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A novel model based on extended Monte Carlo simulation for investigating the effect of co-occurrence of risks considering utility function

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Abstract

Risk assessment is a part of risk management. There are different techniques for risk assessment. Monte Carlo simulation (MCS) is one of the quantitative methods for risk assessment. Extended MCS tried to solve the weakness of classic Monte Carlo simulation through using rotary algorithm. But in the real world, projects face with different risks simultaneously. Co-occurrence of risks cause to exacerbates or diminishes the effects of each other. In this paper, the effect of occurrence of other risks on one risk in each iteration is investigated and finally the utility function is calculated by considering co-occurrence of risks and rotary algorithm. The proposed model tested on petrochemical construction project data. In this project, six risks such as inflation rate, labour, temperature, rain, cost and time are identified through experts' opinion. The results show that the utility function become closer to reality by considering the co-occurrence of risks.

Keywords: Risk management, risk assessment, co-occurrence of risks, utility function, extended Monte Carlo simulation

1-Introduction

Risks are an inevitable part of projects, which have positive or negative effects on them. Failure in confrontation to risks is one of the main reasons of rising costs, falling behind schedule and loss of performance goals. This is exacerbated in large projects with large investments, large partners and stakeholders and high resources. So, it is important to face risks by a risk management regime.

Risk assessment is one of the steps of risk management. There are different techniques for risk assessment such as FMEA ((Liu et al., 2017)), Fuzzy-based approaches for quantitative assessment (Fuzzy Group decision making (Wang and Elhag, 2007), Fuzzy logic and qualitative risk assessment techniques (Nakandala et al., 2017), Fuzzy cognitive map (Jamshidi et al., 2018)), AHP (Dong and Cooper, 2016),Tree based approaches (Gachlou et al., 2019, Sarbayev et al., 2019), Monte Carlo simulation based approaches (MCS) ((Pouillot et al., 2004, Cummins et al., 2009, Schuhmacher et al., 2001)). Regarding research containing risk assessment and fuzzy topics, it should be noted that owing to the imprecise and uncertain nature of various factors affecting the probability and impact of identified risks, fuzzy logic is integrated into the proposed methodologies for assessing risk.

In this paper, we apply MCS which is one of the quantitative risk assessment techniques. In many cases, this method has been used independently or by combination with other techniques to risk assessment. For example in (Bamakan and Dehghanimohammadabadi, 2015), a weighted MCS approach has been proposed to risk assessment in which AHP is applied to assign weights to factors and then MCS is applied to compute estimated risk level of incidents. Table 1 shows different innovation in Monte Carlo simulation, combination of it with other techniques and the application of this method in risk assessment.

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Table 1. Literature review of Monte Carlo simulation based method

Type	Applied technique	Main objectives	Major findings	References
Extending/Development of Monte Carlo simulation techniques	Monte Carlo simulation	• To rationalize classic MCS • Discussing the uncertainty probabilities • presenting rotary algorithm	• Proposing rotary algorithm • Considering the interactions of uncertainties • classic MCS come closer to reality	(Rezaie et al., 2007)
Application of Monte Carlo simulation	Extended Monte Carlo simulation	• determination of safety interval	• Proposing a heuristic approach based on the output of Extended Monte Carlo simulation • determination of safety interval • planning project in real way	(Rezaie et al., 2009)
Combination of Monte Carlo simulation techniques with other techniques (using hybrid methods)	Weighted Monte Carlo simulation(Monte Carlo simulation & AHP)	• risk assessment of Information Security Management System • Applying AHP to weight the importance of the factors • Utilizing Monte Carlo simulation to calculate the estimated risk level of incidents	• consider a probabilistic approach rather than a deterministic one • proposing a weighted Monte Carlo simulation as a risk assessment technique	(Bamakan and Dehghanimohammadabadi, 2015)
Extending/Development of)Monte Carlo simulation techniques	Fuzzy Monte Carlo simulation	• Proposing fuzzy MCS • Comparing the fuzzy MCS and MCS in order to finding influential design options	• Proposing fuzzy MCS which consider the aleatory and epistemic uncertainty • providing a family of probability distributions • comparing the fuzzy MCS and MCS shows that fuzzy MCS provides more meaningful and reliable information to decision makers than MCS.	(Kim, 2017)
Extending/Development of Monte Carlo simulation techniques	Extended Monte Carlo simulation	Extending Monte Carlo simulation to cover the simulation process of the model .	• By proposed method the inputs are repeated and the model is reconstructed repeatedly • a classic and developed model was used to compare the risk analysis of aircraft development costs, • the risk distribution of the developed method was significantly different from the classic	(Huang et al., 2010)
Extending/Development of Monte Carlo simulation techniques	Guided Monte Carlo	• Proposing new risk analysis Guided Monte Carlo • Proposing an efficient and precise technique for calculating probabilistic risk	• The proposed method facilate risk analysis of complex models	(Shorter and Rabitz, 1997)

