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Scratchs Analysis of an LCC Project Using a Bayesian Network Model

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Abstract

Emphasizing the need to use models capable of dealing with the uncertainty of the project environment, especially those that can alleviate any scratchs that may arise during the course of the project, the following question arises: How to assess the scratchs of a project developed in LCC at from measurements from a Bayesian Network model? In this context, the goal of the study is to measure and analyze the scratchs of a project developed by the LCC method from a model elaborated in Bayesian Networks. The RB structure is composed of two parts, one with a qualitative approach, the other with a quantitative approach. From the information collected with a specialist, we sought to understand the strength that each item present in the key factors Requirements, Restrictions, Time Deliveries and Assumptions exerts on the key factor scratchs, in addition to the strength that each item of the key factor scratchs exerts together with the General Project Performance Indicator (IGDP). Based on the generated simulations, it seen which scratchs affected by a larger number of parameters in the project, as well as the scratchs that present a high or moderate probability of inferior performance with the IGDP. The research developed a probabilistic model that supplied the quantification of possible scratchs in the project, based on the belief of an expert. The developed RB allowed project managers to measure, and so deliberate on practical solutions to problems that affected by project scratchs, based on parameterized analyses.

Keywords: probability, management, parameter

1. Introduction

In general, considering the relevance for organizational changes or delivery of more adequate products and services, organizations present distinct types of projects that characterized by distinct levels of complexity and uncertainty. Faced with this context, it is necessary to effectively manage the scratchs directly involved with the project. Appropriate methods must use to deal with insecurity, minimizing the impact of managers on decision making. In project management, elevated levels of scratchs can become obstacles to project progress. Therefore, scratchs management becomes an important complementary element to project management and can even aid in the completion of the project, minimally interfering with the scope, costs, perfecting the quality and delivery schedule (Dandage et al., 2017; Unegbu et al., 2020).

A model capable of dealing with uncertainties arising from the environment, and which can help in scratchs management in projects, is the measurement model based on Bayesian Networks (RB). This is a method that uses probability distributions to quantitatively assess the uncertainties that may arise, being adequate to deal with any scratchs that may arise during the execution of processes. Bayesian networks graphically describe probabilistic relationships of events, and are like conceptual models of scratchs analysis, which makes them increasingly recommended for the application of scratchs analyzes and assessments (Liu et al., 2021; Silva et al., 2021).

Among the various approaches to project management, the Life Cycle Canvas (LCC) produces a proposal to simplify the challenge of managing projects. The modern world and global competition require decision makers to constantly reevaluate their strategies in shorter time intervals. In this way, new strategies often imply new projects. The LCC appears as a visual tool that helps project development in a simple, dynamic and robust way, from a visual screen (canvas), aimed at project management throughout the life cycle (Veras, 2016). However, the LCC still lacks studies on its adoption in different contexts and areas of application, as in the case of scratchs management.

In this sense, the study developed by Silva et al. (2021) enabled the adjustment of predictive procedures through an RB to help check the status of a project structured in LCC, cooperating with the decision-making of project managers. However, the study considered a specific project developed from an LCC model, adjusting for the predictive aspects of this project. To continue the studies on this subject, presenting a proposal with a focus on scratchs management, it is necessary to elaborate and execute an RB applied to another project based on LCC. This, eventually, will supply the verification of convergences and dissonances to the study.

Emphasizing the need to use models capable of dealing with the uncertainty of the project environment, especially those that can alleviate any scratchs that may arise during the course of the project, the following question arises: How to assess the scratchs of a project developed in LCC at from measurements from a Bayesian Network model? In this context, the goal of the study is to measure and analyze the scratchs of a project developed by the LCC method from a model elaborated in Bayesian Networks.

The study developed by Bezerra (2019), structured in LCC, will used as a target project for the implementation of the RB. In her research, the author proposed the use of the visual technique based on LCC, which looked to collaborate with better control and monitoring in the management of research infrastructure projects in a Federal Institution of Higher Education (IFES). The scope and universe of implementation of this study differ from the target project used in the research by Silva et al. (2021).

