PROJECT RISK SIMULATION METHODS – A COMPARATIVE ANALYSIS

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Abstract. *Effective risk management provides a solid basis for decision-making in projects, bringing important benefits. While the financial and economical crisis is present at the global level and the competition in the market is more and more aggressive, the interest in project risk management increases. The paper presents a comparative analysis of the effectiveness of two quantitative risk analysis methods, Monte Carlo simulation and the Three Scenario approach. Two experiments are designed based on real projects, in order to compare the effectiveness of these methods. The conclusions of the comparative analysis are that Three Scenario approach, even if is not as accurate as Monte Carlo, assures the results stability, if the same shape of the probability distribution curve is considered. The Three Scenario approach is easy to be applied in practice and requires a shorter computation time than Monte Carlo.*

Keywords: project risk management, Monte Carlo, Three Scenario approach, simulation.

1. Introduction

While the financial and economical crisis is present at the global level and the competition in the market is more and more aggressive, the interest in risk management increases (Hulett, 2009; Kendrick, 2003; Pritchard, 2011). Effective risk management provides a solid basis for decision-making in projects, bringing important benefits, such as: reduced costs, increased engagement with stakeholders and better change management (Bayati, Gharabaghi and Ebrahimi, 2011). Different project risks management approaches were defined in standards and guidelines such as:

- ICB v3.0, International Competence Baseline, International Project Management Association (IPMA, 2006);
- AS/NZS 4360, Risk Management, Standards Australia/Standards New Zealand (AS/NZS, 2004);
- ISO 21500, Guidance on Project Management, STD v2, International Organization for Standardization (ISO, 2012);
- PMBOK Guide®, Guide to the Project Management Body of Knowledge (PMI, 2008);
- SDPM, Success Driven Project Management, Spider Project Team (Liberzon and Lobanov, 2000).

The project management standards and guidelines recommend similar frameworks for project risk management. What it is really relevant for differentiating between risk management approaches is not the process structure as such, but how the integration of the risk management with all other project management processes is reinforced. Chapman and Ward (2002) identify a lot of limitations and errors arising when the risks are managed in projects, even if the project manager has considerable experience in managing risks. The principal shortcomings relived by Chapman and Ward are the following: the initial activities for managing risks are too detailed and fails to underlay the connections with different projects elements in a balanced manner; the risk identification fails to provide a good structure of the sources of uncertainty, and to identify significant linkages and interdependences between issues; the risk estimates are highly dependent on the project scope hypothesis and not on other kind of assumptions; the risk estimations are costly, but not cost-effective; the risk evaluation fails to combine properly different source of uncertainty because crucial dependences are not captured and a weak implementation of the project plan. The majority of these limitations are linked to the integration of the risk management processes with each other and with the project management processes in large.

What it is considered by many professionals as being critical for an effective risk management in projects it is the risk assessment (Bayati, Gharabaghi and Ebrahimi, 2011; Makait, 2011; Andersen, 2011). If we accept that risk management is all about identifying, measuring and minimizing uncertain events effecting projects, then the secret for a good risk management lies in the ability to quality and quantify the risk elements. This is why these professionals consider the qualitative and quantitative project risk analysis as the core processes in risk management.

The project quantitative risk analysis is considered as the hardest part of the risk management, because it is based on advanced statistics and mathematics methods. A lot of deterministic and probabilistic methods were developed over time and made available, especially through software implementation. But these methods are usually not properly applied, or not applied at all. The main reasons for this are lake of expertise, difficulties in collecting historical data, complexity of risk quantification methods and also the computation effort. Only for a few project types, such as: research and development projects and public and military capital Investments in projects, the risk quantification is regularly performed.

In the absence of easy to use tools and techniques for project risk quantification, most of the project team applies exclusively risk qualitative analysis. A study conducted by the Chartered Institute of Building between December 2007 and January 2008 highlights the fact that despite the development of sophisticated tools and techniques, a large number of construction projects are delayed and over budget and because the project quantitative risk analysis is missing (CIOB, 2008). The more complex the projects are, the less likely it is to achieve the success.

2. Project quantitative risk analysis methods

The experience gained in a large number of projects reveals the fact that using only deterministic methods of scheduling leads to a low probability of success. For this reason project scheduling and monitoring must always include techniques for risk simulation in order to obtain feasible results. Simulation is increasingly applied in business. As a project management method, simulation depends on two essential elements: a model for defining the project outcomes and outcome values and a technique that repeatedly generates scenarios (Schyler, 2001). Variables whose values are not known with certainty, but can be described by probability distributions are called stochastic variables.

