Project cost analysis under risk

Analiza costului unui proiect în condiţii de risc

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Abstract

In this paper, an integrated approach based on Monte Carlo simulation and Six Sigma methodology is used to analyze the risk associated with a project's total cost. Monte Carlo simulation is applied to understand the variability in total cost caused by the probabilistic cost items. By Six Sigma methodology the range of variation of the project cost can be reduced by operating on the input factors with the greatest impact on total cost to cover the variation of 6σ between the limits that were established in the design phase of Six Sigma.

Keywords: *Project cost risk; Six Sigma; Monte Carlo simulation*

Rezumat

În această lucrare este folosită o abordare integrată bazată pe simularea Monte Carlo şi metodologia Six Sigma pentru a analiza riscul asociat costului total al unui proiect. Simularea Monte Carlo este aplicată pentru a înţelege variabilitatea costului total cauzat de elementele de cost probabilistice. Prin metodologia Six Sigma, intervalul de variaţie al costului proiectului poate fi redus operând asupra factorilor de intrare cu cel mai mare impact asupra costului total pentru a cuprinde variaţia de 6σ între limitele pe care au fost stabilite în faza de concepţie a Six Sigma.

Cuvinte-cheie: *Riscul costului unui proiect; Six Sigma; simularea Monte Carlo*

JEL Classification: C63, D24, D81

Introduction

In this paper it is shown how Monte Carlo simulation can be used in a Six Sigma analysis of the cost of a project. The underlying connection between Monte Carlo simulation and Six Sigma is the variability inherent in all business processes (Goldman et al., 2003; Luban, 2007; Luban & Pumnut, 2008).

The Monte Carlo method of estimating project cost is based on the generation of multiple trials to determine the expected value of a random variable (Andreica, Stoica, & Luban, 1998; Hîncu, 2002; Rațiu-Suciu et al., 2009). There are a number of commercial packages that run Monte Carlo simulation; however a basic spreadsheet can be used to run a simulation (Albright, Winston, 2007; Winston, 2007; Luban, 2005).

In an increasingly competitive market, businesses are turning to new practices like Six Sigma, a structured methodology for accelerated process improvement, to help reduce costs and increase efficiency. Since its inception at Motorola in 1984 for measuring defect rates in manufacturing processes, the Six Sigma initiative has changed the way people work around the world (George et al., 2005).

Six-Sigma (6σ) is a customer-focused, facts-based, data-driven, results-oriented, project focused, project management approach to quality that can be used by any business, small or large. Six Sigma improves the process by reduction the variation.

The typical project often overruns its cost estimates (Hullet, 2002.). This happens because cost estimating traditionally fails to take into account the risk that the project will actually cost more or less than provided by even the most competent estimate (Anderson et al., 2007; Ourdev et al., 2007).. The Six Sigma methodology can be used to identify the sources of the variability of the project cost and suggest ways in which costs can be reduced.

Six Sigma is divided into five distinct phases: Define, Measure, Analyze, Improve, and Control (DMAIC).

The define phase

The define phase is one of the most important phases because it sets the framework and goals for the project.

In this paper, it is considered that the total cost of the project is determined by five major components: raw material, labor, equipment, other variable costs, indirects.

The cost risk analysis must answer some questions that include: what is the most likely cost, how likely is the baseline estimate to be overrun, what is the cost risk exposure, where is the risk in this project.

The Six Sigma team can define its goals as understanding and controlling the source of the variability of the project cost in order to reduce cost risk exposure.

The measure phase

During the measure phase, the Six Sigma team gathers data that describe the cost components of the project.

In Table 1 are presented the costs estimated in the traditional way by the specialists of the project.

Initial estimates of the project costs

Table 1

Cost component	*Estimate (monetary units or m.u.)*
Raw materials	2800
Labor	1880
Equipment	2000
Other variable costs	600
Indirects	2400
Total cost	9680

In Table 1 the total cost estimate is shown as 9680 m.u. But how likely is that the project be completed at this cost? Is 9860 m.u. the most probable value of the total project cost? To answer these questions it is need to examine the uncertainty in these initial estimates.

