Risk Dependency Analysis (RDA) in Complex Projects

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Risk Dependency Analysis (RDA) in Complex Projects

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Abstract: Dependencies and interdependencies between major risks are becoming a critical issue for large engineering projects. Current project risk analysis and management (PRAM) process does not focus effectively on relationships between risks, even though risks are often not independent in complex projects. As a consequence, we develop a risk dependency analysis (RDA) procedure to support PRAM. It entails three phases: Dependency Identification, Dependency Assessment, and Dependency Quantification. The aim of Dependency Identification is to describe risk dependencies and interdependencies through a design structure matrix (DSM) and gather them in clusters. Dependency Assessment is an unconventional probabilistic approach, which considers risk dependencies as events with their own probabilities, while Dependency Quantification estimates the impact of risk dependencies on project performance. The application of RDA to the Oil & Gas Industry uses a Monte Carlo simulation model, which aims at estimating schedule delays and capital expenditure (CAPEX) overruns.

1 Introduction

Traditionally, project risk analysis and management (PRAM) is performed focusing on risks, seen as favorable or unfavorable events[1,2] and described by two basic parameters: occurrence probability and impact severity[3]. In particular, PRAM deals with major risks, which individually considered may have a significant impact on project performance.

Less consideration is generally given to the interactions between risks[4,5], even though such interactions may reveal devastating. One of the main causes of this situation is the rising complexity of projects[6,7], which not only may be structural[8–10] but also related to external sociopolitical aspects[11,12].

This article moves the research focus from the traditional project risks to risk dependencies, as project risks cannot always be assumed as independent events[13,14], and their relationships can affect project performance[15].

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The concept of risk dependency refers to the effect that the occurrence of a risk may have on the probability of occurrence of another risk[16].

Three different types of relationships between risks may occur[17,18]:

- Independency: occurrence of a risk is not related to the occurrence of other risks.
- Dependency: this type of relationship implies that the occurrence of a root risk may influence the occurrence probability of a dependent risk.
- Interdependency: this type of relationship is related to a mutual dependency between two or more risks.

This article examines only dependent and interdependent risks, focusing on the impact of their relationships on the project performance in terms of cost overrun and schedule delay.

In a similar manner as PRAM, this analysis of risk relationships is based on a sequence of processes: Dependency Identification, Dependency Assessment, and Dependency Quantification.

The article is organized as follows: Sections 2–5 describe the proposed procedure structured in three phases: Dependency Identification, Dependency Assessment, and Dependency Quantification.

The case study related to some Oil & Gas field development projects is presented in Section 6 to highlight the contribution given by the proposed procedure to the improvement of the PRAM process. The procedure can integrate the results of the traditional cost and schedule risk analysis (CSRA) process, at the stage of final investment decision (FID), giving a deeper awareness of project complexity and an improved "estimate to complete" both in terms of cost overrun and schedule delay. Some conclusions are drawn in Section 7, with some suggestions for future development.

2 Dependency Identification

While approaching the planning of a new project, Dependency Identification is the first process to be accomplished. It concerns the identification of risk dependencies and interdependencies.

Risk Identification is primarily based on data records related to past projects and may require a review of a large number of close out reports (CORs). CORs represent the "post mortem" analysis of a completed project in order to obtain data, performance parameters, and management lessons useful for planning the future projects.

First, the review of CORs enables the identification of the major causes of schedule delay and cost overrun occurred in the projects.

Second, it enables the identification of the major dependencies and interdependencies between the occurred risks through a design structure matrix (DSM).

In general, DSM analyzes dependencies and interdependencies between the elements in a system design process[19,20]. When its use is extended to the analysis of project risk relationships[21–24], it is named risk structure matrix (RSM)[25].

An RSM is created for each finished project. Once all the past projects have been analyzed, the results obtained are summarized by the standard risk structure matrix (SRSM). The SRSM is the global binary and square matrix obtained by merging all the RSMs. The elements of the SRSM are the most recurring risks, which are affected by dependencies and interdependencies in a significant number of finished projects. All the independent risks may be excluded.

