

Validating Cross-Impact Analysis in Project Risk Management

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ABSTRACT

Companies work increasingly more on projects as a means of executing organizational decisions. However, too many enterprise projects result in failure. Hence, firms should follow a risk management method that drives their projects toward success. Nevertheless, project managers often deal with risks intuitively. This is partly because they lack the proper means to correctly manage the underlying risks which affect the entire cycle of their projects. Therefore, one purpose is to identify the critical events that managers may encounter before the beginning of the project and during its development. In addition, we propose CIA-ISM to represent existing relationships between the unforeseen events in the project's lifetime and their key performance indicators. This also predicts the influence of risks on project performance over time by means of scenarios. The tool proposed would thus help practitioners to manage enterprise projects risks in a more effective and proactive way. We have validated the predictive capability of the CIA-ISM model with 22 real projects. The results show a high level of predictive capability in terms of risk analysis and key performance indicators.

Keywords

Scenarios, Cross-Impact Analysis (CIA), Interpretive Structural Modeling (ISM), Risk Events, Project Management.

INTRODUCTION

More and more companies use projects as a means of implementing operational, tactical and strategic decisions and thus achieving their goals. Hence, the project's performance can be critical for business success. By way of illustration, previous studies make clear the benefits of successful enterprise systems implementation by means of projects concerning the firm's profitability performance (Hendricks, Singhal and Stratman, 2007; Koh, Gunasekaran and Rajkumar, 2008). On the other hand, the literature reports many cases in which companies have suffered significant losses stemming from Information Technology (IT) project management failures (Charette, 2005; Verner and Abdullah, 2012). In extreme cases, failures in enterprise projects development have even pushed some firms into bankruptcy (Scott and Vessey, 2000).

Each project developed in a business environment faces numerous difficulties and uncertainty. Since wrong assessments and misjudgments may lead to risks, these might provoke significant damage if practitioners do not proactively monitor and deal with them. In fact, a proper risks management helps practitioners to be aware of

the real situation of their project, its problematic aspects and the potential existing causes for project failure (Iversen, Mathiasen and Nielsen, 2000). They will thus resolve the projects' threats more efficiently. Otherwise, improper risks management lead to the carrying out of avoidable errors and the appearance of potential problems, and this makes the achievement of the outcomes of projects difficult.

Previous studies have focused their efforts on identifying, categorizing, analyzing and prioritizing risks in project development (Amornsawadwatana, 2009; Bannerman, 2008). With the goal of assessing project risks, other works have also applied techniques such as ANOVA, multicriteria decision-making methods, neural networks (NN), fuzzy cognitive maps (FCM) and decision trees (Han and Huang, 2007; Huang, Chang, Li and Ling, 2004; Lopez and Salmeron, 2014; Neumann, 2002; Rodríguez, Ortegaand Concepción, 2015; Salmeron and Lopez, 2010). However, these tools lack certain characteristics which are necessary to model enterprise projects risks in a fairly accurate manner. In fact, only NN are capable of representing all possible interactions between risks. Nevertheless, this is based on a linear structure. In consequence, the propagations follow an established pattern, limiting the model's feedback dynamics. In the same line, a research work defines the most suitable strategy for treating each event (López and Salmeron, 2012). Nonetheless, there is scant research which provides the mechanics to proactively manage unforeseen events throughout the entire risk process.

By focusing on preserving firm performance from failures due to a project's execution, this paper proposes a scenarios-based approach called CIA-ISM (Bañuls and Turoff, 2011). This tool will enable the foreseeing of the project's outcomes in accordance with the probability of occurrence of source and dynamic events. On the basis of the results of its application, practitioners will be able to apply measures aimed at successfully finishing their enterprise projects. The CIA-ISM method was applied with very good results in other areas, such as, for example, in emergency management (Bañuls, Turoff and Hiltz, 2013), critical infrastructure interaction analysis (Turoff et al, 2014) and operational risk analysis (Ramirez de la Huerca, Bañuls and Turoff, 2015). But this is the first time that it has been applied in project risk analysis. Furthermore, in this article we validate the method comparing the results with 22 real cases.

This research is organized in four sections. After the introduction, Section 2 describes preliminary research on project risk management. Section 3 expounds the theoretical background of the scenario-based method proposed. Section 3 provides insight into CIA-ISM usability for risk management in enterprise projects. Finally, Section 4 presents the concluding remarks.

LITERATURE REVIEW

According to the project management body of knowledge (PMI, 2008), a project is defined as "a temporary endeavour undertaken to create a unique product, service or result". Multiple needs, problems and opportunities, such as developing a new product or service (Schmidt, Sarangee and Montoya, 2009), improving business processes (Baloh, Uthickeand Moon, 2008), changing organizational structures, or incorporating emerging technologies and systems (Kumar, Maheshwariand Kumar, 2003) act as the trigger for initiating further projects. With a clear project goal in mind, a project's team members execute it as a unique set of activities with limited time and resources and inherent uncertainties (Nicholas and Steyn, 2012). Accordingly, a generic project is often characterized as temporal, having high constraints, a changing environment, and being complex and unsettled. At the same time, this requires the involvement of a large number of actors from diverse backgrounds. In some cases, the project development even needs the use of unfamiliar technologies and methodologies (F. W. McFarlan, 1981).