In the simulation, in order to emulate the variability of such variables is necessary to generate possible values based on its distribution probability. The information about probabilities is necessary both for building the simulation model and for analyzing the simulation results. To construct the probability distribution of a variable we can apply the following procedure:

– Collect data on values of the stochastic variable;

– Group values into intervals and develop the histogram of the relative frequencies;

– Analyze of the relative frequency histogram graph to determine whether a shape resembling theoretical distributions known. The probability distribution type can be appreciated using correlation tests, such as: Kolmogorov, Smirnov, Pearson (or $\chi 2$), measuring the closeness between the theoretical and probabilistic distribution of values obtained from historical data or expert estimations. Finally, the distribution parameters are calculated.

The risk simulation methods can be semi-probabilistic and probabilistic ones. PERT (Program Evaluation and Review Technique), originally developed in the late

50s is one of the first project planning approach addressing the project risks. PERT takes into consideration the uncertainties using the three points estimation method. Basing on their experience and the historical information the project team estimates for each activity three durations: optimistic, pessimistic and most probable. The probability to meet a project target date (time or cost) is computed considering only the activities on the critical path. Different results in terms of accuracy may be obtained if we use different probability distribution curves. It may be used Beta, Normal or Triangular probability distribution. The critics of PERT are based mainly on the hypothesis included in the method, which leads to errors in results, which are considered optimistic in comparison with other methods.

By the 1960s, Monte Carlo simulation is embedded in PERT, in order to avoid assuming that only one path may be critical and that the probability distribution of the project duration must be normal. In the same time, GERT (Graphical Evaluation and Review Technique) is defined, based on the decision trees embedded in Markov processes. GERT enhances the project manager's ability to understand how the project is affected by the corrective actions, considered as repetitive processes, executed in a specific timeframe window. In 1970s, Chapman developed SCERT (Synergistic Contingency Planning and Review Technique) approach, based on the fault tree and event tree concepts, for safety analysis (Chapman and Ward, 2003).

The next two paragraphs will shortly introduce Monte Carlo simulation and three-scenario approach. In the final part of the paper, we will compare the effectiveness of these two methods, by means of two experiments designed and ran by the authors.

3. Monte Carlo simulation

Recognized by the accuracy of its results, Monte Carlo method is part of the probabilistic methods used in risk simulation. The Monte Carlo method first generates artificial variable values, using a random number generator uniformly distributed in the interval [0, 1] and the associated cumulative distribution function. Then, the Monte Carlo method uses the obtained results to extract values from the probability distribution that describes the behavior of the stochastic variable.

3.1. Monte Carlo simulation with discrete stochastic variable

For discrete stochastic variables, the list of possible values and the corresponding probabilities form a discrete probability distribution. In the terminology of probability theory, one can note the stochastic variable as X, x_i being a particular value of the variable X. The probability that the value of a variable X equals to x_i is denoted as $P(X = x_i) = P(x_i)$. The probability that the value of variable X exceeds a certain value xi is called the cumulative distribution function and it is denoted as $F(x_i)$. The most common theoretical discrete probability distributions are the discrete uniform distribution, the binomial distribution and the Poisson distribution.

The *discrete uniform distribution* describes variables with a small number of possible values, each with the same probability of realization. If the number of possible values is n, and set values possible is $\{x_1, x_2 \ldots x_n\}$, then the probability mass function is P(X = xi) = P(xi) = 1/n for any value x_i, and the cumulative distribution function is F(xi) = P(X ≤ xi) = i/n, for i = 1, 2, ...,n.

The *binomial distribution* is a discrete probability distribution that applies when there are only two possible outcomes: success or failure, admitted or rejected, passed or not passed, etc. For example, the stochastic variable is the number of experiments with "success". If *p*, the probability of "success" is the same for each of the n experiments, and experiments are independent, the probability mass function is defined by the probability that the number of successful experiments to be equal to a value x_i and can be calculated with the expression: $P(X = x_i) = P(x_i) = C_n^{x_i} p^{x_i} (1-p)^{n-x_i}$, for x_i = 0, 1, … , n, where n is the number of experiments. The cumulative distribution function is defined as: $F(x_i) = P(X \leq x_i) = \sum_{v=0}^{x_i} P(v)$, for x_i = 0, 1, … , n. The average, μ has the value n*p, and the dispersion is define as: $\sigma^2 = np(1-p)$.