The SRSM displays risk dependencies and interdependencies without any pattern. For this reason, a clustering algorithm for binary DSM was applied to SRSM. As shown in Figure 1, its application changes the position of risks according to their dependencies and interdependencies. In fact, the root risks are gathered in the lower part of SRSM, while the dependent ones in the upper part. Moreover, the interdependent risks

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	Risk A	Risk B	Risk C	Risk D	Risk E	Risk F	Risk G
Risk A		1					
Risk B							
Risk C					1	1	
Risk D			1		1		
Risk E							
Risk F			1		1		
Risk G		1					

(a)

	Risk B	Risk A	Risk G	Risk E	Risk F	Risk C	Risk D
Risk B							
Risk A	1						
Risk G		1					
Risk E							
Risk F				1		1	
Risk C				1	1		
Risk D				1		1	

(b)

Figure 1. A generic SRSM (a) before and (b) after the application of the clustering algorithm.

have been rearranged in the same cluster, and their dependencies are gathered in clusters so as to maximize the intracluster dependencies and minimize the extracluster propagation of effects.

3 Dependency Assessment

The outcome of the Dependency Identification corresponds to a binary and square matrix, which only gives information about the existence of risk dependencies and interdependencies. Generally, it may be transformed into a numerical one indicating the strength of these relationships using the analytic hierarchy process (AHP)[26] or direct expert judgments.

This article aims at introducing a different procedure, which is rooted in probability theory[27,28] and describes how to determine the occurrence probability of dependent risks through the theorem of total probability.

For this purpose, a significant assumption will be introduced: dependencies are considered to be events characterized by an occurrence probability. As shown in Figure 2, the dependency relationship between risk A and risk B is represented as an intermediate node and indicated with the notation $A \rightarrow B$, while interdependency corresponds to a mutual dependency between risk A and risk B.

In this way, the proposed procedure is divided into two steps: in the first step, the occurrence probability of risk dependency $A \rightarrow B$, defined as $P(A \rightarrow B)$, can be calculated as follows:

$$P(\mathrm{A} \rightarrow \mathrm{B}) = P(\mathrm{A} \rightarrow \mathrm{B}|\mathrm{A}) \cdot P(\mathrm{A}) \tag{1}$$

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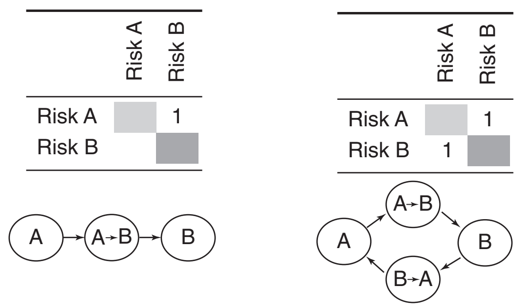

Figure 2. Representation of risk dependency and risk interdependency considered as events.

with

$P(\mathrm{A} \rightarrow \mathrm{B}|\mathrm{A})$ conditional probability of $\mathrm{A} \rightarrow \mathrm{B}$ given risk A
$P(\mathrm{A})$ occurrence probability of risk A.

In the second step, the occurrence probability of dependent risk B can be updated as

$$P(\mathrm{B}) = P(\mathrm{B}|\mathrm{A} \rightarrow \mathrm{B}) \cdot P(\mathrm{A} \rightarrow \mathrm{B}) + P(\mathrm{B}|(\mathrm{A} \rightarrow \mathrm{B})^{\mathrm{C}}) \cdot P(\mathrm{A} \rightarrow \mathrm{B})^{\mathrm{C}} \tag{2}$$

where

$P(\mathrm{B}|\mathrm{A} \rightarrow \mathrm{B})$ the conditional probability of risk B, given risk dependency $\mathrm{A} \rightarrow \mathrm{B}$
$P(\mathrm{B}|(\mathrm{A} \rightarrow \mathrm{B})^{\mathrm{C}})$ the conditional probability of risk B, with no risk dependency $\mathrm{A} \rightarrow \mathrm{B}$.

Equations (1) and (2) need to be approximated in order to apply the procedure when developing PRAM. In the Risk Register, that is, in the preliminary list of the risks identified for the project, the risk probability value, characterized by the subscript “0” in Equations (3) and (4), does not consider any effect of dependency and interdependency. The purpose of this procedure is to obtain an updated risk probability, defined with the subscript “1,” that takes into account both risk probability as reported in the Risk Register and risk dependencies and interdependencies as reported in the risk dependency analysis (RDA).

