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Examining the Value of Monte Carlo Simulation for Project Time Management

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Abstract:

Research Question: This paper investigates whether the Monte Carlo simulation can be widely used as a practicable method for the analysis of the risks that impact project duration. **Motivation:** The main goal was to explore the use of the Monte Carlo simulation for project time management, and shed some light on the key benefits and drawbacks of this method. The paper reviewed the existing literature considering traditional use of the Monte Carlo for quantitative project risk analysis (such as Kwak & Ingall, 2007; Hulett, 2017) and elaborated the issue by suggesting potential improvements in terms of method modification for schedule management, such as event chain methodology proposed by Agarwal & Virine (2017). Another goal was to examine the capability of user-friendly software to provide project managers with some of these benefits. **Idea:** The core idea of this paper was to evaluate the value of the Monte Carlo method for project time and schedule management, by matching traditional foundations with modern techniques. **Data:** The paper used the secondary data extracted from relevant literature and project examples. A literature review reveals how the application of the Monte Carlo simulation evolved as a project management tool, along with specific benefits and concerns for its application. **Tools:** A detailed application of the Monte Carlo in predicting project duration is provided, and the applicability and viability of the method are proven through a case demonstration. Following the presentation of a practical example and discussion of the main features, some limitations and potential improvements to the Monte Carlo method are suggested. Findings: Even with the existence of certain limitations, the Monte Carlo simulation remains the primary method for quantitative analysis of project risks. Despite the Monte Carlo having been found to be applicable, adaptable and predictive of total project duration, it is found to be insufficiently used by practitioners. **Contribution:** The paper urges the need for research on successful diffusion of the Monte Carlo simulation and helps practitioners to understand the adaptability of the Monte Carlo simulation as a tool for risk quantification and its use for effective duration planning of their projects.

Keywords: Monte Carlo, Time management, Project duration, Critical path, Beta distribution

JEL Classification: C53, C63, O22

1. Introduction

The knowledge area of risk management has received an increasing attention from academics and practitioners in the field of project management in recent times (Kwak & Stoddard, 2004). Projects are characterized by uncertainty, which often leads to schedule overruns, regardless of industry (Hulett, 2017). Merrow (2011) estimates that roughly two-thirds of the oil industry's megaprojects come in late, over-budget or fail in other key metrics. Thibodeau (2013) states that more than half of the large IT projects fall behind schedule or fail to meet user expectations. Also, Bisaccia (2014) has found that more than half of capital construction projects fail to meet schedules.

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While a project manager may be able to reduce uncertainty, it cannot be eliminated. In order to be able to develop efficient response to risks, make contingency plans and complete their projects within time and budget limits, project managers should be able to identify, analyse and quantify most of the project risks (Charette, 1996). This systematic approach of risk management should enable project managers to cope with complex situations that are inevitable in the today's dynamic project environment (Kwak & Ingall, 2007).

One of the methods that can provide significant help in the process of risk and schedule analysis is the Monte Carlo simulation. From its early introduction in the first half of the twentieth century, it has been improved by academics and often proposed by standard project management curricula, such as *A Guide to the Project Management Body of Knowledge* (Project Management Institute, 2017). However, despite many improvements and applications, the Monte Carlo has not yet received wider application "on the field" by practitioners and project managers (Agarwal & Virine, 2017; Kwak & Ingall, 2007).

The main goal of this paper is to review the application of the Monte Carlo simulation in project management and its relevance for time management in particular. It should investigate the pros and cons of the use of the Monte Carlo analysis for schedule management, using a case demonstration in a well-known software environment: Oracle Crystal Ball, an add-in for Microsoft Excel. Finally, the paper concludes with potential improvements and limitations to the Monte Carlo simulations, as well as with recommendations for project managers who should take advantage of the benefits that such a simple and useful tool can provide.

