected at random from probability distributions of possible costs or durations, to calculate a distribution of possible total project cost or completion dates." (Project Management Institute, 2004).

It is generally mentioned in project management literature under the topic of risk management, although it can also be seen in the areas of time management (scheduling) and cost management (budgeting).

A standard approach to risk management of projects is outlined by the Project Management Institute (2004) that includes six processes: Risk Management Planning, Risk Identification, Risk Qualification, Risk Quantification, Risk Response Planning, and Risk Monitoring and Control. Monte Carlo simulation is usually listed as a method to use during the Risk Quantification process to better quantify the risks to the project schedule and budget. When this method is used, the project manager is able to justify a schedule reserve, budget reserve, or both to deal with the issues that could adversely affect the project.

Although Monte Carlo simulation is documented as a useful method for project management applications, this method has not been used much by project managers in real-world situations, unless it is needed by the organization's project management processes. Until recently, it was difficult to find software and hardware that could perform Monte Carlo simulation for projects. However, the primary constraints with limited usage of Monte Carlo simulation were with project managers' discomfort with statistical approaches, lack of thorough understanding of the method, and the method was perceived as a burden rather than a benefit to the organization when Monte Carlo simulation was implemented heavily.

Monte Carlo simulation applications in various disciplines

Monte Carlo simulation has been successful in areas outside of project management, primarily in fields related to modeling complex systems in biological research, engineering, geophysics, meteorology, computer applications, public health studies, and finance.

Biology and biochemistry

In the biology and biochemistry, Monte Carlo simulation has been used widely to model molecular activity. Berney and Danuser (2003) described their use of Monte Carlo simulation when modeling the fluorescence resonance energy transfer (FRET) technique, which measures the interactions between two molecules. LeBlanc *et al* (2003) described the use of Monte Carlo simulations of molecular systems belonging to complex energetic landscapes, and offered a new approach to improve the convergence of these simulations.

Other areas of Monte Carlo simulation usage related to biology are in the fields of genetics and evolutionary studies. In genetics, Korol *et al* (1998) used Monte Carlo simulation to demonstrate the advantages of multi-trait analysis in detection of linked quantitative trait effects. One challenge in the field of evolutionary studies is the assembly of a "Tree of Life", a comprehensive phylogenetic tree used to better understand evolutionary processes. Salamin *et al* (2005) have used Monte Carlo simulation to reconstruct large trees such as the Tree of Life, with parameters inferred from four large angiosperm DNA matrices, which could radically assist researchers in creating this tree.

Engineering

In the field of computer engineering and design, Bhanot *et al* (2005) described the use of simulation when optimizing the problem layout of IBM's Blue Gene®/L supercomputer. In geophysical engineering, Monte Carlo analysis has been used to predict slope stability given a variety of factors (El-Ramly, Morgenstern and Cruden, 2002). In marine engineering, Santos and Guedes Soares (2005) described a probabilistic methodology they have developed to assess damaged ship survivability based on Monte Carlo simulation. Lei *et al* (1999) explained their use of Monte Carlo simulation in aerospace engineering to geometrically model an entire spacecraft and its payload, using The Integral Mass Model.

Other disciplines

In meteorology, Monte Carlo simulation is used to model weather systems and their results. For instance, Gebremichael *et al* (2003) have used Monte Carlo analysis to evaluate sampling uncertainty for selected rain gauge networks in the Global Precipitation Climatology Project (GPCP). In public health, simulation has been used to estimate the direct costs of preventing Type 1 diabetes using nasal insulin if it was to be used as part of a routine healthcare system (Hahl *et al*, 2003). Phillips (2001) argued that Monte Carlo simulation should be used by research organizations to determine whether or not future possible research is really worth the cost and effort, by modeling possible outcomes of the research. Boinske (2003) used Monte Carlo simulation in personal financial planning, especially when estimating how much money one needs for retirement and how much one can spend annually once retirement has begun.

Application of Monte Carlo simulation in project management

Review of Monte Carlo simulation applications in project management

Monte Carlo simulation, while not yet widely used in project management, does get some exposure through certain project management practices. This exposure is primarily in the areas of cost and time management to quantify the risk level of a project's budget or planned completion date. Williams (2003) outlined how Monte Carlo simulation is used in project management and explains how it aids the project manager in answering questions such as, "What is the probability of meeting the project due date?" and, "What is (say) the 90 per cent confident project duration?"