The *Poisson distribution* is a discrete probability distribution that applies to independent random events. The stochastic variable is the number of events that can occur in a period of time. The probability mass function is the probability that the number of events occurring within a specified time to a value equal to xi and can be calculated with the expression: $P(X = x_i) = P(x_i) = \frac{\lambda^{x_i} e^{-\lambda}}{x_i!}$, where λ is the average number of events in a time specified.

Procedure for applying the Monte Carlo method with stochastic discrete variables

The following procedure can be applied when stochastic discrete variables are included in the simulation model:

Step 1. Calculate the probability P (X = xi) = P (xi) and cumulative distribution function: $F(x_i) = P(X \leq x_i) = \sum_{v=0}^{x_i} P(v)$, for xi Є $\{x_1, x_2, \ldots, x_m\}$.

Step 2. The random number intervals are associated to each value of to variable discrete. This can be graphic or tabular.

Step 3. Generate a random number u uniformly distributed in the interval [0, 1] using a random number generator.

Step 4. Calculate x_i, the value of discrete stochastic variable. This can be done graphic or tabular. Graphically, function $F(x_i)$ has a specific shape on x0y coordinate. We can set the y value (the probability) and we can found the stochastic variable value on x coordinate.

Steps 1-4 is being repeated until a predetermined number of trials are completed.

3.2. Monte Carlo simulation with continue stochastic variable

Unlike discrete probability distribution, it is not possible to define a continuous probability distribution in order to determine the probability for some particular value of continue stochastic variable. Since a continuous stochastic variable is a variable that can have any value a specified period, it has an infinite number of possible values in that interval and thus the probability that a continuous stochastic variable to have some particular value is zero. For a continuous stochastic variable, it is possible to defined probability as the variable value to be included in a specified interval. In this regards, the distribution is represented by a curve, and the probability is determined by evaluating the area under the curve between the interval margins on x-axis. Function f(x) which calculates the area is called by probability density and shall meet some conditions. In some cases the probability density function is quite difficult to calculate, but there are tables of values or software programs for continuous theoretical distributions, such as: continuous uniform distribution, triangular distribution, normal distribution, beta distribution and exponential distribution.

The continuous uniform distribution. If a stochastic variable uniformly distributed in [a, b], the probability density, f(x) is defined as follow: f (x) = 0 for x < a, f (x) = 1/(b – a) for a ≤ x ≤ b and f (x) = 0 for x > b. The cumulative distribution function, F is defined as follow: F(x) = 0 for x < a, F(x) = (x – a)/(b – a) for a ≤ x ≤ b, and F(x) = 1, for x > b. Media, μ is equals with (a + b)/2 and variance σ2 is equals with (b-a) 2/12.

The triangular distribution. It describes the probability values of a variable by three values: the minimum (a), the most likely (b) and maximum (c). It is assumed that the probability of achieving the minimum and maximum value is zero. The probability density function, f(x) is f(x) = 2 (x-a)/((b – a) (c – a)), for ≤ x ≤ b and f(x) = 2(c – x)/ ((c – a)(c – b)) for b < x ≤ c. The cumulative distribution function, F(x) is define as follow: F(x) = P(X ≤ x) = 0, for x < a, F(x) = $((x-a)^2)/((b – a)(c – a))$, for a ≤ x ≤ b, F(x) = $1 – ((c – x)^2)/((c – a)(c – b))$, for b < x ≤ c, F(x) = 1, for x >c. Mean μ is equals with (a + b + c)/3, and dispersion, σ2 is equals with (a^2 + b2 + c2 – a*b – a*c – b*c)/18.