Since the proposed model is based on Monte Carlo Simulation, we review some papers which focused on this model in table 1.

Based on our knowledge, none of the previous studies address to co-occurrence of risks in risk assessment. If two or more risks occur together, the severity and effect of the risks will change which affects the utility function. Considering co-occurrence of risks help the project decision makers and managers to make the right decision based on the real-world incidences.
In this paper, MCS technique is developed to determine the utility function which is the profit value regard to simultaneous occurrence of risks.

The main objectives of this paper are as follows:

- Considering co-occurrence of risks
- Using co-occurrence of risks in Extended Monte Carlo Simulation for risk assessment
- Calculating utility function based on the co-occurrence of risks

The paper is organized as follows:
Extended Monte Carlo simulation is explained in section 2 .Then, the proposed method (extended Monte Carlo simulation based on co-occurrence of risks for calculating utility function) are presented in section 3. A real-world numerical example of the model is presented in section 4. Finally, section 5 concludes and discusses future work.

2-Extended Monte Carlo simulation method

Uncertainty is a lack of complete certainty. In uncertainty, the outcome of any event is entirely unknown. Risk can be said to be an uncertain event which chances of occurrence can be predicted and measured whereas, uncertainty can also be said to be an uncertain event which chances of occurrence cannot be predicted and measured. The difference is that the probability of a risk event happening can be predicted and measured while the probability of uncertainty cannot be predicted and measured.

However, Monte Carlo simulation as a statistical technique is a powerful tool which considers both opportunity and threat. Despite the benefits of MCS, it initializes uncertainties quite randomly. The uncertainties in the real world are not independent and are influenced by the type and level of their interaction. The lack of attention to the interaction between uncertainties is a disadvantage of MCS which can cause that utility function becomes far from reality. So, Extended Monte Carlo simulation by introducing the rotary algorithm solved this problem (Rezaie et al., 2007). The introduction of the EMCS technique is presented as the following.

In extended Monte Carlo simulation after determining the type and level of relationship between uncertainties, rotary algorithm is used to select the free uncertainty. In the rotary algorithm each uncertainty can effect on the relevant uncertainties which results in a more accurate search compared with Monte Carlo simulation. Free uncertainty is allowed to have a random value in the range of [1,100], but other uncertainties are only allowed to accept a random value in the control range. Each control range is determined by the type and degree of dependence of the free and dependent uncertainties. It is considered 10%, 20% and 40% tolerance for high, medium and low dependency. The general formulation for control interval is shown in equation 1. (Rezaie et al., 2009, Rezaie ***et al.***, 2007):

$$\begin{cases} \left(Max\left(1,(A-5n)\right),Min\left(100,(A+5n)\right)\right) & \text{Direct relationship} \\ \left(Max(1,100-(A+5n))\right),Min\left(100,100-\ (A-5n)\right)\right) & \text{Inverse relationship} \\ [1,100] & \text{None relationship} \end{cases} \quad (1)$$

In equation 1. *n* is the level of dependency between two uncertainties.

Although Extended Monte Carlo simulation eliminates the weakness of Classic Monte Carlo simulation by considering the interaction between the risks and also omit impossible states, but it has not considered the co-occurrence of risks.