Determining the risk associated with project cost can be achieved only by accumulating more information. The Six Sigma analyst must choose relevant persons to be interviewed. In many projects, it can appeal to engineers and business economists who have experience needed for these estimates, the project head and the other employees that are on the same hierarchical level and components of the project team, such as site foreman, etc.. It is possible and questioning of experts outside the organization, but only in a particular case, designated by the contracting authority or to the relationships established. When these people get into a room, the Six Sigma analyst asks about three numbers for each cost component: the pessimistic cost estimate**,** the optimistic cost estimate and the most likely cost estimate. Optimistic cost if it is deemed that all goes well and pessimistic cost is achieved in the worst possible case. Cost is usually the most likely price at which bidding the project, although, as will be seen this cost does not have the lowest level of risk. Usually, this price is quite optimistic as to be smaller but, in reality, it need a certain amount of luck to be gained.

Also, in the measure phase, the experts must be asked about a lower limit and an upper of the total cost of the project.

The analyse phase

In the analyse phase, the team works to understand the variability of the project cost. Monte Carlo simulation can be used as a tool to help analyse the uncertainty of the project cost. Suppose that the expert interview has occurred and the estimates from Table 2 are obtained.

The triangular distributions of the project costs

Table 2

Cost component	*Estimate (monetary units)*		
	Optimistic cost	*Most likely cost*	*Pessimistic cost*
Raw materials	2480	2800	3440
Labor	1800	1880	2360
Equipment	1800	2000	2400
Other variable costs	480	600	800
Indirects	2000	2400	2680

The experts have established the Lower Specification Limit (LSL) and Upper Specification Limit (USL) for the total cost as 9500 m.u. and 10200 m.u. respectively.

The Monte Carlo method involves the artificial generation of experience or data by the use of a random number generator and the cumulative distribution function being considered (Hîncu, 2002; Luban, 2005). A Monte Carlo simulation executes the problem many times. Each solution is called iteration. For each iteration, the Monte Carlo method selects a cost at random from the probability distribution specified for each uncertain cost element. The solution in this case is to add them together since this project cost estimate is a summation model.

Creating the simulation model

The triangular distributions of the cost components will be used to run a Monte Carlo simulation. Estimation of the project costs with the Monte Carlo method is based on replacement of the actual costs with the costs generated randomly on the base of their probability distributions and by performing a large number of simulation iterations.

If x is a value of the triangular probabilistic cost, *a* denotes the value of optimistic cost, *b* is the value of the most likely cost, and *c* denotes the value of pessimistic cost, such that $a < b < c$, the density probability function f(x) is defined by the relation:

$$f(x) = 2(x-a)/((b-a)(c-a)), \text{ for } a \le x \le b$$
$$= 2(c-x)/((c-a)(c-b)), \text{ for } b \le x \le c$$

The cumulative distribution function F(x) is given by:

$$F(x) = P(X \le x) = 0, \text{ for } x<a$$
$$= ((x-a)^2)/((b-a)(c-a)), \text{ for } a \le x \le b$$
$$= 1 - ((c-x)^2)/((c-a)(c-b)), \text{ for } b < x \le c$$
$$= 1 \text{ for } x>c$$

The mean $\mu = (a+b+c)/3$

The variance $\sigma^2 = (a^2 + b^2 + c^2 – ab – ac – bc)/18$

Let be $h = (b-a)/(c-a)$, and let be $u \in [0, 1]$ a random number generated by a random number generator.

Monte Carlo method will provide a value of the cost x, by solving the equation $F(x) = u$.