The normal distribution (Gaussian distribution). It describes the population characteristics or distributions of quantities that are sums of other sizes (according to the central limit theorem). Thus, the total duration of a project, the amount of probabilistic duration of activities on the critical path is a variable with normal distribution. Normal distribution is a symmetrical distribution as a bell. Function f (x) is a probability density function with two parameters, mean, μ and dispersion σ2, having the form: $f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$. Since f(x), the probability density function of the normal distribution cannot be integrated exactly, it is not used directly. Calculation of areas needed to determine the probabilities P(a ≤ x ≤ b) and the cumulative distribution function are based on the standard normal probability distribution, which is a normal distribution of a stochastic variable with mean $\mu = 0$, dispersion σ2 = 1 and standard deviation $\sigma = 1$. To transform a stochastic variable X with normal distribution into a stochastic variable Z with the standard normal distribution, the following formula can be used: $Z = (x - \mu)/\sigma$. In the standard normal distribution tables, there are probabilities $P(0 \leq Z \leq z)$, which represents the value of the area under the curve of probability density function f(z) located between the average value, $\mu = 0$ and z.

The Beta distribution. It has many shapes, by adjusting the following two parameters: a scaling coefficient, and an offset. A beta distribution can range from a symmetric, normal distribution to asymmetric one, with a long tail on the positive side. *The exponential distribution*; It is used to describe the time between events. It can be shown that if the number of arrivals can be described by a Poisson distribution, the interval between arrivals follows an exponential distribution.

4. Three Scenario approach

A semi-probabilistic approach which simulates not only the uncertainties but also the risk events is the Three Scenario approach (Liberzon, 1996). The risk events are selected and grouped using the regular approaches in qualitative risk analysis. The application of this method requires first of all the development of the risk response plan. This highlights the uncertainties in duration and cost estimation together with the risk events for which are established action measures affecting both the project duration and cost. There are obtained three estimations (optimistic, most probable and pessimistic) for all initial project data (duration, volume of work, productivity, calendars, resources) which will be used in rebuilding the probability curves for dates, costs and material requirement. Though it doesn't have the accuracy as comparison with the probabilistic methods, the Three Scenario approach is characterized by its stability in results, and as a consequence, by its precision. Knowing the current probability to achieve the target dates for each phase of the project allows us to establish the probability trends. By using management by trends as a tool in decision making, the probability trend give us a clear imagine about how the project is run and the way the buffers are consumed during the time.

In practice, the quality of initial data for project risk simulation is never good enough to apply an accurate method like Monte Carlo simulation. In addition, collecting, analyzing and processing the initial data require often a lot of time. Included in the Success Driven Project Management Methodology, the Three Scenario approach is a semi-probabilistic method for approximation of probability distribution (Archibald, Liberzon and Souza Mello, 2008) used together with the Management by Trends. The identified risk events are estimated to reflect their effects taking into consideration resource usage or productivity rates, work scope or volume, cost estimates, calendar or weather variation and their consequences are included in the risk response plans. As result, there will be developed not one, but three scenarios of the same project schedule and budgets:

– Optimistic Scenario includes the risk events with a probability exceeding 90%;
– Most Probable Scenario is based on the most probable estimates and includes the risk events with a probability exceeding 50%;
– Pessimistic Scenario is based on the pessimistic estimates and includes all selected risks.

Basing on the risk response plans, the most probable and pessimistic scenarios will include additional activities, work volumes, durations, resources, productivities, costs, calendars, financing and supply, other than the optimistic scenario. The calculated scenarios with resource leveling and project budgeting are used to rebuild the probability curves (for dates, costs, and material requirements) with a predefined shape of probability curve (Figure 1). Defining the desired target probabilities will allow us to obtain the desired dates for finishing the project, costs and material requirements (Liberzon and Archibald, 2003). The project target probabilities are usually defined by the organization risk tolerance, but for regular projects, it should be in the range of 65%-75%. The three scenarios will establish the buffers (for time, costs and materials) which will be available for the project manager during the execution phase.

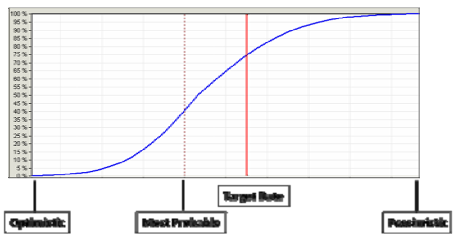

Figure 1. **Three scenario approach - cumulative probability**

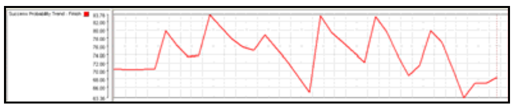

Figure 2. **Success probability trend**

The probabilities to meet the target dates are called success probabilities and they are used to measure the buffer penetration. If the success probability trend is positive, than the buffer consumption was lower than expected, otherwise the buffer consumption was higher than expected and are required corrective actions (Figure 2). That means we will not focus on the activities total floats as it is in the actual approach of project management, but on how the buffers are consumed during the execution phase, as result of risk events.