In Rezaie et al., (2007 and 2009), the EMCS has been proposed to intellectualize the classic Monte Carlo simulation by proposing rotatory algorithm. This leads to the output of MCS come closer to the real world. For this aim, they consider the relationship between uncertainties. In this paper, we consider the co-occurrence of risks by weighting the relationship between risks which the weights are determined by experts' opinion.

So, in this paper, by considering the co-occurrence of risks, extended Monte Carlo simulation is developed and come closer to reality. As MCS technique investigates all states of the project which is a positive point, so in this paper this property with the co-occurrence of risks is applied to calculate the utility function.

3-Proposed method: Extended Monte Carlo simulation based on co-occurrence of risks

Every project is faced with many of risks, which some of them can occur simultaneously. So, this can has different effects on the project. Occasionally, the co-occurrence of risks may exacerbate their effects and in some cases may reduce them. Therefore, considering the co-occurrence of risks helps managers and decision makers who are responsible for ensuring the achieving the objectives of projects to make correct decisions.

As mentioned previously, classic Monte Carlo simulation assigns the value to the uncertainties randomly. In Extended Monte Carlo simulation, the uncertainties are valued conditional. For example if x is considered as a free variable, then the dependent variables valued based on the type and level of their interaction with x. So, in rotary algorithm the uncertainties are illustrated as follows (Rezaie et al., 2007):

$$\begin{pmatrix} f(x) \\ f(y|x) \\ f(z|x) \\ f(t|x) \end{pmatrix} \qquad \begin{pmatrix} f(x|y) \\ f(y) \\ f(z|y) \\ f(t|y) \end{pmatrix} \dots\dots \begin{pmatrix} f(x|t) \\ f(y|t) \\ f(z|t) \\ f(t) \end{pmatrix} \tag{2}$$

In Extended Monte Carlo Simulation based on co-occurrence, in each run, one of the uncertainties is considered as a free uncertainty and valued. Then the value of the rest uncertainties which are valued by EMCS are weighted regard to the effect of co-occurrence of free uncertainty on dependent uncertainties according to equation 2. Also, in rotary algorithm the free uncertainty is changed and the effect of its co-occurrence with dependent uncertainties is investigated in each run. In equation 3. W_{xy} is the weight of co-occurrence of X and Y. $f(y,x)$ shows the value of y when occur with x simultaneously and $f_{y|x}$ is the value of y which is valued by EMCS.

$$f_{(y,x)} = \left(1 \pm W_{xy}\right) \times f_{y|x} \tag{3}$$

The outputs EMCS based on co-occurrence are as follows:

$$\begin{pmatrix} f(x) \\ f(y,x) \\ f(z,x) \\ f(t,x) \end{pmatrix} \qquad \begin{pmatrix} f(y,x) \\ f(y) \\ f(z,y) \\ f(t,y) \end{pmatrix} \dots\dots \begin{pmatrix} f(x,t) \\ f(y,t) \\ f(z,t) \\ f(t) \end{pmatrix} \tag{4}$$

Where, $f(y, x)$ is stand for the uncertainty *y*, if it happen with uncertainty *x* simultaneously. The utility function which is the difference of cost from income can easily calculate based on the outputs of EMCS with considering the co-occurrence.

The algorithm of proposed method is as follows which first seven steps of it are similar to EMCS (Rezaie et al., 2007):

1) Risk identification of the project based on one of the risk identification techniques (Delphi, Brain storm, Expert's opinion, etc.) and also determining the probability function for each risk.
2) Determining the number of run based on complexity and size of project and dividing the area between the graph of the distribution function and the horizontal axis into N squares, where N represents the number of simulation runs.
3) Specify the type (direct, inverse, ineffective) and level (weak, medium, strong) of the dependency for each pair of uncertainties.
4) Determine the free uncertainty for rotary algorithm.
5) Assign a random number A from interval 1 to 100.
6) Determine a control interval for all dependent uncertainties based on equation 1.
7) Specify a random number from interval which is determined in step 6, for each dependent uncertainty.
8) Determine the weight of interaction between pair of uncertainties to find the co-occurrence effect of risks.
9) After determination the value of dependent uncertainties by rotary algorithm(EMCS) (Rezaie et al., 2007), determine the new value of dependent uncertainties by equation 2.
10) Calculate the utility function based on the values of all uncertainties.
11) If the number of runs is completed, go to step 4 for the next uncertainty.