According to this approach, Equation (1) can be approximated as follows:

$$P(\mathrm{A} \rightarrow \mathrm{B}) = P(\mathrm{A} \rightarrow \mathrm{B}|\mathrm{A}) \cdot P(\mathrm{A}) \sim P(\mathrm{A} \rightarrow \mathrm{B}|\mathrm{A})_{\mathrm{hist}} \cdot P(\mathrm{A})_0 \tag{3}$$

and Equation (2) as

$$P(\mathrm{B})_1 = \alpha \cdot P(\mathrm{A} \rightarrow \mathrm{B}) + P(\mathrm{B})_0 \cdot (1 - P(\mathrm{A} \rightarrow \mathrm{B})) \tag{4}$$

where $P(\mathrm{A} \rightarrow \mathrm{B}|\mathrm{A})_{\mathrm{hist}} = \frac{P(\mathrm{A} \rightarrow \mathrm{B} \cap \mathrm{A})_{\mathrm{hist}}}{P(\mathrm{A})_{\mathrm{hist}}} = \frac{P(\mathrm{A} \rightarrow \mathrm{B}\ )_{\mathrm{hist}}}{P(\mathrm{A})_{\mathrm{hist}}}$ is the empirical conditional probability, in which $P(\mathrm{A} \rightarrow \mathrm{B}\ )_{\mathrm{hist}}$ is the dependency probability and $P(\mathrm{A})_{\mathrm{hist}}$ is the occurrence probability of risk A, based on data records obtained from COR analysis.

Based on the assumption that risks are considered independent in the Risk Register, $P(\mathrm{B}|(\mathrm{A} \rightarrow \mathrm{B})^{\mathrm{C}})$ has been approximated by $P(\mathrm{B})_0$ in Equation (4). Moreover, the conditional probability $P(\mathrm{B}|\mathrm{A} \rightarrow \mathrm{B})$ describes the relationship between risk B and risk dependency $\mathrm{A} \rightarrow \mathrm{B}$: in this article, we assume that $P(\mathrm{B}|\mathrm{A} \rightarrow \mathrm{B})$ can be considered as a dependency coefficient called α. According to other studies[29], risk dependencies can be categorized as certain, uncertain, and unpredictable events: α is the parameter that defines the relationship between the dependent risk and its dependency, and we assume $\alpha = 1$ for certain (cause/effect) dependencies, $0 < \alpha < 1$ for uncertain dependencies, and $\alpha = 0$ for the unpredictable ones. For the sake of simplicity, in this article, we consider only certain dependencies.

A more complex procedure needs to be applied in order to update interdependent risks probabilities. In fact, dependency can be considered as a one-way relationship, while interdependency is a mutual

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Table 1. Procedure for updating risk occurrence probabilities of two interdependent risks.

$P(\mathrm{A})_0$	$P(\mathrm{B})_0$	$P(\mathrm{A})_1$	$P(\mathrm{B})_1$
0	0	0	0
>0	0	$P(\mathrm{A})_0$	$P(\mathrm{A} \to \mathrm{B}\vert\mathrm{A})_{\mathrm{hist}} \cdot P(\mathrm{A})_0$
0	>0	$P(\mathrm{B} \to \mathrm{A}\vert\mathrm{B})_{\mathrm{hist}} \cdot P(\mathrm{B})_0$	$P(\mathrm{B})_0$
>0	>0	$P(\mathrm{B} \to \mathrm{A}\vert\mathrm{B})_{\mathrm{hist}} \cdot P(\mathrm{B})_0 + P(\mathrm{A})_0 \cdot (1 - P(\mathrm{B} \to \mathrm{A}\vert\mathrm{B})_{\mathrm{hist}} \cdot P(\mathrm{B})_0$	$P(\mathrm{A} \to \mathrm{B}\vert\mathrm{A})_{\mathrm{hist}} \cdot P(\mathrm{A})_0 + P(\mathrm{B})_0 \cdot (1 - P(\mathrm{A} \to \mathrm{B}\vert\mathrm{A})_{\mathrm{hist}} \cdot P(\mathrm{A})_0)$

relationship. For that reason, in the latter case, first it is compulsory to verify if risks are interdependent directly or indirectly through a loop involving other risks, and second, to take into account all the different possible states of interdependent risks.

In fact, each interdependent risk may have a risk occurrence probability either 0 or bigger than 0, so we have two possible states for each interdependent risk. That gives us 2^N combinations of risk occurrence probabilities, where N indicates the number of interdependent risks included in the loop. Table 1 describes how to update risk probabilities in the simplest case of interdependency, which involves only two risks directly interdependent.

4 The Probabilistic Dependency Network (PDN)

The previous phases of Dependency Identification and Dependency Assessment are compulsory in order to estimate risk occurrence probabilities including their dependencies and interdependencies.

For that reason, the binary SRSM is transformed into the probabilistic dependency network (PDN).