If $u \leq h$, than the equation $F(x) = u$ has the form:

$$((x-a)^2)/((b-a)(c-a)) = u \longleftrightarrow (x-a)^2)=u(c-a)^2((b-a)/(c-a)) = uh(c-a)^2$$

$$x = a + (c-a)*(uh)^{½}$$

If $u > h$, than the equation $F(x) = u$ has the form:

$$((c-x)^2)/((c-a)(c-b)) =1- u$$

$$x = a + (c-a)*(1-((1-h)*(1-u))^{½})$$

The general form of the solution is:

x=a+(c-a)*(IF(u<=h, SQRT(u*h), (1-SQRT((1-h)*(1-u)))))

This solution will be used to run Monte Carlo simulation with Microsoft Excel. The simulation results after 1000 iterations are presented in Figure 1.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	**Project cost simulation**												
2		*Optimistic coost likely cosimistic cost*											
3	*Cost component*	a	b	c	c-a	h=(b-a)/(c-a)							
4	Raw materials	2480	2800	3440	960	0.33							
5	Labor	1800	1880	2360	560	0.14							
6	Equipment	1800	2000	2400	600	0.33							
7	Other variable costs	480	600	800	320	0.38							
8	Indirects	2000	2400	2680	680	0.59							
9			9680										
10	Simulation												
11	Iteration	Random number	Raw materials	Random number	Labor	Random number	Equipment	Random number	Other variable costs	Random number	Indirects	Total project cost	
12	1	0.7080	3016.471	0.9189	2212.341	0.2926	1987.380	0.1797	563.078	0.9584	2591.024	10370.295	
13	2	0.8330	3119.718	0.1700	1887.649	0.0594	1884.461	0.8674	707.861	0.5145	2374.098	9973.788	
1011	1000	0.4446	2855.831	0.1770	1889.655	0.6978	2130.691	0.1084	544.529	0.5144	2374.068	9794.774	
1012			2910.531		2015.559		2068.868		628.895		2364.503	9988.356	Mean
1013												297.204	Std deviation

Figure 1. Monte Carlo simulation results

The formula used for the simulation experiments are presented in Table 3.

The simulation model in EXCEL

Table3

	Cell	*Formula*
Random number	B12	=RAND()
Raw materials	C12	=$B$4+$E$4*(IF(B12<=$F$4,SQRT(B12*$F$4),(1-SQRT((1-$F$4)*(1-B12)))))
Random number	D12	=RAND()
Labor	E12	=$B$5+$E$5*(IF(D12<=$F$5,SQRT(D12*$F$5),(1-SQRT((1-$F$5)*(1-D12)))))
Random number	F12	=RAND()
Equipment	G12	=$B$6+$E$6*(IF(F12<=$F$6,SQRT(F12*$F$6),(1-SQRT((1-$F$6)*(1-F12)))))
Random number	H12	=RAND()
Other variable costs	I12	=$B$7+$E$7*(IF(H12<=$F$7,SQRT(H12*$F$7),(1-SQRT((1-$F$7)*(1-H12)))))
Random number	J12	=RAND()
Indirects	K12	=$B$8+$E$8*(IF(J12<=$F$8,SQRT(J12*$F$8),(1-SQRT((1-$F$8)*(1-J12)))))
Total cost	L12	=C12+E12+G12+I12+K12

The line B12:L12 is then copied in B13:L1011 to make 1000 iterations.

Simulation results

When 1000 iterations are completed the results can be analysed using histogram presented in Figure 2.

The mean cost 9988.356 m.u. with a standard deviation of 297.204 m.u.

The probability P(Total project cost <= 9680) can be determined with =PERCENTRANK(L12:L1011,9680). It can be seen that the estimated cost at completion of 9680 m.u. is not very likely. The results indicate that the actual cost is about 18% likely to be 9680 or less and 82% likely to be overrun. The total cost of 9680 m.u. is not even the most likely cost. The probability P(9500 <= Total project cost <= 10200) = PERCENTRANK(L12:L1011,10200).-PERCENTRANK(L12:L1011,9500) = 0,73