4-Numerical example

Considering the co-occurrence of risks causes to help decision makers pay more attention to all aspect of project and risks. Because in the real world most of projects face with different risks which in some cases some of them occur simultaneously which cause to exacerbate or diminish the effect of risks on each other. As calculating the utility function is on the effect of risks, so co-occurrence of them may change the result of utility function. In order to evaluate the proposed method, the project of construction of petrochemical is considered in Iranian company (Rezaie et al., 2009). Six uncertainties are considered in this project. The uncertainties and their distribution functions are shown in table 2. Also, the utility function is calculated by difference of income and cost (Rezaie et al., 2007).

Table 2. Distribution function of Risks (Rezaie et al., 2009)

Risks	Distribution function	Unit
x_1:**Time**	T(300, 350, 570)	Day
x_2:**Cost**	N(700,15)	Billion(IRR)
x_3:**Temperature**	T(10, 21, 31)	Day
x_4:**Rain**	T(22, 32, 43)	Hour
x_5:**Labor**	N(386,15)	Unit
x_6:**Interest Rate**	T(13, 13.8, 15.5)	Unit

Table 3 illustrates the coefficient of type and level of interaction between risks in order to determine control intervals.

Table 3. The coefficient of type and level of interrelationship between risks (Rezaie et al., 2009)

Risk	Time	Cost	Temperature	Rain	Labor	Interest Rate
Time	0	-1	+4	+4	-1	0
Cost	-1	0	+4	+4	+2	+1
Temperature	+4	+4	0	0	0	0
Rain	+4	+4	0	0	0	0
Labor	-1	+2	0	0	0	0
Interest Rate	0	+1	0	0	0	0

Table 4 shows the weight of co-occurrence of risks.

Table 4. Weight of co-occurrence of risks

Risk	Time	Cost	Temperature	Rain	Labor	Interest Rate
Time	0	-0.75	+0.25	+0.25	-0.75	0
Cost	-.075	0	+0.25	+0.25	+0.5	+0.75
Temperature	-.075	+0.25	0	0	0	0
Rain	+0.25	+0.25	0	0	0	0
Labor	-0.75	+0.5	0	0	0	0
Interest Rate	0	+0.75	0	0	0	0

The utility function corresponding to the four runs (500, 1000, 2000, and 5000) of EMCS with considering the co-occurrence of risks is shown in figure 1.

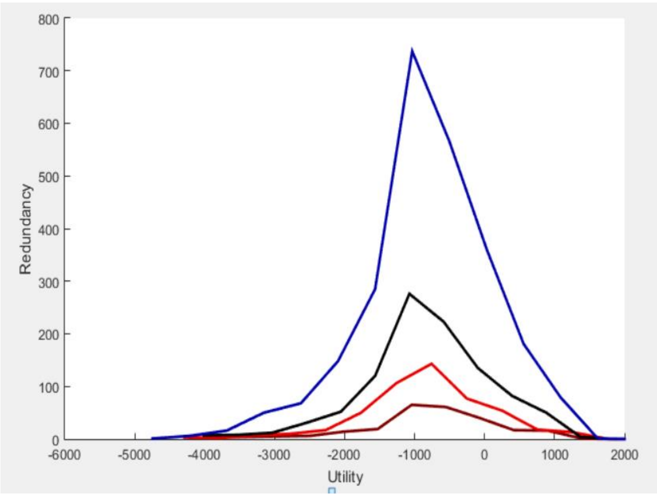

Fig 1. The output of EMCS approach based on co-occurrence

The utility function corresponding to each run of EMCS without considering the co-occurrence of risks is shown in figure 2.