The above-mentioned characteristics mean that many controllable and uncontrollable risks can arise throughout the whole project (Keil, Cule, Lyytinen and Schmidt, 1998; Salmeron and Lopez, 2012). There is not a clear consensus in the literature concerning the use of the term risk definition (Heckmann, Comes and Nickel, 2015). In general, risk is an event characterized by uncertainty because it may or may not occur (PMI, 2008). If this risk becomes a real problem, this may negatively impact the project's success. Hence, to avoid undesired outcomes, managers have to continuously manage in a proactive way the risks existing in their enterprise projects (Mobey and Parker, 2002). In other words, they must be aware of the risk level of their projects, as well as the achievable outcomes under alternative scenarios about the future. Notwithstanding, managers often consider risk management in projects as expensive and pointless extra work (Aloini, Dulmin and Mininno, 2007).

Over the past couple of decades, many standards and methodologies have been proposed to guide the activity of project managers (Samad and Naveed, 2006). Table 1 shows the most common phases identified to successfully manage risk in general projects. This process shows managers the real situation of their projects and how to

manage threats proactively. If the project team identifies, assesses, monitors and deals with the existing risks in its projects, the probability of failure decreases. Hence, this has given rise to a proliferation of studies about project risk management (Amornsawadwatana, 2009; Bannerman, 2008). This research primordialy focuses on the identification and assessment phases established in risks management methodologies. Therefore, there is an apparent lack of specific methods for supporting the whole risk management process.

#	Phase	Description
1	Identification	Identify and categorize risks that affect a project.
2	Assessment	Calculate the risk of exposure associated with each element and prioritize them.
3	Scheduling	Define an action plan to minimize the risks identified.
4	Treating	Implement the measures included in the action plan.
5	Control	Monitor and correct deviations and vulnerabilities experienced.

Table 1. Main stages in project risk management.

More specifically, in the last decade, numerous studies have identified and prioritized project risks from more to less problematic (Huang et al., 2004). Previous research also provides specific systems to manage risks in project development (Zafeiropoulos, Metaxiotis and Askounis, 2005). Other works even develop risk evaluation models based on Bayesian Networks (BN) (Fan and Yu, 2004; Lee, Park and Shin, 2009), Neural Networks (NN) (Neumann, 2002)(Chen and Hartman, 2000), systems dynamics (SD) (Yi and Xiao, 2008) or Fuzzy Cognitive Maps (FCM) (Lopez and Salmeron, 2014). These have been developed to assess project risks. However, practitioners frequently have trouble understanding the use of these tools (López and Salmeron, 2012). Moreover, they do not support the entire risk management process in the project's execution. With these issues in mind, a recent study proposes an integrated DSS framework to model, analyze and control project risks (Fang and Marle, 2012). Yet it does not provide insight into the risks' effects on business performance, which is critical to improve a project's success (Wang, Lin and Huang, 2010).

Risks and project performance are complex, closely related concepts. Moreover, their representation is complicated, unstructured and not readily quantifiable. Hence, the modeling technique selected must fulfill certain requirements. Table 2 shows the requirements demanded in the modeling technique selection.

#	Requirement	Explanation
1	Capable of representing all possible connections	Projects risks are closely interrelated (Büyükožkan and Ruan, 2010).
2	Does not ignore what is uncertain	Projects undertaken in conditions of uncertainty (Costa, Barros and Travassos, 2007)
3	Directed graph with cycles	Directed acyclic graph limits model evolution at successive times (Baldi and Rosen-Zvi, 2005)
4	The propagation does not follow an established pattern	The conditioned propagation limits the feedback dynamics (Wu, Kefan, Gang and Ping, 2010)
5	Assumes information is scarce	There are not widely-accepted risks measures.
6	Capable of estimating both the probability of occurrence and its impact	Risk of exposure determines the critical level of each event (Boehm, 1988)

Table 2. Requirements for the modeling technique selected

Finally, the CIA-ISM (Bañuls and Turoff, 2011) was the modeling tool chosen because it was the only one which met all the requirements demanded. Table 3 depicts a comparison between modeling tools. CIA-ISM

addresses the limitations of current methods regarding modeling complexity in project risk management. This technique has emerged as a useful tool for generating and analyzing scenarios using cross-impact analysis. This approach aims at allowing project managers to work with large sets of risks without using great computational infrastructures, as it is a graphical representation of complex systems following a simplified structured process. Moreover, it enables a set of plausible snapshots of the future to be obtained, as well as an analysis of the interaction between critical events in the time horizon specified. The scenario generation models can be integrated with other predictive models designed to estimate the evolution of particular risks (such as conflict and non-cooperation between project team members), and provide a broader view of effects which could occur in critical situations (Bañuls, Turoff and Hiltz, 2013). In fact, CIA-ISM has been successfully applied in such different fields as emergency management (Lage, Bañuls and Borges, 2013) and operational risk management in industrial environments (Ramirez de la Hueraga, Bañuls and Turoff, 2015).