2. Application of Monte Carlo in Project Time Management

Kroese et al. (2014) define the Monte Carlo method as a wide class of computational algorithms that rely on repeated random sampling to obtain numerical results, often used for sampling, estimation and optimization. The method was named after the casinos of Monaco, since the model random outcomes seem very similar to games like dice, roulette and slot machines. The technique was first developed by Stanislaw Ulam, a mathematician who worked on the Manhattan Project (Eckhardt, 1987). The first paper on the Monte Carlo method was published in 1949 (Metropolis & Ulam, 1949).

In the project management literature, the Monte Carlo simulation is defined as a technique in which the project model is computed many times (iterated), with variable input values (e.g., cost estimates or activity durations). Values are chosen at random for each iteration from the probability distributions of these variables (Project Management Institute, 2017). Despite the fact that the Monte Carlo mainly deals with problems of schedule and cost management, it is generally considered as a risk management tool. The Project Management Institute (PMI) recommends the use of the Monte Carlo in risk quantification processes in order to deal with the issues that could adversely affect a project and justify a schedule or budget reserve.

Although the Monte Carlo is clearly documented in project management industry standards (such as *A Guide to Project Management Body of Knowledge*), it is insufficiently applied in real-time situations. Kwak and Ingall (2007) state that the primary reasons for the limited use of the Monte Carlo simulation are the lack of understanding of the method by project managers and the discomfort with advanced statistical approaches. Therefore, the Monte Carlo is often perceived as an aggravating factor, rather than a benefit that can help organizations in meeting budgets or schedules.

Despite its generally rare application in project management, the Monte Carlo is still applied in some project management practices. Its use is mainly connected to knowledge areas of cost and time management in order to quantify the level of risk on a projected budget or competition time (Acebes et al. 2015; Hazir, 2015). Therefore, the Monte Carlo simulation can help to reveal the probability of meeting a planned finish date, or to point to the expected results in terms of time and cost, with a certain degree of reliability, for example 90% confidence (Williams, 2003).

When it comes to time management, the Monte Carlo can be used in the process of schedule development to quantify the confidence of meeting a targeted completion date. The simulation of project schedules using the Monte Carlo method is one of the foundations of quantitative risk analysis (Salkeld, 2016; Vanhoucke, 2016; Wanner, 2013). In order to get the best possible activity duration estimates, industry experts assign a certain probability distribution function to each project activity. The use of the three-point estimate (optimistic, most likely, pessimistic) represents a simplified way of assigning probability distributions to each activity.
Once defined, these measures are usually fitted to normal, beta or triangular distribution for each project activity. This is done by the project manager, who is then able to calculate the probability of achieving the planned date or completing the project in any other time period. This type of risk quantification enables

setting schedule reserves on a more objective basis. The execution of the Monte Carlo simulation can be done with one of the project management software packages (such as Primavera Project Planner or Microsoft Project), with software specialized in project risk analysis (such as Tamara or Safran Risk) or with some simulation add-ins (such as Oracle Crystal Ball, ModelRisk or @RISK).

3. Case Study and Data Analysis

A simple case will be used to illustrate how uncertainty in scheduling projects can be managed with the use of Monte Carlo simulations. The key advantages of a simulation approach include the use of optimistic, most likely and pessimistic values for each probabilistic input and standard distributions for the events, which would otherwise need to be divided into a limited number of categories. The definition of distributions is followed by a random selection of inputs (usually thousands of times) in order to generate a frequency distribution of the outcome variable. This outcome should provide the probabilities of meeting the deadline or finishing the project earlier than planned, as well as much other useful information for the decision-making process.

In order to apply a proper risk analysis, certain assumptions need to be made about the probability distributions that describe key parameters and independent variables. These are usually very difficult to define, which makes this step one of the most significant in the whole process. In order to estimate the probability of the outcome variable and different risk profiles, a simulation software is used. The simulation software (in this case the Oracle Crystal Ball) represents the decision support system, which uses a mathematical model and selects samples from the assumed distributions for each input. Selected inputs are then plugged into the model thousands of times, and the outcomes are calculated and displayed. The key output represents the distribution of the outcome variable.