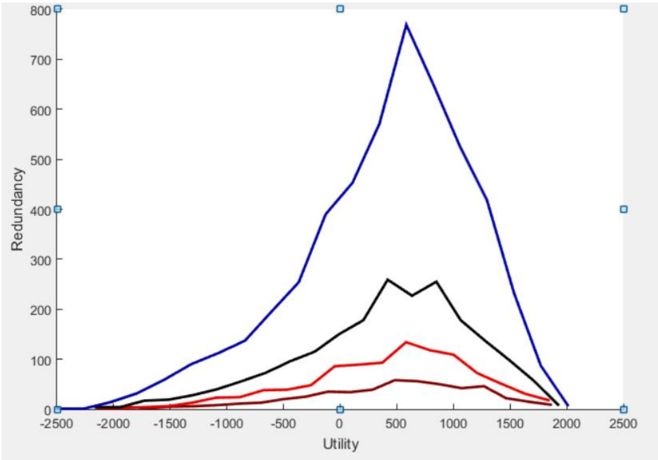

Fig 2. The output of EMCS without considering the co-occurrence of risks

As figure 1 and figure 2 show, the frequency of utility function is between 700 and 800. Figure 1 illustrates that the utility function is negative when the frequency of the proposed model is 700. So, the most probable utilities based on EMCS with considering the co-occurrence of risks are about -1000. This is because of considering the co-occurrence of risks which leads to an increase in their negative effects. In other word, if multiple risks occur simultaneously and they have a direct impact, by exacerbating their effects, the utility function becomes negative. In contrast, as one can show in figure 2. The most probable value for utility is about 600. By comparing the results shown in figure 1 and figure 2, there are significant difference between the most probable of value utility in EMCS with considering the co-occurrence and without it.

Also, the sensitivity analysis of the proposed model is shown in figure 3.

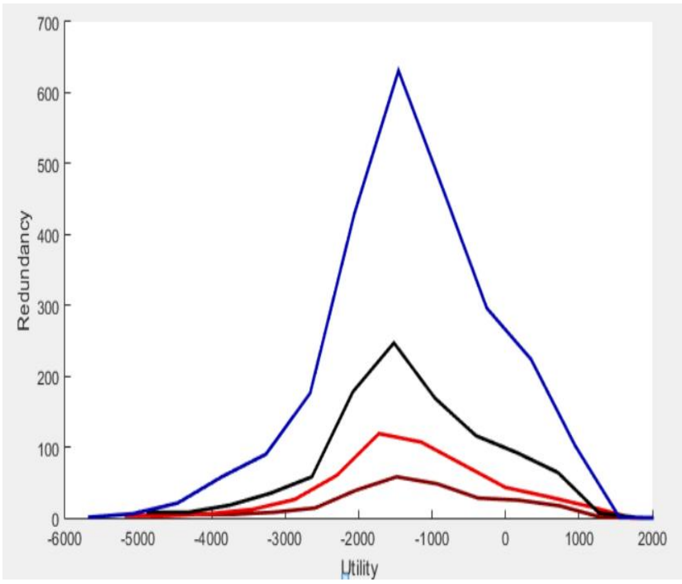

Fig 3. Sensitivity Analysis

5-Conclusion

In the real world, many risks occur simultaneously which can have an effect on the severity of risks. In this paper, by considering the co-occurrence of risks, the Extended Monte Carlo simulation technique comes closer to reality. The frequency diagram of utility function corresponding to the Extended Monte Carlo based on co-occurrence illustrates the effect of simultaneous occurrence of risks on each other and ultimately on utility function. However, in the some parts of the diagram, the simultaneous occurrence of risks leads to intensify effects of each other and in some other parts leads to reduce effects of each other and ultimately it causes to increase utility, which are not considered in EMCS.

Data Deposition Information

All data generated or analysed during this study are included in this published article and available from the corresponding author on reasonable request.

Conflict of interest

The authors confirm there are no conflicts of interest. Also, the authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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