2. Project Management with Life Cycle Canvas

Projects can define as temporary undertakings conducted to obtain a result. Project management, on the other hand, can defined as the implementation of skills, knowledge, techniques and tools that can accommodate the prerequisites of a project, meeting a pre-established deadline, demanding adequate quality and cost, using human resources. and technicians (Picciotto, 2020; Sanchez et al., 2020). One of the increments of the change from traditional project management practices to innovative approaches focuses on expanding the use of tools and visual models. Such tools used under an integration of screens or frames, called Canvas (Brito et al., 2020). A technique capable of working with both traditional approaches and emerging approaches in project management is the Life Cycle Canvas (LCC) technique.

The Life Cycle Canvas (LCC) developed by Veras (2016), being a tool that supports project management, during the life cycle, in a simplified way. Arranged in frames (Canvas), project management with LCC can either adopted by all stages of the project, or used in specific stages, in addition to adapting to any scope of projects. The technique presents a structured conceptual foundation, based on the best global project management practices. Project management with the LCC conducted in a simple, dynamic and intuitive way, following the entire project life cycle, promoting a better understanding along with the project status indicators (Cruz et al., 2017; Medeiros Júnior et al., 2018). In Figure 1 it is possible to see a visual illustration of the LCC tool.

Figure 1. Life Cycle Canvas (LCC)

Note. Adapted from Veras, M. (2016). *Gestão dinâmica de projetos: Life Cycle Canvas*. Brasport.

In the image of the LCC it is possible to see five large blocks characterized by colors that consider the fifteen key factors estimated to be primordial to project management. Such factors deployed throughout the project life cycle. The fields of these factors must be sequentially registered using the 5W2H approach, as follows: Why (Why)? determines the existential motivation of the project, through the fields of justification, objectives and benefits; What)? outlines what the project is, through the fields product, requirements and constraints; Who (Who)? shows the groups of main agents involved in the project, as well as the ways they communicate, through the fields interested parties, team and communications; How? elucidates the essential conditions, the phases to be delivered, as well as the obstacles to project implementation, conceived by the premises, deliveries and acquisitions fields; Finally, When and How much? This block presents the scratchs, pre-dated deliveries and the main costs of the project, exposed in the fields scratchs, time and cost (Cruz et al., 2017; Veras, 2016).

The LCC also incorporates the Initiation, Planning, Execution, Monitoring and Control, and Closing processes as stages of project management, currently considered as the main ones in the project life cycle. Each of the stages includes one of the project frames, with a cohesive division of initiation and completion of each management stage, demarcating a sequence for the project. There is an exception only for the Execution and Monitoring and Control steps, which happen simultaneously (Veras, 2016). The LCC seeks to incorporate good practices showed for project management, while offering greater dynamism to project management processes, presenting itself as a technique capable of monitoring and managing the entire project life cycle (Cruz et al., 2017; Medeiros et al., 2017).

Regardless of the project management technique or approach adopted, there is still debate about scratchs management. Scratchs analysis estimated with projects that present high investments, however, such analysis can apply to projects that do not present high demand for investments (Shaktawat & Vadhera, 2020). Scratchs management is a useful tool capable of reducing costs and time with the project, helping with control and monitoring (Poursoltan et al., 2020). An explanation with more details about scratchs management will be presented in the next topic.

2.1 Scratchs Management

Among the various existing activities in a project, scratchs management is a vital part of achieving the intended results. In general, scratchs must found and checked at all stages of the Project and, if they occur, they must deal with so as not to compromise the execution of the Project. Scratchs is an uncertain event or condition that, if it occurs, will have a positive or negative effect on at least one of the project goals (Project Management Institute, 2017).

The projects' less predictable profile makes them more difficult than the routine actions present in most organizations. The life cycles of a project deal with sequences of activities that deal from the outline of a project to its completion, with Scratchs(s) always associated with these sequences. Depending on the complexity involved in the elaboration of the project, this could pose great scratchs. Scratchs management at all stages is important to minimize project failure rates. The scratchs can minimized, managed, transferred, shared or accepted, however, it cannot ignore (Dandage et al., 2017). In this way, scratchs management becomes one of the basic processes in project management. scratchs management is an essential procedure for a good development of the project stages (Firmenich, 2017).