		Requirements					
		1	2	3	4	5	6
Modeling techniques	Systems Dynamics	■		■	■		
	Bayesian Networks	■	■				
	Neural Networks	■	■			■	
	Fuzzy Cognitive Maps	■	■	■	■	■	
	CIA-ISM	■	■	■	■	■	■

Table 3. Comparison of modeling techniques to manage project risks

METHODOLOGICAL BACKGROUND

Cross-Impact Analysis

Cross-Impact Analysis (CIA) is a methodology developed to help determine how relationships between events may impact the resulting events and reduce uncertainty in the future. Due to this ability of CIA to analyze complex contexts with various interactions, CIA is one of the most commonly-used techniques for generating and analyzing scenarios, both historically (Turoff, 1971) and currently (Bañuls and Turoff, 2011; Bañuls, Turoff and Hiltz, 2013; Ramirez de la Hueraga, Bañuls and Turoff, 2015). The analytical approach proposed by Turoff (1972) was developed specifically for restructuring the cross-impact formalisms in a manner suitable for use in an interactive computer terminal. This requires users being able to modify or iterate their estimates until they consider that the conclusion inferred from their estimates is consistent with their views. Furthermore, Turoff's approach is based on the idea that an event may be unique in that it can only happen once (i.e., the development of a particular discovery or the outbreak of a particular war). Following Turoff, for this type of event there is usually no statistically significant history of occurrence which would allow the inference of the probability of the occurrence. So, the cross-impact problem is to infer casual relationships from some relationships among the different world views. This is established by perturbing the participant's initial view with assumed certain knowledge, such as the outcome of individual events. That is, a subject's estimates actually cause a subject to estimate causality. Analytically, by asking subjects about the probabilities, the correlation coefficients (C_{ij}) can be calculated using a variation of the Fermi-Dirac distribution function (1).

$$P_i = 1 / [1 + \exp(-G_i - \sum_{i \neq k} C_{ik} P_k)] \quad (1)$$

Where:

- P_i represents the probability of occurrence of the i -th event.
- The coefficient C_{ik} represents the impact of the k -th event on the i -th event.
- G_i (the gamma factor) is the effect of all events not specified being the model.
- A positive C_{ik} means that it enhances the occurrence of the event and if it is negative it detracts from the occurrence.

For further details see (Turoff, 1972)

Given the linear influence factors, we can show estimators of the consistent relative relationships between any event and those that influence it by plotting these relationships on a linear scale. We can then use a different modeling method - Interpretative Structural Modeling (ISM) - to analyze the complexity of the resulting weighted influence graph (Warfield, 1976). The following extension would allow individuals to receive a graphical visualization of their judgments and improve their ability to make improvements. The extension will also allow a group to receive a linear visualization of their collective results.

Interpretive Structural Modeling

ISM is a methodology for dealing with complex issues such as societal systems (Warfield, 1976). The starting point of ISM methodology is a system that is made up of a set of n elements of a set S .

$$S = \{s_1, s_2, s_3, \dots, s_n\} \quad (2)$$

The relationship between the elements in set S is a binary relation. An $n \times n$ binary matrix A can come from the binary relation out. This is also called adjacency matrix to binary relation. All the path lengths being 1 in adjacency matrix A indicates that it is likely to be reached. Since every node can reach its own node path, lengths being 0 or 1 can then be used to indicate the possibility of reachability once the adjacency matrix is added to the identity matrix. Its mathematical equation can be shown as follows in expression 3.

$$N = A + I \quad (3)$$

Matrix N is known as the element connection matrix. From this matrix we can obtain the reachability matrix (M), which is a square, transitive, reflexive, binary matrix which serves to analyze which model relation is antecedent to it. Suppose s_i and s_j are elements of the set S . If $M(s_i, s_j) = 1$, this indicates that there is a path between node s_i and node s_j . If $M(s_i, s_j) = 0$, this indicates that it is impossible to go from node s_i to node s_j . Every element in set S can be considered as a node and solved by graph theory. For a further explanation see (Warfield, 1976).

Methodology Proposed

The methodology proposed in this study is a combination of Cross-Impact Analysis (CIA) and Interpretative Structural Modeling (ISM) methods applied in a case study. The CIA-ISM combination has been used in the past to analyze risk scenarios in different studies with very interesting results, as we mentioned before.

The comparison of modeling techniques to manage project risks (Table 3) shows how the combination of CIA-ISM will be a powerful tool for risk analysis, in particular if we work with the organization's previous knowledge.

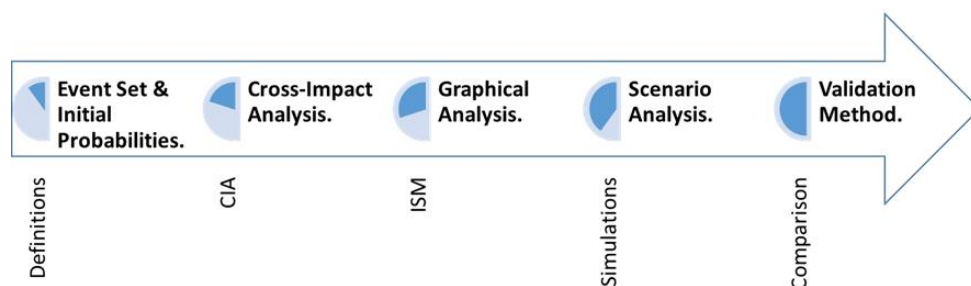


Figure 1: Proposed Methodology

The methodology used in this case study is divided into 5 different phases or steps.

- i) Event Set and Initial probabilities: The first step of this study is define the working model and its components, the initial even set and the initial probabilities.
- ii) Cross-Impact Analysis: The second phase of this study is to apply the CIA method to the Event set in order to calculate the impact values (Impact Matrix).
- iii) Graphical Analysis: After the C_{ij} values are calculated, we are able to graphically represent the scenarios in order to examine the relationship between events.
- iv) Scenario Analysis: Once the first scenario has been created it is possible to recreate dynamic simulations in order to generate predictions and forecast results.
- v) Validation Method: Finally we validate the CIA-ISM model, comparing predictions with 22 real finished projects.