In time management, Monte Carlo simulation may be applied to project schedules to quantify the confidence the project manager should have in the target project completion date or total project duration. Project manager and subject matter experts assigns a probability distribution function of duration to each task or group of tasks in the project network to get better estimates. A three-point estimate is often used to simplify this practice, where the expert supplies the most-likely, worst-case, and best-case durations for each task or group of tasks. The project manager can then fit these three estimates to a duration probability distribution, such as a normal, Beta, or triangular distribution, for the task. Once the simulation is complete, the project manager is able to report the probability of completing the project on any particular date, which allows him/her to set a schedule reserve for the project. The above can be easily completed using standard project management software, such as Microsoft Project or Primavera, along with Monte Carlo simulation add-ins, such as @Risk or Risk+.

In cost management, project manager can use Monte Carlo simulation to better understand project budget and estimate final budget at completion. Instead of assigning a probability distribution to the project task durations, project manager assigns the distribution to the project costs. These estimates are normally produced by a project cost expert, and the final product is a probability distribution of the final total project cost. Project managers often use this distribution to set aside a project budget reserve, to be used when contingency plans are necessary to respond to risk events.

Monte Carlo simulation can also be used in other areas of project management, primarily in program and portfolio management when making capital budgeting and investment decisions. Smith (1994) outlined how simulation assists managers in choosing among different potential investments and projects. He explained that by replacing estimates of net cash flow for each year with probability distributions for each factor affecting net cash flow, managers can develop a distribution of possible Net Present Values (NPV) of an investment instead of a single value. This is helpful when choosing between different capital investment opportunities that may have similar mean NPV but differing levels of variance in the NPV distribution.

Monte Carlo simulation has been used in construction projects to better understand certain risks to the project. For example, noise and its detrimental effects on the surrounding community is a risk in many urban construction projects. Gilchrist *et al* (2003) have developed a Monte Carlo simulation model that allows construction contractors to predict and mitigate the occurrence and impact of construction noise on their projects. This model was tested and validated using field measurements during various stages of the construction of an eight-story parking garage in London, Ontario, Canada.

Advantages of Monte Carlo simulation applications in project management

The primary advantage of using Monte Carlo simulation in projects is that it is an extremely powerful tool when trying to understand and quantify the potential effects of uncertainty of the project. Without the consideration of uncertainty in both project schedules and budgets, the project manager puts oneself at risk of exceeding the project targets. Monte Carlo simulation aids the project manager in quantifying and justifying appropriate project reserves to deal with the risk events that will occur during the life of the project.

Williams (2003) gave a thorough explanation of the advantages of Monte Carlo simulation over other methods of project analysis that try to incorporate uncertainty. He explained that although there are many analytical approaches to project scheduling, the problem with these analytical approaches was "the restrictive assumptions that they all require, making them unusable in any practical situations". These analytical methods often only provided certain moments of the project duration, instead of project duration distributions, which were much more useful in answering questions about the confidence level of project completion dates. Program Evaluation and Review Technique (PERT) was the previous method of choice for evaluating project schedule networks, but this method does not statistically account for path convergence and therefore normally tends to underestimate project duration. Monte Carlo simulation, by actually running through hundreds or thousands of project cycles handles these path convergence situations.

Limitations of Monte Carlo simulation applications in project management

The primary drawbacks of Monte Carlo simulation in the past have been high use of computing power and the amount of time and resources spent to complete the simulation activity (Williams, 2003). A lack of easy-to-use software tools to run complex simulation against project schedules was also a problem. Dramatic improvements in computing power and the introduction of Monte Carlo simulation software add-ins to the popular project management scheduling tools have made these concerns virtually obsolete.

Monte Carlo simulation showing project duration distributions that are very wide is another drawback. Williams (2003) explained that this was because “the simulations simply carry through each iteration unintelligently, assuming no management action”. In the real world, it is likely that management will take action to recover projects that are severely behind schedule, and some of these actions may (though not always) help bring the project back into an acceptable schedule range. Some researchers were attempting to create models that incorporate management action into the simulation, but to-date these models have a high level of complexity while still not incorporating sufficient generality with sufficient transparency for practitioner acceptance (Williams, 2003).

Although Monte Carlo simulation is an extremely powerful tool, it is only as good as the model it is simulating and the information that is fed into it. If the project model or network is lacking, the simulation will not reflect real-world activities accurately. If project task duration distributions used for a project duration simulation are incorrect or inadequate, the simulation will be off as well. Estimating the durations of project activities normally requires expert knowledge, and even when a three-point estimate is given to incorporate uncertainty into the model, there is still some latent uncertainty in the three-point estimate. Prior experience and detailed data from previous projects of the same type are both useful in mitigating this estimate uncertainty, although these data are often not available. Therefore, project manager must be very careful in both reviewing estimates and choosing probability distributions with which to model these estimates to avoid “Garbage In, Gospel Out” syndrome.