The success probability trends measure and show not only project performance but also project health taking into consideration both internal and external factors. The main advantage of three scenarios approach is that it can be applied easily in medium and large projects.

Probability Distribution Curve. Having the three scenarios we know the range of most frequent values for project duration, total cost, material requirements, resources etc. In order to build the probability distribution curve we rely on the three points with the probabilities according to the three scenarios: the point with zero probability for the optimistic scenario, the point with 100 % probability for the pessimistic scenario and the point for which the probability distribution has the maximum value (Figure 3). What we don't know is the shape of the probability distribution curve. This can be Beta, Normal or Triangular. In fact, in the Three Scenario approach method the shape of the probability distribution curve is not so important. We know from the very beginning that the results are not accurate so they are not close to the exact value, but successive measurements will give results very close each other. That means the results are characterized by precision. During the project execution the same shape of the probability distribution curve will be used. In this way, even the shape is not the correct one; we will be able to establish if the probability will become greater or smaller as a result of risk events or the application of preventive or corrective measures (Liberzon and Souza Mello, 2011). To exemplify the probability computation for a certain target date we will use the triangular distribution (Figure 4). The probability to achieve the target date is represented by the area under the probability distribution curve at the left side of the target date. $P = \frac{s}{S}$, where: P is the probability to achieve the target date; s – the area between the target date and the probabilistic date and S – the total area under the probability distribution curve.

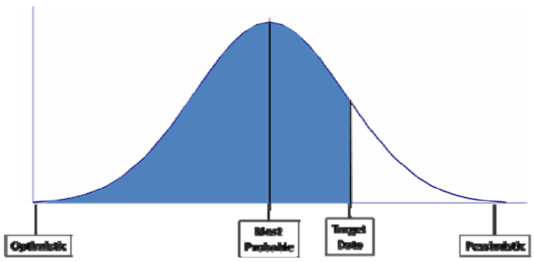

Figure 3. **The probability distribution curve**

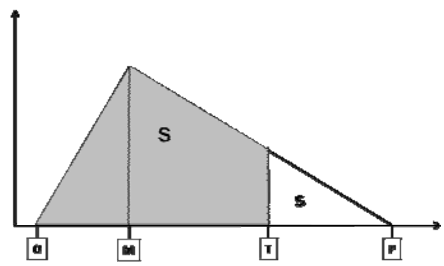

Figure 4. **Triangular distribution**

Considering that X is the probability to achieve the target date, O is the optimistic scenario value, M is the most probable scenario value, P is the pessimistic scenario value and T is the target date value, the probability to achieve the target date will be: $X = 1 - \frac{(P-T)^2}{(P-O)\times(P-M)}$. Let us consider the following project where the optimistic duration is 15 days, the most probable duration is 20 days and the pessimistic duration is 29 days, presented in Figure 5.

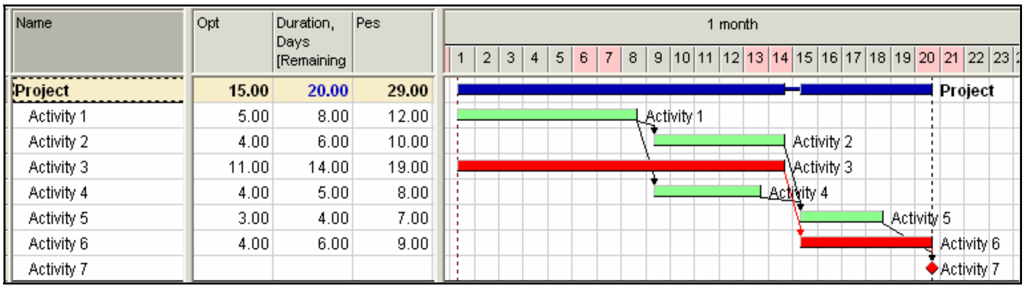

Figure 5. **Numerical example**

If we define the desired target date as being the 23 days duration, the probability to achieve it based on the triangular distribution curve will be 71.43%. During the project execution the optimistic, most probable and pessimistic scenarios durations will change. For each update stage we will compute the current probability to achieve the target date, in our example, 23 days. The results of optimistic, most probable and pessimistic scenarios duration and the current probability to achieve the target date are presented in Table 1.