In addition to all the understanding exposed so far about scratchs management, it seen that its proper application can collaborate with decision-making, supplying efficient operability in complex, dynamic and uncertain conjunctures (Poursoltan et al., 2020). Thus, it is important to point out that for effective project scratchs management it is necessary to use methods or tools that can collaborate in this context. The project management model such as the LCC already uses the project monitoring status from the analysis of performance indices (Dantas, 2020). However, it is possible to have a better scratchs analysis of a project developed in LCC, based on the results from the application of a Bayesian network model. Simulations conducted on a network can present probabilistic indices of project scratchs and this monitoring improves the project's alert indices (Silva et al., 2021).

In the study by Silva et al. (2021), who implemented a Bayesian network along with a project previously developed in LCC, it was observed that the network provided probabilistic results that, in a possible practical application, could directly help the managers responsible for the project, depending on the incidence of a climate favorable or unfavorable. The use of a knowledge-based model may allow the identification of scratchs during the project. As in the case of the study, an adverse climate change, such as a high incidence of rainfall, will increase the scratchs indexes of the project, demanding a decision-making process that may, depending on the interference of this scratchs to the project, pause or even abort the project. . Minimizing future damage. In the next topic it is possible to have a better understanding of how Bayesian networks work.

2.2 Bayesian Networks

Bayesian Networks (RBs), also known as decision networks, belief networks or Bayes networks, are probabilistic graphic structures that represent a conglomeration of variables and their conditional links through a Directed Acyclic Graph (DAG), where the representation of the variables or states are observed next to the nodules in the DAG (Liu et al., 2021). RBs can help in decision-making about an event that may occur, predicting the probability that a given cause may be the triggering factor. To have an understanding, in studies RBs used to simulate the probabilistic affinities between symptoms and diseases. Depending on the symptoms, the network will be able to calculate the probabilities of incidence along with various diseases (Boutkhamouine et al., 2020; Shi et al., 2020).

The RBs graphs whose nodes simulate the variables may stand for unknown parameters, observable quantities, hypotheses or latent variables. Links simulate conditional dependencies. Nodes may not interconnect, standing for variables that considered independent (Eustacio et al., 2020). The nodes connected to a probabilistic function that admits, as input, a set of inductions for the variables of the node considered the parent node, presenting as a result the probability(s) of the variable simulated by the node (Detilleux, 2020). For example, Figure 2 simulates an RB where, from the connections between the nodes, it seen that Na is the parent node of Np1. Node Nc is a descendant of nodes Np1 and Np2, while node Nc is the parent of node Nd (Eustacio et al., 2020).

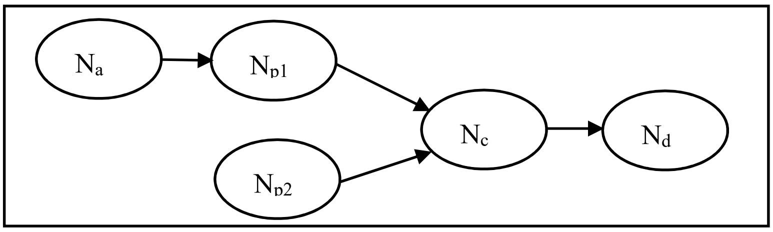

Figure 2. Representation of a DAG in RB

Note. Adapted from Eustacio, H. B. S., Ty, R. S. D., & Ocampo, S. R. (2020). An application of dynamic bayesian networks in the context of philippine rice food security. In *DLSU research congress*.

The mathematical model used in the RBs is based on Bayes' probability theorem, which is based on earlier knowledge about hypothesis H, with its results updated based on the belief of determined evidence E (Liu et al., 2021). Equation 1, as noted in Wipulanusat et al. (2020), presents the probabilistic construction of Bayes' theorem.

$$P\left(\frac{H}{E}\right) = \frac{P\left(\frac{E}{H}\right)\ P(H)}{P(E)} \quad (1)$$