We found this proposed methodology very interesting in order to enhance the contributions of the CIA-ISM combination method to the literature. This combination allows us to improve the results of traditional risk analysis, offering us the possibility of making predictions, forecasting scenarios and generating event maps in order to have a better knowledge of the big picture of risk analysis in this area.

In particular, the new simulation analysis capabilities enable us compare our results with historical results in order to validate the model and the methods. Additionally, they permit us be able to simulate different situations in order to prepare the organization to confront different future situations and, most importantly, to prevent a critical situation or disaster.

CASE STUDY

The task for validating the study proposed has been the designing of a structural model to analyze the key risk factors for the proper performance of the consulting projects of an Industrial Engineering company. This working model will be able to support decision processes (before and during real projects) by generating different scenarios. The working model should be dynamic, in the sense that it ought to be able to adjust the probabilities of the outcomes events as soon as new information about the source / dynamic events of a project is available.

Event Set and Initial Probabilities

The events set and the initial probabilities have been developed by both the CEO and the CIO of the company (by means of discussion and consensus). The data are based on historical records of the company and the considerable experience of the two CEOs (more than 20 years managing large engineering projects). They define a set of 13 events: 4 source events, 5 dynamic events and 4 outcomes events. The results thus help the practitioners to identify potential risks in their projects. At this point it is important to remark that they have total freedom to define the event set and initial probabilities. We now present each one of these items.

Table 4 depicts source events identified and their initial probability. In this case the initial probability represents a ratio of occurrence of the event based on the company's historical records. Experts also indicated the probability of occurrence of each element. For this purpose, they can assign a score between 0 and 100, where 100 means that the occurrence of the event is extremely probable and 0 extremely improbable. For instance, a value of 70 in "Project Profitability" (Table 4) represents that 70% of the projects of the company are profitable. Each source item represents a risk that might become a real problem before starting the project.

Event number	Label	Description	Initial Probability
1	Suitable Profile	The profile of the Project Team (project manager and consultants) selected is adequate in terms of experience and abilities	80
2	Requirements identification	Customer needs have been identified and analyzed in detail before starting the project.	70
3	Appropriate approach	The Projects Goals have been clearly established and a suitable methodological approach has been proposed for fulfilling them	75
4	Internal Relevance	The project is relevant to the client's decision-makers. It has internal support from someone relevant in the company	70

Table 4. Source Events: Events that might happen before starting the project
Long Paper – Analytical Modeling and Simulation
Proceedings of the ISCRAM 2016 Conference – Rio de Janeiro, Brazil, May 2016
Tapia, Antunes, Bañuls, Moore and Porto de Albuquerque, eds.

Table 5 shows each dynamic event identified and its initial probability. A dynamic event represents all relevant risks which might arise during the project's lifetime. These elements only impact on outcomes elements. Finally, Table 6 indicates the outcomes events and their initial probabilities. These represent key performance indicators of projects. They might be affected by the behavior of source and dynamic events.

Event number	Label	Description	Initial Probability
5	Customer collaboration	The client responds to requests from project managers at all times	60
6	Adequate planning	Planning fits with the project's progress on schedule with minimal deviations	60
7	Proper Project Management	The project is managed properly both in managerial and technical terms	75
8	Proper execution by the consultants	The project is correctly executed by the consultants	70
9	Changes in customer requirements	The client incorporates new requirements to the final product / service during the project, these being significant enough to affect it	40

Table 5. Dynamic Events: Events that might occur during the project's lifetime

Event number	Label	Description	Initial Probability
10	Delivery on Time	The product / service is delivered on time	60
11	Customer Satisfaction	The customer is satisfied with the product / service	75
12	Project Profitability	The project has been profitable in the margin initially planned	70
13	Professional Image	The company's corporate image has benefited in professional terms due to the results of the project	75

Table 6. Outcome Events: Events that might occur after the project

Cross Impact analysis

Once the set of events in the model had been established, we built the cross-impact matrix through the inputs elicitation process. Following the CIA methodology, by asking subjects about the initial and the conditional probabilities, the correlation coefficients (C_{ij}) can be calculated using expression 1 (Turoff, 1972). Based on the resulting estimations, we obtained the cross-impact matrix represented in Table 7.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	OVP	2.56	1.31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	OVP	0.00	3.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	5.78	OVP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	OVP	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	1.57	2.56	2.39	2.56	OVP	2.99	1.08	1.16	0.00	0.00	0.00	0.00	0.00
6	1.01	1.79	2.39	0.00	1.35	OVP	2.39	1.16	-2.99	0.00	0.00	0.00	0.00
7	0.31	2.15	2.01	1.57	2.51	4.14	OVP	1.57	-2.17	0.00	0.00	0.00	0.00
8	2.43	1.21	2.26	0.00	2.82	3.72	1.67	OVP	-3.72	0.00	0.00	0.00	0.00
9	-1.28	-1.79	-0.54	-1.79	-1.35	-2.09	-1.67	-0.58	OVP	0.00	0.00	0.00	0.00
10	1.01	1.16	2.39	1.79	4.34	2.99	2.39	3.72	-4.34	OVP	0.00	0.00	0.00
11	3.54	5.78	4.39	2.15	1.83	4.14	2.29	4.05	-1.83	4.72	OVP	0.00	0.00
12	0.81	1.79	2.98	1.21	2.09	5.07	2.98	1.79	-3.72	3.72	1.13	OVP	0.00
13	3.54	4.71	3.78	2.15	1.83	4.14	3.78	4.05	-1.83	4.72	4.39	0.99	OVP
G	-1.39	-1.39	-2.94	0.85	-9.64	-5.67	-7.48	-7.33	7.25	-11.31	-20.81	-13.51	-24.71