Table 1

Duration for optimistic, most probable and pessimistic scenarios and the current probability to achieve the target date

	Optimistic duration	Most probable duration	Pessimistic duration	Target data	Current probability
1	15	20	29	23	71.43%
2	13.9	15.9	21	23	88.95%
3	12.25	14.25	20.5	23	87.88%
4	11.7	13.7	20.5	23	89.56%
5	11.15	13.15	19.75	23	81.39%
6	10.6	12.6	19.5	23	80.05%
7	10.05	12.05	19	23	74.28%
8	9.5	11.5	18.5	23	67.86%

The probability trend is presented in the Figure 6.

Figure 6. **Probability trend**

If the probability trend is positive then no action should be taken. If, on contrary, the probability trend is negative, then corrective actions are needed. Using such an approach allows us to identify as soon as possible the manifestation of the risk events and to take the proper decisions to.

5. A comparative analysis of the Monte Carlo and Three Scenario approach methods

In our endeavor to compare the results of Monte Carlo and Three Scenario approach methods we used the same software which has implemented both methods and has the same specific heuristics for resource constrained scheduling, Spider Project. It avoid us to obtain not valid results as time as different project management software use different algorithms for resource constrained scheduling than other software that has implemented Monte Carlo method (Liberzon, Shavyrina and Makar-Limanov, 2012). In order to highlight the advantages of using one or another risk simulation method, we applied them in two real projects of medium size and we calculated the probabilities to achieve the target dates (for the finish date and total cost). The analysis was performed with a computer having a processor of 2.7 GHz Intel Core I7, with RAM of 4 GB at 1333 MHz DDR3. The probability distribution curve used in computation was the Beta distribution and the number of iterations for Monte Carlo method was 1000.

5.1. The first experiment

The first project is the construction of an office building with ground floor and four stories with a duration estimation of 10 months (Figure 7). The project model took into consideration only the infrastructure and superstructure works, together with architectural works.

The required level of detail lead to a project model consisted of 221 activities, 54 different types of resources (manpower and equipments) grouped into 8 resource centers, and 94 different types of materials grouped into 3 material centers. The project costs were modeled using 11 cost components grouped into 5 cost centers. Three scenarios (optimistic, most probable and pessimistic) were developed taking into account the identified risk. Different productivities, material consumption, activity calendars, resource team's structures and costs resulted from the risk response plan. The target dates were established for project duration and cost as following: the target duration is 182 days and the target total c is 465.000 Euros.

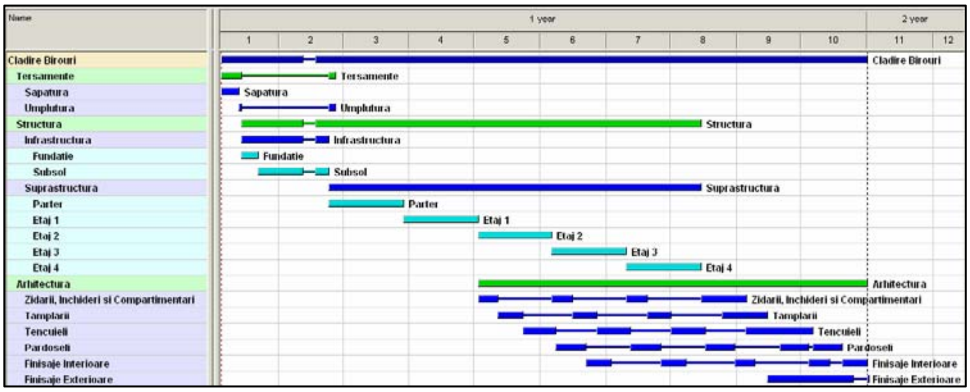

Figure 7. **Office building model**

Using both Monte Carlo and Three Scenario approach we obtained the probabilities to achieve the target dates as shown in Figures 8 and 9.