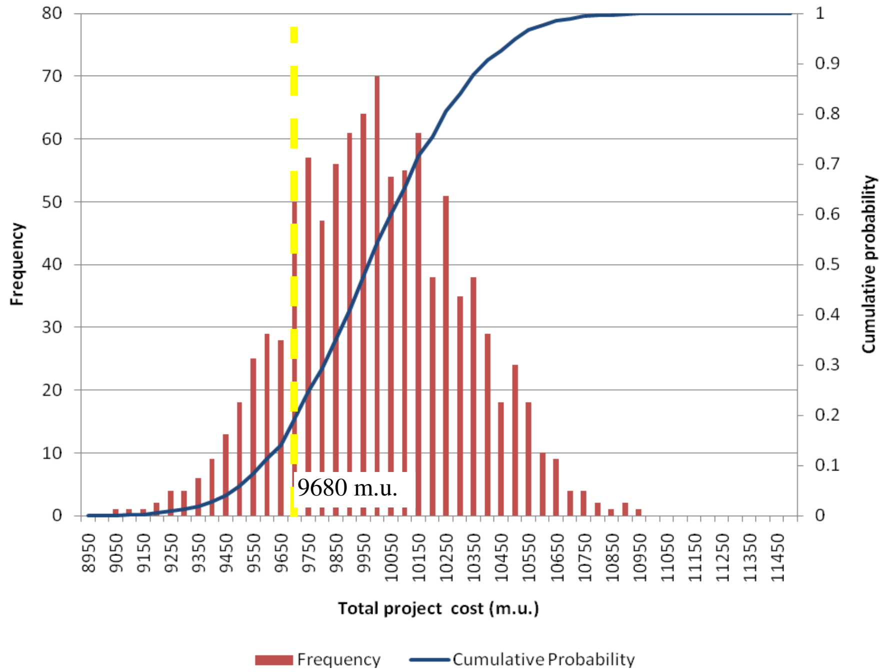

Figure 2. Probability distribution for total project cost

Where is the Risk in the Project?

To understand the variability of the total project cost and to identify the high – risk cost elements, in Table 4 is computed the differences between the estimate for each cost component and the average of cost obtained by Monte Carlo simulation.

Differences between simulated costs and initial costs

Table 4

Cost component	*Estimate*	*Average simulated cost*	*Difference*
Raw materials	2800	2910.531	110.531
Labor	1880	2015.559	135.559
Equipment	2000	2068.868	68.868
Other variable costs	600	628.895	28.895
Indirects	2400	2364.503	-35.497
Total project cost	9680	9988.356	308.356

The labor costs contribute about 44% to the contingency of 308.356 m.u. at the mean. Raw materials (36%) and equipment contribute the next most. Indirects are expected to underrun.

The improvement phase

After the understanding the effects of uncertainty on the project cost the Six Sigma analyst and project manager can try to make improvements to the process in order to increase the sigma level of the project. Notice that the actual level is about 2.36 sigma between the specification limits LSL and USL.

One way to improve the sigma level is to apply statistical allocation. Allocation techniques use Sensitivity Analysis or Monte Carlo analysis to work the problem backward and identify the input factor standard deviation (roughly a measure of the spread of their distributions) that will reduce the probability of non-compliance (PNC) to a desired level. If Monte Carlo analysis is employed, then allocation becomes a brute-force iterative process.

In this paper the simulation will be used to analyze the effect of changing the suppliers of raw materials and the human resource management. It is expected that the pessimistic cost of raw materials will decrease from 3440 m.u. to 3200 m.u. and the pessimistic cost of labor will decrease from 2360 m.u. to 2200 m.u.

The certainty increase to 82.60% for the project costs between 9500 u.m. and 10200 u.m. The average total cost is 9848.153 m.u. The standard deviation dropped to 256.918 and the design has improved from 2.36 sigma to 2.72 sigma.

The control phase

The Control phase completes the Six Sigma methodology. In this continuing process, the project manager monitor the status of the costs to detect when fine tuning or new improvements are necessary.

Conclusion

Monte Carlo simulation has a crucial role to play in multiple phases of a Six Sigma analysis project. By moving to a probabilistic methodology, Six Sigma analysts can better quantify the effects of variability and can implement process improvements with greater insight and confidence.

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