Table 7. Cross-impact matrix and G vector

The rows (i) and the columns (j) of the matrix are the events; the cells are the influence factors C_{ij} , the diagonal being the overall probabilities (OPV). Note that the cross-impact matrix is associated with the G vector. This represents the influence of external events (not explicitly specified in the model) on each i-th event. To read the C_{ij} components from this matrix, we must proceed in the following way. Given that requirements identification (source event 4) happens, this generates an impact of +2.56 on customer collaboration (dynamic event 5). In this

way, we can identify, categorize and sort the greatest impacts and which of them are globally more important. In order to estimate the impact of source events (arising before the beginning of the project) and dynamic events (emerging during its development), we apply the following linear sums of C_{ij} for the cross-impact matrix:

$$|\text{Source event influences}| = \left| \sum_{i=1}^{i=4} c_{ij} \right| \text{ for each } j \text{ from } 5 - 13 \quad (4)$$

$$|\text{Dynamic event influences}| = \left| \sum_{i=5}^{i=9} c_{ij} \right| \text{ for each } j \text{ from } 10 - 13 \quad (5)$$

Table 8 summarizes the influences of the source and dynamic events. Customer collaboration (event 5) is the dynamic event most impacted by source events with a score of 9.08 (in this example we add the absolute C_{ij} values of all source events, columns 1 to 4, in the row 5). That is, 28.7% of the total impact of source events influences Customer collaboration. The findings also reveal that customer satisfaction (event 11) is the outcome event which has received the strongest impact from source events. Hence, we can conclude that if managers seek to avoid customer problems in their projects, they should proactively manage events arising before the beginning of the project. On the other hand, the findings show that dynamic events have a greater influence on Delivery on time (event 10) than the rest of outcomes sources. Yet it can also be observed that the influence on outcome sources is similar.

	5	6	7	8	9	10	11	12	13
Source events influences	9.08	5.19	6.04	5.9	5.4	6.35	15.86	6.79	14.18
Dynamic events influences						17.78	14.14	15.65	15.63

Table 8. Total influences of source and dynamic events

Graphical Analysis

By applying the CIA–ISM approach described in Section 3 we can represent the scenario forecasted by means of a diagraph. Figure 2 represents the interrelations between the risks. The CEOs considered it to be the most representative in accordance with their mental model of the problem. The limit of this forecasted scenario is $|C_{ij}|=2.03$, so it includes 60% of the estimations and 80% of the C_{ij} sum. All the events have positive impacts between each other except for event 9 (changes in customer requirements).

The graph shows the sequence and potential cascading effects between risks. This is the representation of Node 4 (Internal Relevance) being a triggering event in the risk scenario. Hence, in order to avoid failures in the project's execution and unsuccessful outcomes, practitioners should carefully mitigate its potential consequences.

Scenario Analysis

Once this first scenario has been created as a starting point, it is possible to recreate a simulation using a predictions system developed by (Turoff, 1972). Equation 1 was used to calculate the predictions. Table 10 presents an illustrative scenario-based analysis. This is just an example of the scenario-based capabilities. Findings specifically state how to vary the probability of occurrence of both dynamic and outcome events based on all possible combinations of source events. A total of 16 combinations were selected. In this table risks are in red. Please note that in order to do it simpler and more coherently, we have changed sense event 9. We have used a verbal scale to make it clearer for the experts. Table 9 provides the probability scale used.

This table is especially interesting for intermediate scenarios where we are assuming that the project starts with certain threats. This helps to control specific risks in the planning stage. For instance, in scenario 3 we are assuming no risk in source events except for the approach not being appropriate. This fact will mostly affect a risk of failures in planning and the project's profitability (Table 9).