P(H/E) will assume the posterior probability, this being the probability that hypothesis H still is in a particular state, after the impact of evidence E. The probability P(H/E), in this case, will be recognized as the probability conditional, which according to the hypothesis to be verified will be the probability of the evidence. P(H), in this case, will call the prior probability of the hypothesis, which, according to a given state, will be the probability of the occurrence of hypothesis H before the verification of an eventual evidence E. P(E) is autonomous, estimated as a model scale. Using Bayes' theorem as a basis, the RBs present an interconnection of variables N1,N2,...,Nn, exactly standing for the nodes of the network. The network of parent nodes with direct connection to Ni can conceived by pi (π). In this way, the classification of conditional probabilities can be represented by P(N_i |π_i) (Wipulanusat et al., 2020). Equation 2 adapted from Wipulanusat et al. (2020) presented below:

$$P(N_1, N_2, \ldots, N_n) = \prod_{i=1}^{N} P(N_i | \pi_i) \quad (2)$$

Another issue that RB deals with is sensitivity analysis. This part of the diagnostic deduction method of how the output node improbability can coupled to the various sources of the input node improbability (Zheng et al., 2020). With this, it is possible to find which are the input nodes that present the greatest decrease in improbabilities with the predictions of the output node. Therefore, sensitivity analysis is a relevant instrument for decision makers, from these analyzes they will be able to decide the critical input nodes (variables), and how changes in these nodes probabilistically change the results of the output node (variable) (Shi et al., 2020; Wipulanusat et al., 2020).

For a better understanding of the sensitivity analysis, S conjectured as an output node, so E will be the input node. It is possible to denote the degree of sensitivity of S in E by reducing the variance (Vr) (Wipulanusat et al., 2020). Equation 3, adapted from Wipulanusat et al. (2020), presents the expected reduction in the variance of the output node, resulting from the value of an input node.

$$V_r = V(S) - V(\frac{S}{E}) \tag{3}$$

Where V(S) is the variance of the output node S, and V(S/E) is the variance of the output node according to the input node E. The input node with the greatest variance decrease will be the node which will decompose the beliefs of the output node by the largest amount, resulting, therefore, in the explanatory capacity about the output node (variable) (Wipulanusat et al., 2020). A high variance decrease for the input node will suggest that the output node has a high sensitivity to changes close to the input node (Boutkhamouine et al., 2020). Based on the literature, it is possible to develop a method capable of analyzing the results and helping the scratchs management of the research base project.

2. Method

To measure and analyze the scratchs of a project developed using the LCC method based on a model developed in Bayesian Networks, relevant information collected about the project by Bezerra (2019). The project developed using the LCC model can see in Figure 3.

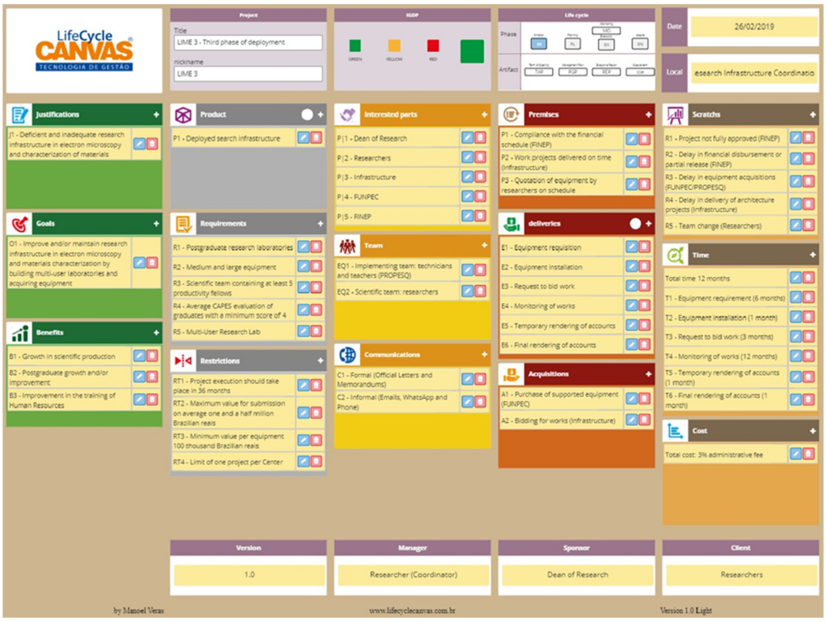

Figure 3. LCC main screen of the LIME 3 project - Third phase of implementation

Note. Adapted from Bezerra, K. A. (2019). *Proposta de implantação de painéis de monitoramento e controle para projetos institucionais de infraestrutura de pesquisa em uma IFES baseada na técnica Life Cycle Canvas* [Dissertação (Mestrado) - Curso de Gestão de Processos Institucionais, Programa de Pós-Graduação em Gestão de Processos Institucionais, Universidade Federal do Rio Grande do Norte]. https://repositorio.ufrn.br/bitstream/123456789/27040/1/Propostaimplantaçãopainéis_Bezerra_2019.pdf