Table 1: Activities and their attributes for selected project

ID	Activity name	Predecessor ID	Optimistic duration (a)	Most likely duration (m)	Pessimistic duration (b)	Expected duration (TE)	Variance (σ^2)	Total slack
1	A	-	10	22	22	20	4	0
2	B	-	20	20	20	20	0	1
3	C	-	4	10	16	10	4	4
4	D	1	2	14	32	15	25	0
5	E	2;3	8	8	20	10	4	5
6	F	3;2	8	14	20	14	4	9
7	G	2;3	4	4	4	4	0	1
8	H	3	2	12	16	11	5.4	4
9	I	8;7	6	16	38	18	28.4	1
10	J	4;5	2	8	14	8	4	0

The described process will be illustrated using fictive project data, adapted from Meredith and Mantel (2011). It was chosen due to its capability to illustrate the key benefits and drawbacks of such an approach in a simplified way. Table 1 includes information regarding dependencies, durations and other derived values, such as total slack (float), expected durations, and variance for each project activity. Finding the duration of the critical path, as well as the durations of other paths in the network, is based on an analytical approach, and on the assumption that probability distribution for activity duration is best described as beta distribution. Although the beta distribution was used for illustration purposes, the Oracle Crystal Ball software allows the use of a wide variety of probability distributions to generate random numbers for the simulation.

Expected durations for each activity (TE) are calculated using three time estimates (a–optimistic, b–pessimistic, and m–most likely time estimate or mode), which indicate the risk associated with the time required to complete each activity. Expected durations (TE) are calculated using the formula based on the beta statistical distribution (eq. 1). The beta statistical distribution is used more often than a common normal distribution, as it is very flexible in form and is able to deal with extremes such as when a = m, or b = m. In other words, the expected duration (TE) represents a weighted average of three values (a, m, b) with associated weights 1-4-1, respectively.

$$TE = (a + 4m + b)/6 \tag{1}$$

The process of estimating the activity duration has been criticized by a number of academics. A general opinion is that estimated activity times are often considered as targets, and the success of the Critical Path Method (CPM) or the Program Evaluation and Review Technique (PERT) is attributed to the process of time estimation rather than to the estimates themselves. Therefore, duration estimates often become "self-fulfilling prophesies". Additionally, due to the impact of Parkinson's Law, which states that work tends to expand to the maximum time allowed, actual activity durations are rarely shorter than the estimate of the mode. In most of the cases these estimates are greater, which accounts for the right skew of the distribution (Williams, 1995).