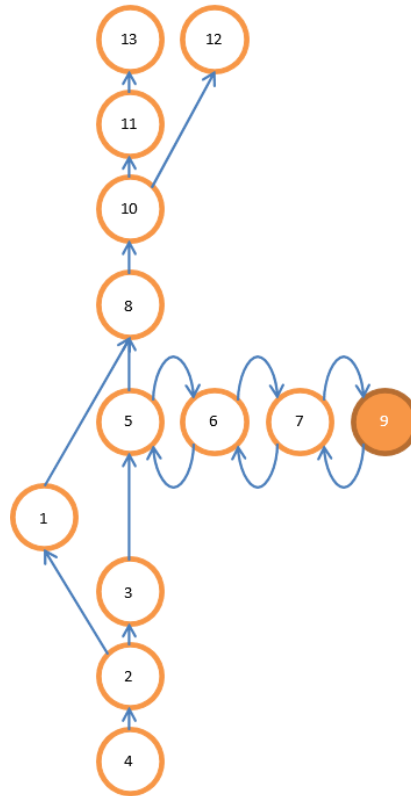


Figure 2. Diagraph for P40 => |C_{ij}>2.03

Numeric	Probability Possibility	Validity Degree of Truth	Odds ratio	Log(odds) WOE(10)	Ln(odds) ¹ WOE(e)
1.00 (.99)	Certain to occur	Certain to be True	99.00	2.00	4.60
.90-.98 (.95)	Very probable	Very probably true	19.00	1.28	2.94
.80-.89 (.85)	Highly probable	Highly probably true	5.67	.75	1.74
.70-.79 (.75)	Probable	Probably true	3.00	.48	1.10
.60-.69 (.65)	Likely	Likely to be true	1.86	.27	.62
.56-.59 (.57)	Possible	Possibly true	1.33	.12	.29
.45-.55 (.50)	Unknown/ no judgment	Unknown no judgment	1.00	0.00	0.00
.41-.44 (.43)	Possibly not	Possibly not true	.75	-.12	-.29
.31-.40 (.35)	Unlikely	Unlikely to be true	.54	-.27	-.62
.21-.30 (.25)	Improbable	Improbably true	.33	-.48	-1.10
.11-.20 (.15)	Highly improbable	Highly improbably true	.18	-.74	-1.71
.02-.10 (.05)	Very improbable	Very improbably true	.05	-1.30	-3.00
0.00 (.01)	Certain to not occur	Certain to be false	.01	-2.00	-4.61

Table 9. Probability Scale

¹ The original work on WOE used log to the base 10 but we really need to use Ln to the base e, natural logs since that is what is used in our distribution function and the calculation of the C_{ij}.

Scenario		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Source events	Profile selection is appropriate	Yes	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No	No	No	No	Yes	No
	The requirements are correctly identified	Yes	Yes	Yes	No	Yes	No	Yes	No	No	Yes	Yes	No	No	Yes	No	No
	The approach is suitable	Yes	Yes	No	Yes	Yes	Yes	No	No	Yes	No	Yes	No	Yes	No	No	No
	The project is internally relevant	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No	Yes	No	Yes	No	No	No	No
Dynamic Events	There is customer collaboration	Very probable	Possible	Likely	Possible	Probable	Improbable	Highly improbable	Highly improbable	Very improbable	Improbable	Improbable	Very improbable	Very improbable	Very improbable	Very improbable	Very improbable
	There is adequacy in planning	Highly probable	Highly probable	Unlikely	Possibly not	Likely	Improbable	Unlikely	Very improbable	Possibly not	Highly improbable	Likely	Very improbable	Improbable	Highly improbable	Very improbable	Very improbable
	There is proper project management	Very probable	Probable	Likely	Likely	Very probable	Possible	Unlikely	Improbable	Improbable	Likely	Probable	Highly improbable	Improbable	Improbable	Very improbable	Very improbable
	There is a correct implementation of the consultants	Very probable	Very probable	Unknown	Probable	Possibly not	Improbable	Unknown	Improbable	Probable	Very improbable	Possibly not	Very improbable	Improbable	Very improbable	Improbable	Very improbable
	There are no changes in customer requirements	Highly probable	Unknown	Probable	Unknown	Likely	Improbable	Unlikely	Unlikely	Highly improbable	Unknown	Improbable	Highly improbable	Very improbable	Highly improbable	Very improbable	Very improbable
Outcome Events	The project is delivered on time	Highly probable	Possible	Possibly not	Probable	Probable	Possibly not	Highly improbable	Highly improbable	Improbable	Improbable	Unlikely	Very improbable	Highly improbable	Very improbable	Very improbable	Very improbable
	The customer is satisfied	Very probable	Very probable	Probable	Unlikely	Highly probable	Very improbable	Improbable	Very improbable	Very improbable	Very improbable	Unlikely	Very improbable	Very improbable	Very improbable	Very improbable	Very improbable
	The project is profitable	Very probable	Highly probable	Possibly not	Probable	Highly probable	Unknown	Highly improbable	Highly improbable	Possibly not	Improbable	Likely	Very improbable	Improbable	Very improbable	Very improbable	Very improbable
	It provides a professional image	Very probable	Very probable	Probable	Unknown	Probable	Very improbable	Improbable	Very improbable	Highly improbable	Very improbable	Improbable	Very improbable	Very improbable	Very improbable	Very improbable	Very improbable

Table 10. Risks scenarios

Validation of the method

In order to validate CIA-ISM for supporting project risk management, we compare predictions of the method with information obtained from 22 real finished projects. They have all been projects carried out in the company during one year after creating the CIA-ISM model. The simulations have been made using the CIASS software (www.ciass.org). Through this validation method we are introducing partial information into the model for each of these 22 projects and then comparing the expected values with the real values. Table 11 presents a comparative analysis of the real and expected results. In column S(%) we find the deviation, in percentage, between the expected values and the real values of all the dynamic and outcome events when we introduce just the 4 source events into the simulator. In column S&D we see the deviation between the expected values and the real values when we introduce dynamics and source events into the simulator. The value represents the failure of the model in predicting a risk. A value of 100% would represent that the model had failed in all the forecasts concerning an event. A value of 0% that the model predicted correctly all that had been forecasted concerning one event. Focusing on the deviation of source events, the results show that the model failed in 6.35% of the forecast, the failure when introducing the dynamic and the source events being 3.57%. In the light of these results, we can conclude that the model presents a fairly high explanatory capacity. Therefore, it may be considered valid for project risk management.