PDN is a probabilistic framework, indicating the empirical conditional probabilities based on data records obtained from COR analysis.

Defining Risk "i" as any risk belonging to SRSM, for new projects, it is possible to use PDN for calculating the variation of occurrence probability due to dependencies:

$$\Delta P(i) = P(i)_1 - P(i)_0 \ \forall \ \text{Risk "}i\text{"} \in (\text{SRSM}) \tag{5}$$

$P(i)_0$ is the occurrence probability of Risk "i" reported in the Risk Register, while $P(i)_1$ is the updated occurrence probability for dependent and interdependent risks, obtained according to PDN and the procedure described in Equations (3) and (4) and Table 1.

5 Dependency Quantification

Dependency Quantification describes the procedure for quantifying the effect of risk dependencies and interdependencies on project objectives in terms of cost overrun and schedule delay. It is divided into two different subsections: the regression model and the Monte Carlo simulation model.

The regression model corresponds to a deterministic estimate. Defining "N" as the number of risks in SRSM, $\Delta P(i)$ obtained with the implementation of PDN for the specific project, and $\mathrm{Imp}(i)_{\mathrm{hist}}$ the average impact due to the occurrence of Risk "i," a variable called *Project exposure to risk dependencies* is calculated as follows:

$$X = \sum_{i=1}^{N} \Delta P(i) \cdot \mathrm{Imp}(i)_{\mathrm{hist}} \tag{6}$$

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$\text{Imp}(i)_{\text{hist}}$ has been derived from a review of CORs related to past projects: it is estimated in months for schedule delay or weighted on the approved budget for cost overrun.

For calibrating the procedure, the "Project exposure to risk dependencies" needs to be calculated for the finished projects and compared to the actual project resulting in a Cartesian coordinate system, where the "Project exposure to risk dependencies" is in abscissa, and the actual project results in ordinate.

In this way, it is possible to obtain a predictive function based on linear regression analysis that estimates the total cost overrun (or delay) for new projects. In the regression model, projects are considered as single activities, whose cost and duration are the planned ones.

The regression model is the basis for the Monte Carlo simulation model, in which the uncertainty affecting the project is related to the occurrence probability and impact of risk dependencies and interdependencies identified in the SRSM.

For the sake of simplicity, the impact of dependencies whose $\Delta P(i) > 0$ has been expressed by a Trigen distribution, whose minimum and maximum values correspond, respectively, to the minimum and maximum impact identified by the CORs review, while the most likely has been estimated using the most frequent observation. The Trigen distribution is commonly used as an alternative to the Triangular distribution when it is easier to specify "nearly" minimum and maximum values than the absolute minimum and maximum values. In this article, the minimum value refers to the 10th percentile, while the maximum refers to the 90th percentile of the Trigen distribution.

Monte Carlo simulation model provides an output distribution that reveals only variability of performance parameters caused by risk dependencies. Its application to new projects can integrate the traditional CSRA because, through the inclusion of the impact of risk dependencies and interdependencies, this may reveal in advance unrealistic outcome expectations before the execution of the project.

6 Case Study

The procedure introduced above has been applied in order to estimate cost overruns and schedule delays for Oil & Gas field development projects.

Oil & Gas projects can be considered typical complex projects[30] because they require complex organizational structures with a large number of interfaces[31,32].

Oil & Gas industry uses most of the state-of-the-art knowledge and tools in both project management and PRAM. Moreover, CORs of finished projects may provide a large database of data records that can be applied to decrease the uncertainty in new projects[32].

The first phase of RDA consists in the review of a large number of CORs related to field development projects from different countries. Recurring risks are identified, and risk dependencies and interdependencies are also recognized by interviews and the review of lessons learned, corresponding to the new knowledge provided by a closed project in order to improve the project management system of the company.

As this phase also analyzes the impact areas of the recurrent risks, the SRSM is split into two square matrices: schedule standard risk structure matrix (SSRSM) and cost standard risk structure matrix (CSRSM). The elements of the SSRSM comprise all the dependent risks that affected the first hydrocarbon slippage. Similarly, the elements of the CSRSM indicate the different clusters of risks that through propagation may increase the CAPEX (capital expenditure) approved at the FID.

Using an ex-post analysis by comparing, for each finished project, the risks that occurred and those initially identified in the Risk Register approved at the FID, we observe that in most cases, the root risks occurred during project execution were anticipated in the Risk Register. Generally, they were "force majeure" risks, but in other cases, they were related to issues affecting the detailed engineering or procurement and indirectly generating an impact on the construction process.