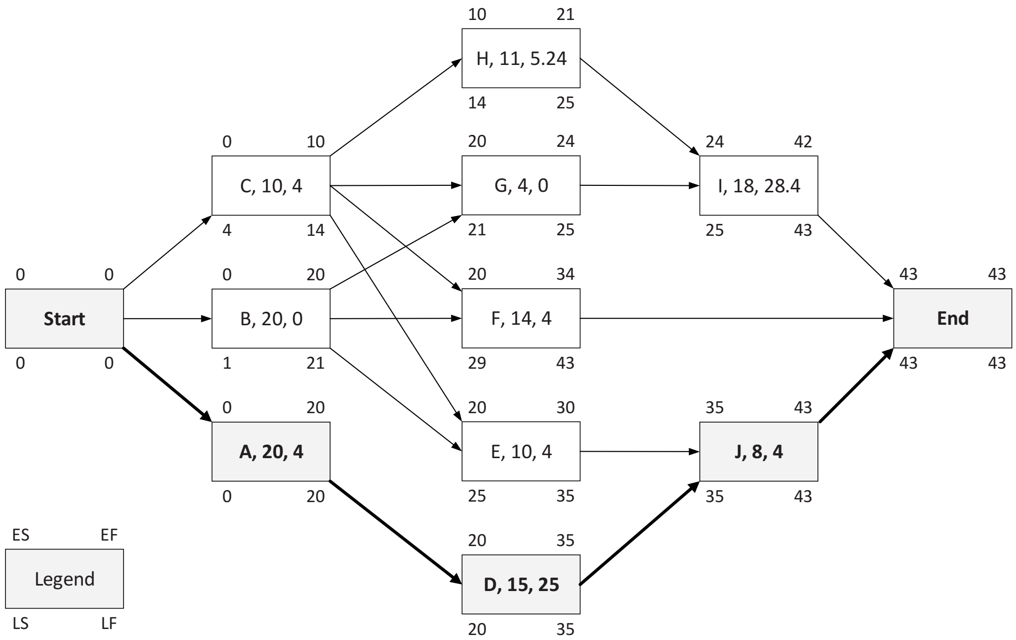

Figure 1: The "activity-on-node" network diagram for selected project

Also included in Table 1 and in the nodes in Figure 1 are measures of the uncertainty related to the duration of each project activity: the variance and the standard deviation (eq. 2). The calculation of the standard deviation(σ) is based on the assumption that the standard deviation of a beta distribution is approximately one-sixth of its range $((b-a)/6)$. Using the numbers given in the table, variance can be used to calculate the probability of completing the project in time (for example 89% for competition of critical path within 50 days). The last column in Table 1 represents the total float or slack, i.e., the difference between the late start (LS) and the early start (ES) for an activity.

$$\sigma^2 = ((b-a)/6)^2;\ \ \sigma = \sqrt{\sigma^2} \tag{2}$$

The use of the Monte Carlo simulation for project time management, besides sound statistical background, requires knowledge in key project management concepts, such as the CPM/PERT. The CPM is a scheduling algorithm, which calculates early and late start and finish times of each project activity, as well as determines a critical path, activity floats, and other schedule parameters (East, 2015; Plotnik & O'Brien, 2009; Kerzner, 2017). As can be seen from Figure 1, the critical path consists of activities A-D-J, and the shortest time in which the entire project with predefined dependencies can be completed is 43 days.

Nevertheless, noncritical paths that include activities with large variances or durations close to critical (activities with little slack) should also be monitored. A situation in which two or more paths come together or merge is known as the "merge bias" problem (Hulett, 2012). The probability of both paths finishing on time is equal to the product of probabilities for each individual path. In case one of the alternative paths has a low slack and/or significant path variance, it should not be ignored, and a simulation approach should be used.

The use of simulations is one of the best ways to investigate the nature and interactions between probabilistic paths in a network diagram. In earlier times, simulation processes were difficult and time consuming, but available software has significantly simplified the procedure. As stated by Levine (1996), although there are many software environments in which simulations can be performed, they are most commonly performed in extensions or add-ins to a well-known spreadsheet or project management software. The Crystal Ball was chosen as it allows simple simulations of interactions within project networks, provides data on probability of completing paths by specific deadlines and includes results of potential path mergers.

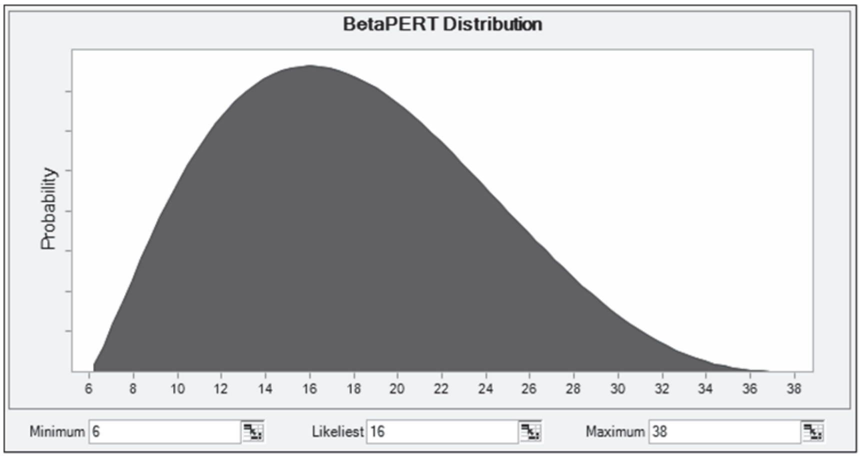

Figure 2: Defining assumption for activity "I"

In order to make a model that simulates project completion times, firstly labelling columns for each activity, each path through the network diagram and "completion time" needs to be done. One of the most difficult tasks is identification of all paths, and project management software can be of major assistance. The next step consists of defining assumptions, which includes a selection of the appropriate probability distribution for each project activity, and entering of parameters (as shown in Figure 2). For this purpose a BetaPERT probability distribution was used, which represents a special case of the beta distribution that takes three parameters (minimum, maximum, and mode). Unlike the triangular, the BetaPERT uses these parameters to create a smooth curve that fits well to the normal or lognormal distributions (Davis, 2008).