Event	S (%)	S&D (%)
5	19%	-
6	0%	-
7	0%	-
8	0%	-
9	14%	-
10	9.52%	4.76%
11	0%	0%
12	14.29%	9.52%
13	0%	0%
Average	6.35%	3.57%

Table 11. Comparison between the method's predictions and the real results

CONCLUSIONS

Project management is the technical and managerial discipline concerned with achieving the goal on time, at a minimum cost. Active risk management is the key to attaining the success of enterprise projects. With this in mind, the present study suggests a scenario-based approach to properly manage risks during the whole project's lifetime. In this context, CIA-ISM provides the project manager with a structured process to identify, assess, plan, deal with and control risks in general projects.

The CIA-ISM technique aims at helping project managers to handle and measure cascading effects and contributes to addressing this research question, enabling experts to work with a broad range of events. It specifically models risk effects on key performance indicators of projects over time. It even allows the differentiating between the influence of source and dynamic effects.

Through the dynamic behavior of the model developed, the usefulness of this method in project risk management was explored. In fact, the generation of risk scenarios in this study has enabled:

- i) Anticipating events that may happen in case of a risk becoming a real problem.
- ii) Analyzing their interrelations and effects on enterprise performance.
- iii) Making plans for mitigating the possible negative consequences.
- iv) Controlling the evolution of risks during the project's development.

In spite of the progress made, some limitations of the CIA-ISM approach should be considered. During the definition stage, practitioners describe the event set with their initial probabilities. A wrong inputs statement may carry the risk of producing findings that are unrealistic for the context. Hence, the accuracy of the CIA-ISM method is strongly dependent on the practitioners' judgments. In order to execute CIA-ISM properly, the panel of participants must be carefully selected, and other instruments must also be added to validate the results provided by the method.

With a view to validating this approach, the risk scenarios obtained in the case study were compared with real finished projects. The comparison highlights that the method proposed has a high predictability rate. Hence, we can conclude that CIA-ISM will help practitioners to manage their projects in a most effective way. Future studies would focus on encouraging alternative ways to corroborate findings when historical information is not available. Notwithstanding, it would be interesting to validate the different risk scenarios included in Table 10 with more real cases. From now on, it should be also stressed that the CIA-ISM method is easily generalizable and adaptable to meet the specifics of a wide range of projects. Extended research using CIA-ISM to foresee risk scenarios in other areas would therefore be very appropriate.

REFERENCES

1. Aloini, D., Dulmin, R. and Mininno, V. (2007). Risk management in ERP project introduction: Review of the literature. *Information and Management*, 44(6), 547–567.
2. Ahmed, A., Kayis B. and Amornsawadwatana, S. (2009). A review of techniques for risk management in projects. *Benchmarking: An International Journal*, 14(1), 22–36.
3. Baldi, P. and Rosen-Zvi, M. (2005). On the relationship between deterministic and probabilistic directed Graphical models: From Bayesian networks to recursive neural networks. *Neural Networks*, 18(June 2005), 1080–1086.
4. Baloh, P., Uthicke, K. and Moon, G. (2008). A business process-oriented method of KM solution design: A case study of Samsung Electronics. *International Journal of Information Management*, 28, 433–437.
5. Bannerman, P. L. (2008). Risk and risk management in software projects: A reassessment. *Journal of Systems and Software*, 81(12), 2118–2133.
6. Bañuls, V. A. and Turoff, M. (2011). Scenario construction via Delphi and cross-impact analysis. *Technological Forecasting and Social Change*, 78(9), 1579–1602.
7. Bañuls, V. A., Turoff, M. and Hiltz, S. R. (2013). Collaborative scenario modeling in emergency management through cross-impact. *Technological Forecasting and Social Change*, 80(9), 1756–1774.
8. Boehm, B. (1988). A Spiral Model of Software Development and Enhancement. *Computer*, 21(5), 61–72.
9. Büyüközkan, G. and Ruan, D. (2010). Choquet integral based aggregation approach to software development risk assessment. *Information Sciences*, 180(3), 441–451.
10. Charette, R. N. (2005). Why software fails. *IEEE Spectrum*, 42(9), 42–49.
11. Costa, H. R., Barros, M. de O. and Travassos, G. H. (2007). Evaluating software project portfolio risks. *Journal of Systems and Software*, 80(1), 16–31.
12. Chen, D. and Hartman, F. T. (2000). A Neural Network Approach to Risk Assessment and Contingency Allocation. RI7A.
13. McFarlan, F. W. (1981). Portfolio Approach to Information Systems. *Harvard Business Review*, 59(5), 142–150. Retrieved from <https://hbr.org/1981/09/portfolio-approach-to-information-systems>
14. Fan, C. and Yu, Y.-C. (2004). BBN-based software project risk management. *The Journal of Systems and Software*, 73(2), 1–23.
15. Fang, C. and Marle, F. (2012). A simulation-based risk network model for decision support in project risk management. *Decision Support Systems*, 52(3), 635–644.
16. Han, W.-M. and Huang, S.-J. (2007). An empirical analysis of risk components and performance on software projects. *Journal of Systems and Software*, 80(1), 42–50.
17. Heckmann, I., Comes, T. and Nickel, S. (2015). A critical review on supply chain risk – Definition, measure and modeling. *Omega*, 52, 119–132.
18. Hendricks, K. B., Singhal, V. R. and Stratman, J. K. (2007). The impact of enterprise systems on corporate performance: A study of ERP, SCM and CRM system implementations. *Journal of Operations Management*, 25(1), 65–82.