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As SSRSM and CSRSM have been completed, the definition of the RDN and the regression model were applied in two different comparisons: one for estimating the CAPEX overrun and another for the first hydrocarbon slippage, that is, the completion delay of the project.

Project results were compared to their estimates considering the same scope of work. Some parameters of the projects were investigated to obtain a better estimate. For this purpose, finished projects were divided according to their relevance, their typology, and their geographical area; the geographical area revealed significant for explaining cost overruns, so each dependency impact was multiplied by a location factor (LF), expressing the different comparative levels of construction cost associated with each location. Defining $\text{CAPEX}_{\text{real}}$ as the actual CAPEX at the end of the project, $\text{CAPEX}_{\text{est}}$ as the CAPEX estimated considering the effects of risk dependencies and interdependencies, and $\text{CAPEX}_{\text{app}}$ as the CAPEX approved at FID, Figure 3 shows the comparison between the expected and real CAPEX overruns for the finished projects, while Figure 4 shows the comparison between the expected and real first hydrocarbon slippage for the same set of projects.

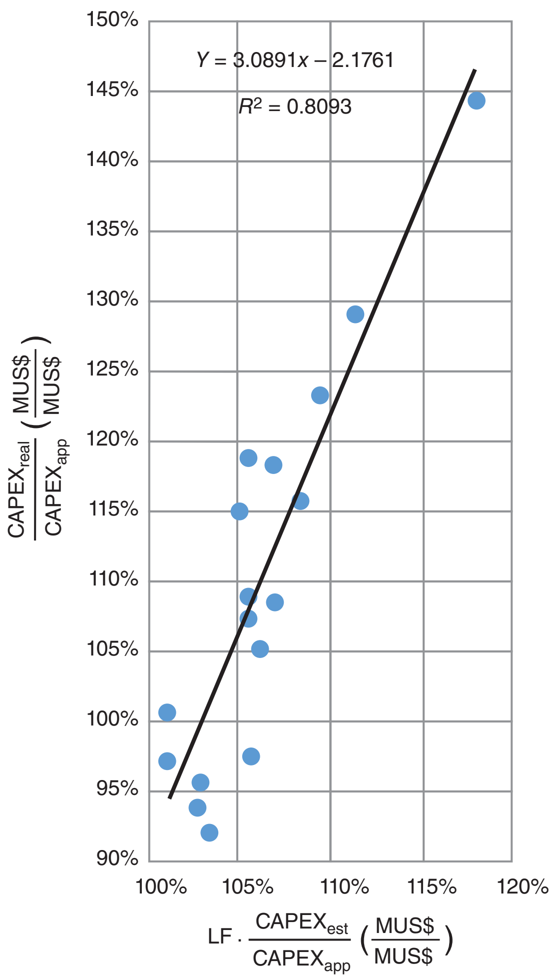

Figure 3. Comparison between expected (with the application of LF) and actual CAPEX overruns for finished projects.

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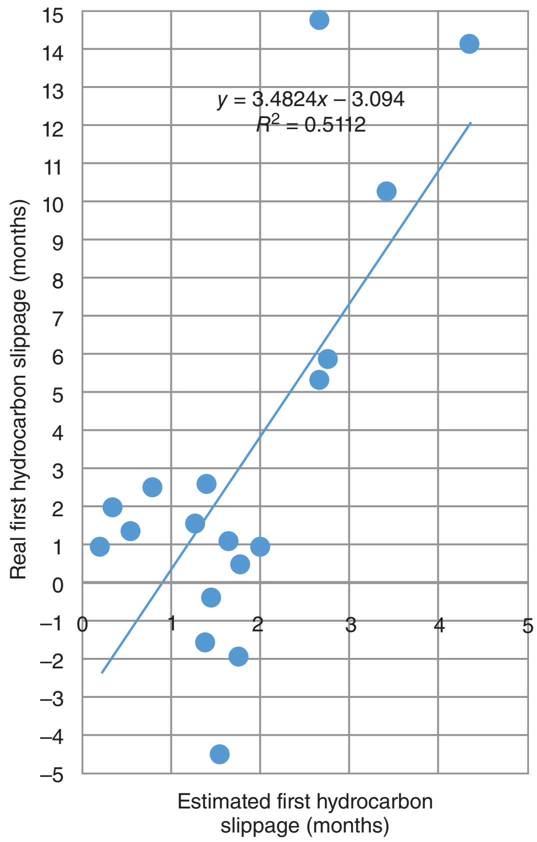

Figure 4. Comparison between expected and actual first hydrocarbon slippage for finished projects.