The LIME 3 project - Third phase of implementation, present in the study by Bezerra (2019), aimed to improve and/or support the research infrastructure in electronic microscopy and characterization of materials through the construction of multi-user laboratories and the acquisition of equipment. Having as a product of the project the implanted research infrastructure. The LIME 3 project justified due to the research infrastructure in electron microscopy and the characterization of materials being, before its realization, deficient and inadequate. Developed through the LCC model, LIME 3 contemplated the justification, goal, benefits, products, requirements, restrictions, interested parties, team, communications, premises, deliveries, acquisitions, scratchs, time and costs.

With the information on the base project in hand, the structuring of the Bayesian Network begins, which will have the intention of aiding in the analysis of the project's scratchs . The RB structure is composed of two parts, one with a qualitative approach, the other with a quantitative approach (Efe et al., 2018). The qualitative approach, also referred to as structural learning, is the graphic design of the existing independence between the variables and presents the formatting of a structure of acyclic directed graphs. The quantitative approach, versed as parameter learning, presents dependent connections as joint conditioning from the probabilistic distributions present in the variables. The quantitative approach uses the cause-and-effect relationships arising from the first parameters obtained in the qualitative approach. These parameters come from sources such as surveys with specialist(s), literature review and/or historical data (Lee et al., 2009).

The data source used to initially feed the Bayesian Network was a specialist who had direct contact with the project studied by Bezerra (2019). To apply the questionnaire, the Google Forms application used. Through the questionnaire, an attempt was made to understand, according to the perception of the project specialist, the strength that each item present in the key factors Requirements, Restrictions, Time Deliveries and Assumptions exerts on the key factor scratchs, in addition to the strength that each item of the factor Key scratchs exerts along the General Project Performance Indicator (IGDP). The choice for these key factors was due to the understanding that they have a significant impact on project scratchs management. The comparison of the items generated a questionnaire with 105 objective questions that used a 10-position Likert scale, starting from position 1 (lowest strength) to position 10 (greatest strength). According to Dawes (2008), the 10-point scale presents greater reliability for the respondent when using a numerical response choice. Another fact is that respondents are already familiar with a notion of a 10-point rating.

With the answers to the questionnaire, a standardization performed with the data, considering that they not presented in a probabilistic context, which is the standard used with the RBs. In Google Forms itself, a file with an .xlsx extension generated to adapt the data to a format that adapts to the structure of the RB. Initially, the data divided by the groupings that will compose the RB, key factors: Requirements and Scratchs, Restrictions and Scratchs, Time Deliveries and Scratchs, Assumptions and Scratchs and Scratchs and the IGDP. Equation 4, developed in the study itself, will apply to each of these groupings, this presents a standardization that admitted by the structure of the RB.

$$PG_{RB} = \frac{EG_{RB}}{TG_{RB}} \quad (4)$$

Where PG_{RB} is the standardization performed on each of the elements that will compose the group (node) of the RB; EG_{RB} stands for the non-standard element (before treatment) that integrates the group; TG_{RB} is the sum of the non-standard elements of that group. The purpose of this equation is to proportionally standardize your participation within the group, to the point that the sum of all elements in the group should be 1. Data grouping and initial organization conducted in a joint action between Microsoft Excel tools and Python Anaconda. To calculate the equation, the Python programming language adopted, using the Anaconda package manager.

For modeling and execution of the Bayesian Network, Netica software from Norsys Software Corp. used. This is a robust and easy-to-execute software for the treatment and modeling of RBs. The program presents a practical interface for building networks so that relationships between variables can fed as individual probabilities (Norsys - Netica Application, 1995). Depending on the RB modeled and the amount of total conditional probabilities present, it may be necessary to select scenarios within the simulations in the RB, limiting these to the size of the study.

The study presents a typology with descriptive and applied attributes. Descriptive research describes the phenomenon and its characteristics (Nassaji, 2015). The applicability of the research includes the practical use of science. It is based on knowledge, techniques and/or theories arising from the academic environment to solve a particular purpose (Hair Junior et al., 2005). The stages of selection and survey of the variables included in the descriptive typology. The BI planning and construction phase considered applied (Schenekenberg et al., 2011). Next, the RB will model, implemented and executed, as well as the results achieved after the execution of the network.