In total, eight paths through the network were identified (A-D-J, B-E-J, B-F, B-G-I, C-E-J, C-F, C-G-I, C-H-I), and formulae that sum up the duration for each of identified paths were defined. Path durations represent the sum of TEs for project activities on each path (SUM function). The last step includes definition of forecast (Project Completion Time), given as the formula which finds the longest of the paths for each executed simulation (MAX function). In other words, this variable represents the critical path for any of 1,000 executed trials. Since central-tendency statistics such as mean, median, and mode usually stabilize sufficiently at 500 to 1,000 trials per simulation, the number of trials was set at 1,000. This is also the default number of trials in the Oracle Crystal Ball.

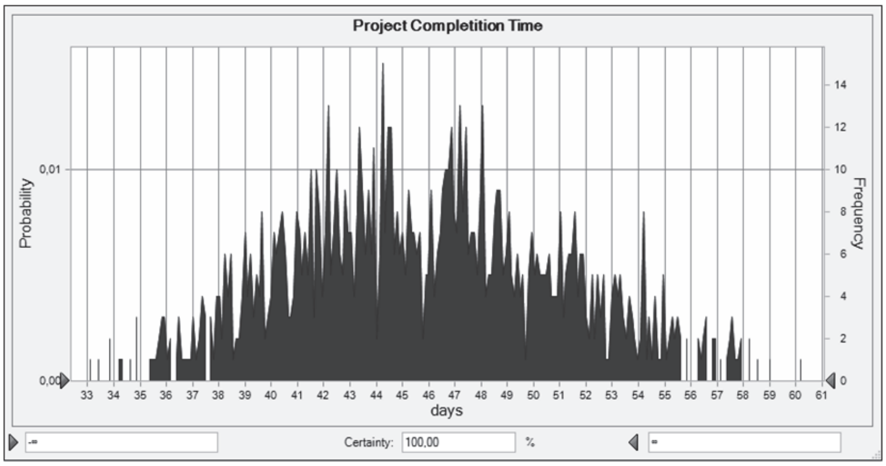

Figure 3: Frequency chart for project completion time

After running the simulation for 1,000 trials, the statistical distribution looks like the project completion time frequency chart depicted in Figure 3. The statistical distribution has a mean of 45.89 days and a median of 45.67 days. The expected critical path completion time, calculated earlier with the beta distribution, was 43 days. The simulation found greater mean time due to the impact of path mergers. The percentiles data in Table 2 show the percent of the trials completed at or below days shown.

Table 2: Summary statistics and percentile probabilities of completing the project in "n" days

Statistics	Project Completition Time	Percentiles	Project Completition Time
Trials	1,000	0%	33
Base Case	24.00	10%	39
Mean	45.89	20%	41
Median	45.67	30%	43
Mode	---	40%	44
Standard Deviation	5.17	50%	46
Variance	26.73	60%	47
Skewness	0.16	70%	49
Kurtosis	2.55	80%	51
Coeff. of Variation	0.11	90%	53
Minimum	33.04	100%	61
Maximum	60.52	--	--
Range Width	27.48	--	--
Mean Std. Error	0.16	--	--

Another useful output of simulation is finding out the likelihood of completing the project in a specific timeframe. The probability of completing the project in 50 days, for example, appears as a certainty value, and in this case it amounts to 77.69%. Adding another dependent variable in terms of the longest path, the simulation enables gathering interesting information regarding the critical path change. If each path (A-D-J, B-E-J, B-F, B-G-I, C-E-J, C-F, C-G-I, C-H-I) were denoted as a number from 1 to 8, respectively, the frequency output after 1,000 iterations would look similar to Figure 4.