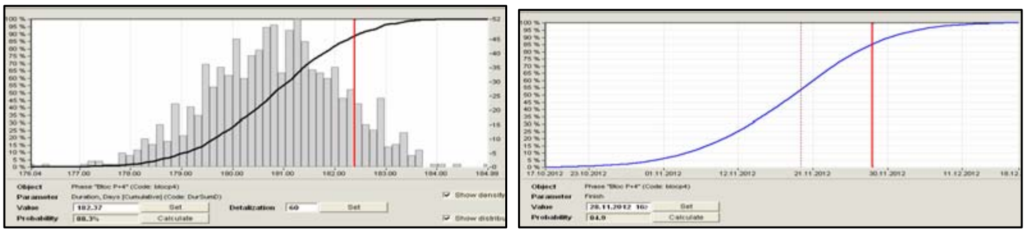

Figure 8. **Probability curves in (a) Monte Carlo and (b) Three Scenario approach for parameter project duration**

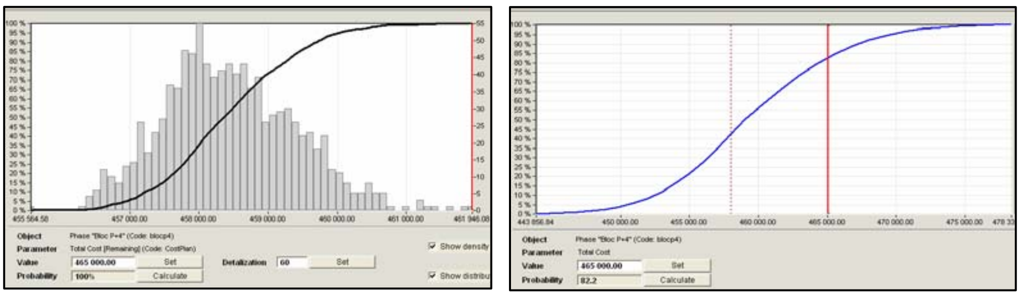

Figure 9. **Probability curves in (a) Monte Carlo and (b) Three Scenario approach for parameter project total cost**

Using the Monte Carlo method, the probabilities obtained are higher than the probabilities obtained using Three Scenario approach. The computation duration is also much larger than in the Three Scenario approach (Table 2).

Table 2

Probabilities to achieve the target date with Monte Carlo and Three Scenario approach

Method	Parameter duration	Parameter total cost	Computation duration (seconds)
Monte Carlo	88.30%	99.90%	675
Three Scenario Approach	84.90%	71.90%	3

5.2. The second experiment

The second experiment is based on an oil and gas project, which represents the periodic maintenance of an installation. The project has 453 activities, 12 different types of resources (manpower and equipments) grouped into 4 resource centers and 3 cost components grouped in two cost centers. The most probable project duration was estimated to 13.8 days, using a calendar of 6 days working days (Figure 10).

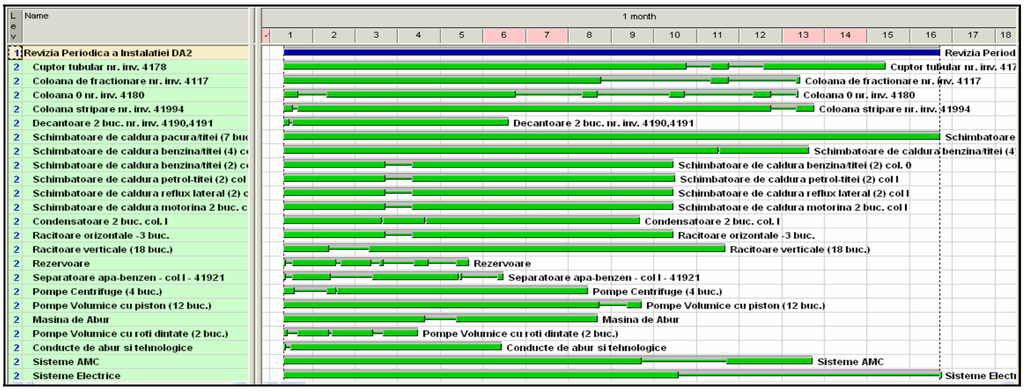

Figure 10. **Oil and gas project model**

Taking into account the identified risk events and the risk response plan, it was decided to establish the probability to achieve the following project data: target duration: 15.6 days and target total cost: 640.000 Euros. The different activities from the optimistic, most probable and pessimistic scenario, different productivities, resources and costs, lead to the following results in Monte Carlo and Three Scenario Approach methods for the project target dates are shown in Figures 11 and 12.