Suggested improvements of Monte Carlo simulation applications in project management

Many researchers have proposed minor modifications to current Monte Carlo simulation practice in real-life projects. Most of these attempts are to complement and mitigate the weaknesses of Monte Carlo simulation.

Graves (2001) discussed different types of probability distributions that can be used for project task duration estimates. He proposed using open-ended distributions, namely the lognormal distribution, instead of using closed-ended distributions (such as the triangular distribution) in Monte Carlo simulations. A closed-ended distribution explicitly denies any possibility of the task duration completing before the minimum duration or continuing beyond the duration upper limit. In real world projects, this is not a realistic assumption, since sometimes "showstopper" issues may come up that were never expected and cause problems in the project. An open-ended duration distribution allowed for possibility of exceeding the upper limit of the task duration, making the simulation more realistic. Graves (2001) also suggested that in creating this open-ended distribution, the project manager should get a base estimate, a contingency amount, and an overrun probability estimate, instead of the usual most-likely, worst case, and best case estimates.

Button (2003) has proposed a way to improve the project models used in Monte Carlo simulation, to better simulate how organizations normally get their work done in real life situations. He argued that because today's work environment rarely utilizes the single project, dedicated resource model, organizations may find that traditional Monte Carlo simulation of project task durations is insufficient. Button's model simulated "both project and non-project work in a multi-project organization," and it did this by modeling periodic resource output across all active tasks for each resource, based on project task priority rules set by the organization's management. There was a strong argument for the advanced accuracy of this model in multi-project organizations where resources are diluted across many different projects and activities. However, the complexity of the model and its non-existence in commercially available software packages currently makes it a poor candidate for practical use.

Other researchers attempted to improve the performance of Monte Carlo simulation in the area of finance and project portfolio investment risk analysis. In the area of simulating NPV of potential investments and projects, Hurley (1998) argued that "the conventional approaches to multi-period uncertainty," with regards to the variables used in the NPV calculation and their probability distributions, "may be unrealistic for some parameters," and the two currently most popular approaches give drastically different variance results. Hurley (1998) suggested that each parameter should be modeled over time as a Martingale with an additive error term having shrinking variances, so the error variance gets smaller in each successive period of the project. He argued that this approach results in "more realistic parameter time series that are consistent with the initial assumptions about uncertainty," and that the resulting simulation is more accurate than other methods. As this approach gave results that are between the two existing approaches and it is easily implemented with existing software, it would probably be beneficial to those making investment decisions to use all three approaches and give various weights to each result, depending on previous organization experience and data.

Balcombe and Smith (1999) have revisited the process of quantifying investment risk using Monte Carlo simulation and have identified areas where current practices may be improved. Their primary concern was creating a model that was as accurate as possible without being too complex for practical applicability. They proposed that simulation models include trends, cycles, and correlations, where, in addition to the information required for an NPV calculation, the appraiser is only required to state 'likely bounds' for the variables of interest at the beginning and end of the project life along with an approximate correlation matrix. This approach seemed to be a practical and possibly more accurate alternative to straight NPV simulation that does not incorporate trends, cycles, or correlations.

Javid and Seneviratne (2000) have developed a model to simulate investment risk, specifically for airport parking facility construction and development. This model takes a standard risk management approach, identifying the possible sources of risk on the project, and then estimating the probability distributions of certain parameters affecting the rate of return, such as parking demand and construction cost overruns. The model used Monte Carlo simulation to estimate and understand the impacts of cash flow uncertainties on project feasibility and to provide a sensitivity analysis.

Alternatives to Monte Carlo simulation applications in project management

Owing to the need for powerful computing capability and resources to complete the Monte Carlo simulation, some researchers have proposed alternatives to Monte Carlo simulation in assessing project risks. While all of these proposals have certain advantages over Monte Carlo simulation in one way or another, the recent advances in computing power and cost, as well as the availability of easy-to-use Monte Carlo simulation software, make many of these researchers' arguments obsolete, or at the very least, less striking than they may have been even a few years ago.

Skitmore and Ng (2002) proposed an analytical approach to estimating total project cost and its variance in place of Monte Carlo simulation. They argued that Monte Carlo simulation is used for this calculation because others feel that analytical approaches are too complicated, but they have derived a "relatively straightforward" calculation to determine the project cost variance. Although this approach does seem straightforward for someone who actively performs statistical calculations, it is not necessarily practical for use by project managers, especially when there is no tool or interface currently available to assist the project manager in using it. Moreover, the authors failed to validate their results against Monte Carlo simulation or real project results questioning the model accuracy.