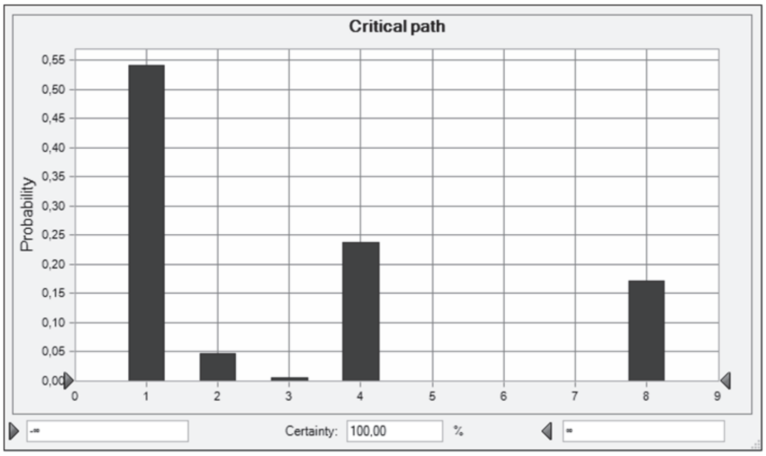

Figure 4: Critical path frequency chart

From Figure 4, it can be seen that the most important path through the network is path 1 (A-D-J), which accounts for 55% of all critical paths identified during simulations. This path was originally identified as critical using the beta distribution and expected completion time. Besides the critical path A-D-J, one needs to take into account paths B-G-I and C-H-I, since they become critical in around 40% of cases when pessimistic scenarios concerning the activities that comprise these paths come true.

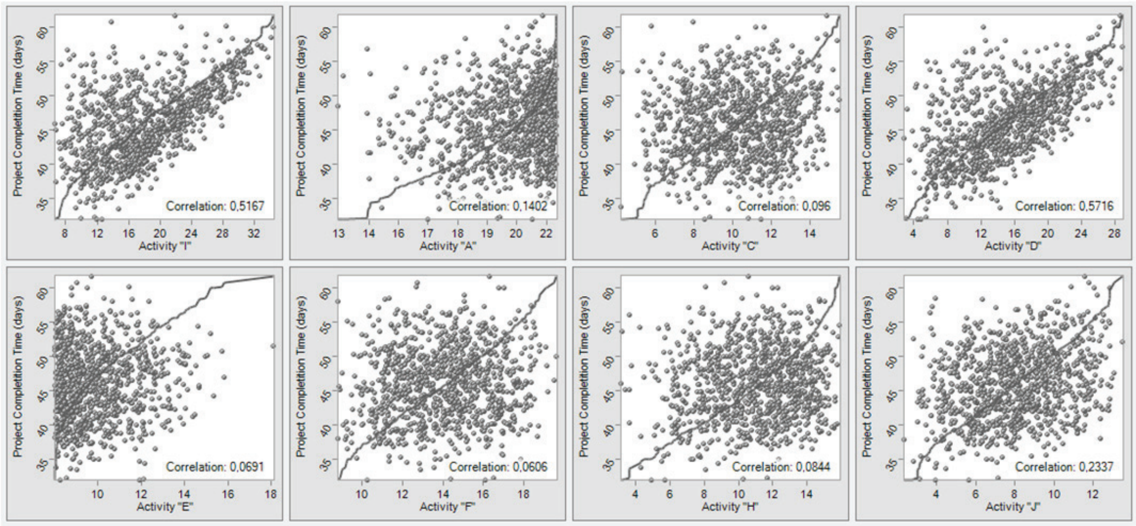

Figure 5: Activity and project duration correlation chart

The best way to illustrate the interdependence between the total project duration and individual activity duration is by using the scattered diagram, as shown in Figure 5. The greatest impact on the total project duration can be that of the activities “I” and “D”, since these activities have the largest duration variance. These correlations are significant and should be closely monitored during project execution, as these activities will most likely become part of the critical path.