Table 2. Estimated probability to respect project approved cost and comparison between real CAPEX overruns and estimated CAPEX overrun distributions.

Project	Probability to respect $CAPEX_{app}$ (%)	Real CAPEX overrun (%)	Estimate CAPEX overrun (%) (best case)	Estimate CAPEX overrun (%) (most likely)	Estimate CAPEX overrun (%) (worst case)
A	36	23.23	0	12.39	42.81
B	33	38.72	0	15.20	48.05
C	34	51.24	0	13.10	63.35
D	30	27.36	0	8.41	29.96
E	22	33.81	0	17.31	50.26
F	20	89.78	0	35.35	93.77

The second phase of RDA procedure deals with the application of a Monte Carlo simulation model for six new development field projects, which are treated as blind tests: it means that their results were unveiled for being compared to the estimates obtained from the simulation.

Table 2 shows the comparison between the actual results and estimates for CAPEX overruns, while Table 3 shows the comparison between the real and estimated first hydrocarbon slippage for the same projects.

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Table 3. Estimated probability to respect project approved duration and comparison between real delays and estimated delay distributions.

Project	Probability to respect approved duration (%)	Real delay (months)	Estimate delay (months) (best case)	Estimate delay (months) (most likely)	Estimate delay (months) (worst case)
A	63	−1	0	0	1.53
B	14	22.4	0	6.26	16.2
C	67	2	0	0	2.53
D	55	3.6	0	0	4.7
E	22	10.3	0	4.16	13.6
F	29	10.5	0	4.2	11.36

The outcomes obtained from the blind tests highlight some interesting issues. First, all the blind tests had a $\mathrm{CAPEX}_{\mathrm{real}}$ bigger than the $\mathrm{CAPEX}_{\mathrm{app}}$. Generally, $\mathrm{CAPEX}_{\mathrm{app}}$ refers to the median value of CAPEX obtained from a CSRA, in which the risk probability values do not consider risk dependencies and interdependencies. One of the consequences of this reductionist approach is an underestimation of the Management Reserve at the stage of FID, that is, the reserve set up for dealing with risks in case they may materialize.

Second, the RDA procedure does not prevent the propagation of risks, but it may give a deeper awareness of the limits of the forecasting process with the widening of the distribution of the risk impact on project performance.

In fact, it should be noted that if a project has a wide distribution of the effects of risk dependencies, its final performance may significantly differ from expectation. This alert can give the opportunity to take better response actions to prevent the root risks before project execution.

7 Conclusion

This article presents a RDA procedure to estimate the impact of risk dependencies and interdependencies on project time and cost objectives of complex projects. The RDA procedure gives a contribution to the traditional PRAM process that focuses exclusively on risk events, without considering relationships between them. The RDA procedure entails three phases to overcome this weakness: Dependency Identification, Dependency Assessment, and Dependency Quantification.

The RDA verifies the existence of risk dependencies and interdependencies, estimates their effects, and has shown that major risks are not only dependent but also that they can be gathered in clusters.

Future studies could implement a fourth phase of RDA, called *Dependency Response Planning*, which may propose strategies to prevent clusters of risks and to avoid root risks and consequent possible domino effect.

The application of RDA in the Oil & Gas industry underlines that the reductionist approach of PRAM underestimates the uncertainty impact on complex projects performance. In fact, the Monte Carlo simulation model can give additional support to the project team in order to reveal in advance unrealistic outcome expectations and an excessive optimistic contingency at the stage of project approval.

We suggest for future works to evaluate risk dependencies at a lower level of detail, not considering projects as macroactivities. Moreover, this article analyzes only dependencies and interdependencies between conventional negative project risks (threats). In future contributions, positive risks and their relationships with positive effects could also be considered in order to exploit such opportunities.

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Related Articles

Risk Measurement, Foundations of; **Statistics of Risk Management**; **Analytical Methods for Risk Management: An Engineering Systems Perspective**; **Methods of Risks Estimation and Analysis of Business Processes**; **Methods of Risks Estimation and Analysis of Business Processes**; **Bayesian Inference**; **Assessment of Probabilities**; **Bayesian Forecasting**; **Elicitation**; **Forecasting**; **Bayesian Statistics in Quantitative Risk Assessment**; **Expert Judgment**; **Subjective Probabilities: Overview**; **Mathematics of Risk and Reliability: A Select History**; **Probabilistic Risk Assessment**; **Simulation in Risk Management**.

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