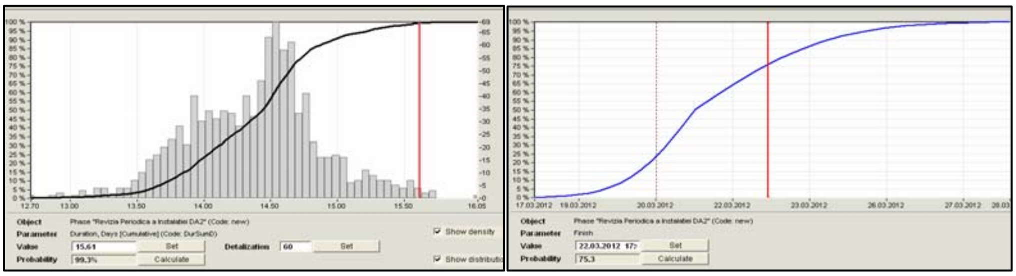

Figure 11. **Probability curves in (a) Monte Carlo and (b) Three Scenario approach for parameter project duration**

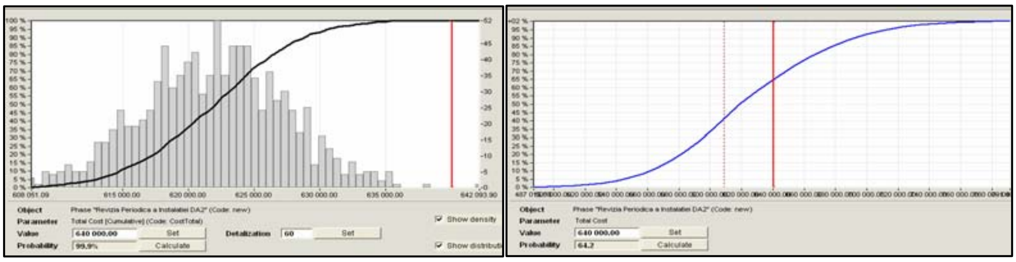

Figure 12. **Probability curves in (a) Monte Carlo and (b) Three Scenario approach for parameter project total cost**

Similar to the first project, the probabilities to achieve the target dates are higher in Monte Carlo method than in Three Scenario approach (Table 3).

Table 3

Probabilities to achieve the target date with Monte Carlo and Three Scenario approach

Method	Duration parameter	Total cost parameter	Computation duration (seconds)
Monte Carlo	99.30%	99.90%	321
Three Scenario Approach	75.30%	64.20%	3

The reason Three Scenario approach method leads systematically to lower probabilities than Monte Carlo method is that it allows taking into account the unknown unknowns which are present in every project. The computation duration in Monte Carlo method depends on the number of activities, resources, cost components, calendars, and is bigger as the number of information contained in the project model is bigger. The Three Scenario approach takes into consideration the same amount of information, but the algorithm is not iterative and the computation duration is measured in seconds.

6. Conclusions

Project risk management represents a significant area in project management. The authors analyzed several risk management standards and guidelines and concluded that what it is really relevant for differentiating risk management approaches is not the process structure as such, but how the integration of risk management with all other project management processes is reinforced. The authors focused on risk simulation methods recommended and used in project quantitative risk analysis, investigating theoretical and in practice two methods, Monte Carlo and the Three Scenario approach. In order to compare the effectiveness of the methods, two experiments were designed based on real projects.

Even if the Monte Carlo method is very accurate, its practical application is not feasible because of the iterations, which require effort and time for computation. The application of Monte Carlo needs a great amount of time for the preparation of input data when the projects are of medium and large size, with hundreds and thousands activities, resources, materials and cost components. As time as the project environment is in continuous changing the accuracy of the results using Monte Carlo method does not help the project managers too much in decision making. Though the Three Scenario approach is a semi-probabilistic method and it is not as accurate as Monte Carlo, the use of the same shape of the probability distribution curve gives it stability in results. It is easy to be applied in practice and requires a very short time for computation. Time and cost buffers are set by defining reliable targets that have reasonable probabilities to meet.

The application of management by trends of the probability to achieve the target dates is in fact the management of buffers penetration allows project managers to identify timely the risk events and to react properly. Trends of probabilities to meet project targets (success probabilities) are most valuable and integrated project performance indicators. They depend not only on project performance but also on project environment.

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