4. Discussion of the Potential Benefits and Limitations

This example has demonstrated some of the most common benefits of simulation when it comes to project time planning: expected critical path completion time, likelihood of completing the project in a specific timeframe and significance of certain activities and paths through the network. Using analytical methods in a traditional environment for dealing with large amounts of data, calculation of path mergers and probabilities of completion for different project durations and calculation of impact of different assumptions about activity distributions can be very difficult. On the other hand, simulations deal with these problems very easily.

Project managers tend to disregard the benefits of simulations by suggesting that the only significant pieces of information they need are the expected, fastest and longest possible times of completion (Meredith & Mantel, 2011). These can easily be found by examining optimistic and pessimistic durations for each activity. In that sense, the shortest time in which the illustrated project can be completed is 30 days (critical path B-E-J), and the longest is 70 days (critical path C-H-I). The probability of either of these two scenarios (B-E-J to take the minimum values or C-H-I to take maximum values at the same time) is so small that it is often ignored.

The probability that the activity will take longer than pessimistic, estimated at 3 level, is equal to 0.0013 (1 - 0.9987). Similarly, the probability that these three activities will simultaneously take values above their estimates is 0.000000002 (0.0013^3). It should also be considered that all other activities should simultaneously maintain required values, which is even less likely. Other scenarios in which the project can be extended to last beyond 70 days, caused by external factors, are also possible, regardless of insignificant probability. This is the reason for continual risk identification and analysis throughout project execution.

4.1 Limitations of the Monte Carlo Method

In earlier years, among the most significant obstacles concerning the use of Monte Carlo simulations were the lack of computer power and the amount of time required to execute the simulation activity (Williams, 2003). Another drawback was the lack of easy-to-use software environments in which simulations could be performed. As demonstrated by the case study, these concerns became obsolete and lost their foundations when different add-ins to traditional scheduling software and spreadsheet tools were introduced (such as the Oracle Crystal Ball).

One of the key drawbacks of the Monte Carlo use is the selection of appropriate probability distribution for each activity (Williams, 2004). If the activity duration distribution is inadequate, simulation results will be inadequate as well. Therefore, the activity duration estimation process normally requires prior experience and expert knowledge. Even when duration is given by an expert in the form of a three-point estimate and applied into the model, there is still some residual uncertainty, which might cause a longer or shorter duration than expected.

Data and experience from similar projects in the past are crucial assets in obtaining correct probability distribution and mitigating uncertainty in time estimates. The sample project in this study used a three-point estimate based on expert knowledge and historical information. However, these data are often not available (Agarwal & Virine, 2017). And the project team must build the model with caution in terms of definition of estimates and choosing appropriate probability distribution in order to get the most useful information for the simulation process (Davis, 2008).

Another potential drawback of the Monte Carlo is the use of very wide project duration distribution and the presence of managerial interventions along the way (Williams, 2003). Simulations execute each iteration according to defined parameters and selected distribution, assuming that there will not be additional management action. In reality, managers faced with severe delays will execute different actions in order to recover the lost time and put the project back on track (Vanhoucke, 2013).

There were attempts in the past to build such simulation models with integrated management action, but their application was almost impossible in practice due to high complexity (Williams, 2003). The Monte Carlo can serve as a very powerful tool, but only as long as the model and information used reflect the actual situation in the field. In cases where the project network or model used deviates from reality, simulation results will be inaccurate and of little use to the project team.

4.2 Improvements of Monte Carlo Method

In order to improve the performance of the Monte Carlo approach in practice, many researchers have investigated these drawbacks and suggested various modifications. Graves (2001) investigated different probability distributions that can be used for project activity duration, and proposed the use of lognormal distribution. Instead of close-ended distributions, he suggested the use of open-ended distributions, which allow for the occurrence of the never-expected scenario that the activity will be completed beyond minimum and maximum values.