19. Huang, S.-M., Chang, I.-C., Li, S.-H. and Lin, M.-T. (2004). Assessing risk in ERP projects: identify and prioritize the factors. *Industrial Management and Data Systems*, 104(8), 681–688.
20. Iversen, J. H., Mathiassen, L. and Nielsen, P. (2000). Managing Risk in software process improvement: an action research approach. *Mis Quarterly*, 28(3), 395–433.
21. Keil, M., Cule, P. E., Lyytinen, K. and Schmidt, R. C. (1998). A framework for identifying software project risk. *Communications of the ACM*, 41(11), 76–83.
22. Koh, S. C. L., Gunasekaran, A. and Rajkumar, D. (2008). ERP II: The involvement, benefits and impediments of collaborative information sharing. *International Journal of Production Economics*, 113(1), 245–268.
23. Kumar, V., Maheshwari, B. and Kumar, U. (2003). An investigation of critical management issues in ERP implementation: empirical evidence from Canadian organizations. *Technovation*, 23(10), 793–807.
24. Lage, B.B., Bañuls, V. and Borges, M. (2013). Supporting course of actions development in emergency preparedness through cross-impact analysis. In *Proceedings of the 10 th International ISCRAM Conference* (pp. 714–723). Baden-Baden, Germany.
25. Lee, E., Park, Y. and Shin, J. G. (2009). Large engineering project risk management using a Bayesian belief network. *Expert Systems with Applications*, 36(3), 5880–5887.
26. Lopez, C. and Salmeron, J. L. (2014). Dynamic risks modelling in ERP maintenance projects with FCM. *Information Sciences*, 256, 25–45.
27. López, C. and Salmeron, J. L. (2012). Risks Response Strategies for Supporting Practitioners Decision-Making in Software Projects. *Procedia Technology*, 5, 437–444.
28. Mobey, A. and Parker, D. (2002). Risk evaluation and its importance to project implementation. *Work Study*, 51(4), 202–208.
29. Neumann, D. E. (2002). An Enhanced Neural Network Technique for Software Risk Analysis. *IEEE Transactions on Software Engineering*, 28(9), 904–912.
30. Nicholas, J.M. and Steyn, H. (2012). *Project Management for Business, Engineering and Technology* (4 ed.). Routledge, New York.
31. PMI. (2008). *A Guide to the Project Management Body of Knowledge: (PMBOK Guide). Fundamentos* (Fourth Edi). Pennsylvania, EE.UU: Project Management Institute (PMI).
32. Ramírez de la Hueriga, M. Bañuls, V. A. and Turoff, M. (2015). A Scenario-based approach for analyzing complex cascading effects in Operational Risk Management. *Engineering Applications of Artificial Intelligence*, 46, 289–302.
33. Rodríguez, A., Ortega, F. and Concepción, R. (2015). A method for the evaluation of risk in IT projects. *Expert Systems With Applications*, 45, 273–285.
34. Salmeron, J. L. and Lopez, C. (2010). A multicriteria approach for risks assessment in ERP maintenance. *Journal of Systems and Software*, 83(10), 1941–1953.
35. Salmeron, J. and Lopez, C. (2012). Forecasting risk impact on ERP maintenance with augmented fuzzy cognitive maps. *Software Engineering, IEEE*. Retrieved from: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5680917
36. Samad, J. and Naveed, I. (2006). Managing the Risks: An Evaluation of Risk Management Processes. In *Multitopic Conference, 2006. INMIC '06. IEEE* (pp. 281–287). Islamabad.
37. Schmidt, J. B., Sarangee, K. R. and Montoya, M. M. (2009). Exploring New Product Development Project Review Practices. *Journal of Product Innovation Management*, 26(5), 520–535.
38. Scott, J.E. and Vessey, I. (2000). Implementing Enterprise Resource Planning Systems : The Role of Learning from Failure. *Information Systems Frontiers*, 2(2), 213–232.
39. Turoff, M. (1972). An alternative approach to cross impact analysis. *Technological Forecasting and Social Change*, 3, 309–339.

40. Turoff, M., Bañuls, V., Hiltz, S.R. and Plotnick, L. (2014). A development of a dynamic scenario model for the interaction of critical infrastructures. *Proceedings of the ISCRAM 2014*, State College, US.
41. Verner, J. M. and Abdullah, L. M. (2012). Exploratory case study research: Outsourced project failure". *Information and Software Technology*, 54(8), 866–886.
42. Wang, J., Lin, W. and Huang, Y.-H. (2010). A performance-oriented risk management framework for innovative RD projects. *Technovation*, 30(11-12), 601–611.
43. Warfield, J.N., 1976. Societal Systems: planning, policy and complexity. *John Wiley and Sons*, New York, NY.
44. Wu, D. D., Kefan, X., Gang, C. and Ping, G. (2010). A risk analysis model in concurrent engineering product development. *Risk Analysis*, 30(9), 1440–1453.
45. Yi, T. and Xiao, G. (2008). Applying System dynamics to analyze the impact of incentive factors allocation on construction cost and risk. *Machine Learning and Cybernetics, 2008 International Conference*, 2 July, 676–680.
46. Zafeiropoulos, I., Metaxiotis, K. and Askounis, D. (2005). Dynamic risk management system for the modeling, optimal adaptation and implementation of an ERP system. *Information Management and Computer Security*, 13(3), 212–234.