Others were concerned with the complexity involved in Monte Carlo simulation. Lorterapong and Moselhi (1996) proposed the use of fuzzy sets theory, instead of Monte Carlo simulation, in analyzing project networks. Their method incorporated new techniques that represent imprecise activity durations, calculate scheduling parameters, and interpret the fuzzy results that are generated through the calculations. They argued that this new approach to project completion calculations produced results that are in close agreement with those obtained using Monte Carlo simulation. They also believed that their model was necessary because Monte Carlo simulation requires complicated calculations that normally must be done by computers if they are to be completed in any reasonable amount of time. Their argument, however, was lessened by the advancement of computing power and the availability of Monte Carlo simulation software. The lack of readily available fuzzy sets calculation tools also diminished the impact of this proposal, since project managers would be required to do the fuzzy sets calculations.

One of the results of Monte Carlo simulation of a project network and schedule is a criticality index for each task, which reflects the rate at which the task appears on the critical path of the project throughout the many simulation iterations. Cho and Yum (2004) proposed a new analytical approach that estimated the criticality index of a task as a function of the task's expected duration and also analyzed the sensitivity of the expected project completion time with respect to each task's expected duration. They found that this method's accuracy was comparable to that of direct Monte Carlo simulation, with one minor computational error, where the amount of change in project completion time for a change in task duration is underestimated when the ratio of the standard deviation of the task duration to the mean task duration is large. They also claimed that their approach was better than Monte Carlo simulation because it was computationally more efficient, requiring less iteration than direct simulation. This consideration, however, would only be critical in extremely large project networks, which would cause especially long time to Monte Carlo simulation. While this model did have potential for applicability, the lack of a readily available tool a project manager could use to implement it limited its practicality.

Summary, recommendation, and future directions

This research examines the Monte Carlo simulation method and its uses in various fields, focusing primarily on its use in the field of project management. Examples of practical use of the simulation method have been listed and discussed, as well as its advantages and limitations. With respect to the use of

Monte Carlo simulation in project management, researchers outlined how simulation is used in both project cost (budget) management and time (schedule) management and how these processes are integrated with risk management to produce reasonable project budget and schedule reserves. The use of Monte Carlo simulation in the area of investment risk analysis has also been discussed.

Many researchers have proposed improvements to the standard methods of Monte Carlo simulation currently used in project management, and most of these improvements deserve strong consideration and possible future implementation, depending on individual project needs and the practicality of the improvement. One would expect that as Monte Carlo simulation becomes more popular in project management, more creative studies will propose practical, applicable improvements to current practices and continue to contribute positively to the field.

Few proposed alternatives to Monte Carlo simulation have also been reviewed. These alternatives have been brought forward in order to respond to observed deficiencies in Monte Carlo simulation, namely the computing power and time necessary to complete a simulation. However, these concerns have drastically eliminated with recent advancements in computing technology and the availability of Monte Carlo simulation software packages that integrate into popular project scheduling products. Most of the alternatives to Monte Carlo simulation that were identified were not expected to be as accurate as Monte Carlo simulation, and none of them had a readily available tool to allow project managers to easily implement them into their current practice. Therefore, even in the face of possible alternatives, Monte Carlo simulation still stands out as the primary means of quantitatively analyzing project risks.

Monte Carlo simulation can certainly be the project manager's best weapon for analyzing project risks. It is an extremely powerful tool that allows project managers to incorporate uncertainty and risk in their project plans and set reasonable expectations on their projects, with respect to both schedule and budget. The results of simulation are quantifiable, allowing project managers to better communicate their arguments when management is pushing for unrealistic project expectations. Recent advancements in computing capability and Monte Carlo simulation software allow project managers to implement the method with relative ease and excitement.

However, Monte Carlo simulation is still not a popular tool in current project management practice considering the practical usefulness of the method in project schedule, cost, and risk management. This is primarily due to its statistical nature, which many project managers are reluctant to tackle. More project management education and training programs that demonstrate the simulation and hands on experience with the Monte Carlo Simulation techniques to current and potential project managers are needed to overcome project managers' reluctance to use Monte Carlo simulation, once the Monte Carlo simulation technique is thoroughly explained and demonstrated, hands-on experience will allow project managers to realize that the statistical knowledge they are required to apply is quite minimal, and the tools are relatively easy to use once their project network and schedule have been created.

Business organizations that currently apply project management processes and practices must also realize the value of Monte Carlo simulation. They will be able to estimate and forecast more realistic project schedules and budgets, with reasonable reserves necessary to deal with issues to predict, control, and complete more projects successfully. If the value of Monte Carlo simulation is realized, more project managers will encourage the use of Monte Carlo simulation on projects in their organizations. As computing power and software tools continue to improve, and once both business managers and project managers realize the value and practical applicability of Monte Carlo simulation to their projects and business results, the Monte Carlo simulation method will gradually become more popular and acceptable to the project management community.

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