Another improvement related to real-life situations was proposed by Button (2003), who stated that organizations rarely execute single projects and suggested an improved model for a more complex programme environment. In order to account for multi-project organizations and non-project work, he modelled a periodic resource output for each resource across all project activities using predefined priority rules. Although the model proved to be more accurate for multi-project organizations where resources are used on many different activities, it did not experience a wider use. The main reason was its complexity and incompatibility with the commercially available software environment.

Some improvements of the Monte Carlo simulation have aimed at being industry-specific, such as for finance and investment risk analysis (Arnold & Yildiz, 2015). Hurley (1998) investigated simulation of net present value (NPV) and suggested the use of Martingale, in order to shrink variance and reduce the error in each successive period of the project. Balcombe and Smith (1999) proposed easy-to-use models that included trends, cycles, and correlation matrices, which would lead to a more accurate quantification of investment risk in regard to traditional NPV simulation. Javid and Seneviratne (2000) developed a model of the Monte Carlo to examine the impacts of uncertainties of cash flow on project feasibility and to provide a sensitivity analysis.

Several studies have tried to overcome the problem of defining statistical distribution that characterizes the duration of a project activity. In cases where there are not enough empirical data or where expert judgment is not sufficient to define statistical distribution, one of the solutions can be to combine risk events with statistical distributions. The analysis of project risks with events, also known as “risk events,” has been used since early 2000s (Virine & Trumper, 2009, 2016). The Intaver Institute (2017) defines the event chain methodology as uncertainty modelling and schedules an analysis technique that aims at identification of management events and event chains that affect schedules.

The event chain methodology is an extension of traditional event-based quantitative risk analysis, as it provides modelling and analysis of a variety of problems related to project schedule risks. According to this methodology, project activities are affected by risk events that transform them from one state to another (excitation process), which means that activities will perform differently if the event occurs. Events are characterized by probability, impacts, excited state and moment of event, and can be related not only to project activities, but also to project resources. In order to visualize how event chains affect the project schedule, event chains are usually created.

For the last 10 years, the event chain methodology has been used in many actual project schedules of different sizes and industries. These have included private companies, government agencies and non-profit organizations in construction, pharmaceutical, aerospace, information technology, oil and gas and other sectors. In many of these cases, it was possible to compare the performance of the traditional Monte Carlo method and risk-adjusted schedules using the event chain methodology. Agarwal and Virine (2017) concluded that risk-adjusted schedules performed better and were much closer to actual performance in comparison with schedules created using the traditional Monte Carlo method.

Conslusion

This paper has investigated the use of Monte Carlo simulation, primarily focusing on project time management. Taking into account the inseparable relationship of time management with project cost and risk management, and the nature of the Monte Carlo methodology, most of the findings related to schedule management and time reserves can also be attributed to management of potential risks, budget and cost reserves. In order to make these benefits and drawbacks of the Monte Carlo method more tangible, practical use was illustrated using a short example.

The practical example has shown that Monte Carlo simulations can handle analysis of schedule risk very easily. The Monte Carlo proved to be a significant tool that project managers can use to incorporate uncertainty into their project schedules and networks, in order to obtain reasonable duration expectations. The results Monte Carlo provides are purely quantitative and provide a sound basis for contingency decision making. Advances in information technology allowed implementation of simulation much more easily than before.

Building on a practical example and the main features, some limitations and potential improvements to the Monte Carlo simulation have been reviewed. Even with the existence of identified limitations, the Monte Carlo simulation remains the primary method for quantitative time and schedule analysis. Additional value can be obtained using different improvements on the traditional approach, such as the use of risk-adjusted schedules and event chain methodology. The future implementation of these improvements mostly depends on industry and individual project requirements, so their applicability needs to be carefully considered before practical use.

The development of easy-to-use tools and their integration with traditional project scheduling environments narrows the gap between required and existing statistical knowledge that project managers usually face during risk and time management processes. As more studies propose applicable and practical improvements, it is expected that the Monte Carlo simulation will become more popular and experience a wider use in practice. In order to realize the full advantages of the Monte Carlo simulation, another important activity would be the development of quality training programmes which demonstrate hands-on experience for practitioners.

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