3. Results

After the stages of collecting information with the specialist and standardization, the study tried with the modeling of the RB. In its construction, the network structure presented a composition with 6 nodes, represented by the key factors Requirements, Restrictions, Time Deliveries, Premises and Scratchs, adding to these the IGDP node. The nodes are interrelated in the network from 5 connections (arcs), generating 110 total conditional probabilities. Due to the scope of this study, the researchers decided to consider only the parameters that presented an expert belief index greater than 4 on the Likert scale of the questionnaire, in addition to considering only one trigger per node. In this way, the study simulated 12 individual shots on the net. This number of shots will already help in measuring and analyzing project scratchs .

In a first simulation, the RT1 parameter of the Restrictions node triggered. This trigger simulates the non-occurrence of project execution within 36 months (100% trigger), as shown in Figure 4, which is one of the constraints of the project.

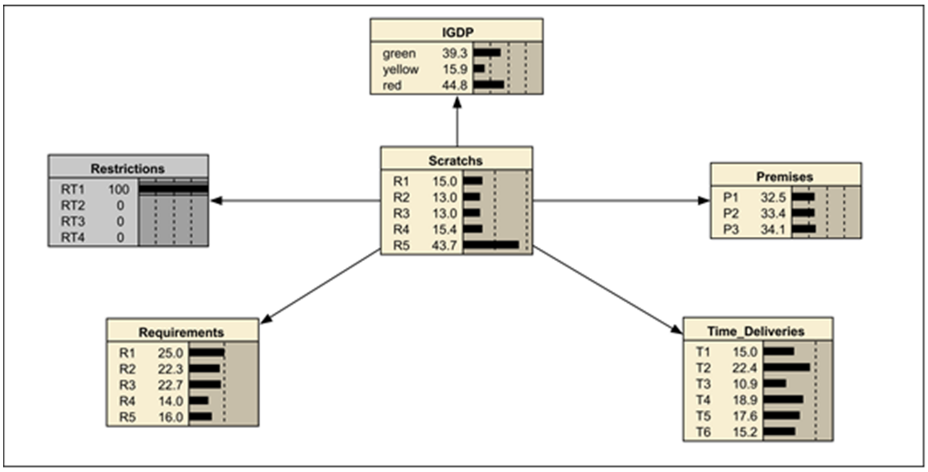

Figure 4. Initial simulation of the RB with triggering the RT1 parameter, belonging to the Restrictions node

It can see with this trigger that there is an estimated risk of 43.7% change in the team of researchers (R5), which is the highest visible risk in the scenario. The risk of the project not fully approved by FINEP (R1), and of delay in the delivery of architectural projects (R4) are 15.4% and 15% respectively. The risk of delay in the financial disbursement or partial release by the Financier of Studies and Projects - FINEP (R2) and the risk of delay in the acquisition of equipment by the North-Riograndense Research and Culture Foundation - FUNPEC and the Dean of Research/UFRN - PROPESQ (R3) are 13% in both. According to Dandage et al. (2017), good risk management can be decisive for a project to successfully completed, minimizing the interferences that arise in the restrictions that imposed on its scope.

In addition to an estimation of considerable risk in changing the team, it is important to note the IGDP signaling a 44.8% probability that the project execution status points to a red light. According to Veras (2016), the IGDP with red status means that there is at least one indicator with red status or more than half with yellow status throughout the project. The red sign refers to an area of inferior project performance, which is the indicator that demands greater attention in the IGDP. With these estimates in hand, based on checking these parameters, it is possible that the project management can predict its actions so that the project takes place within 36 months, the deadline stipulated in the first project constraint (RT1).

From Table 1, it will be possible to see, in addition to the simulation, other simulations conducted with RB. In the structuring of the frame, the parameter that will be triggered (100% action on the network) found next to its respective node. Information on project risk probabilities and IGDP occurrence probabilities will also be present. For a better understanding of the information available in the table, it will use the same design nomenclature in the parameters.

Table 1. Simulations of conditional probabilities performed in the RB

Trigger parameters (100% parameter trigger)	RB node	Scratchs from the project (%)[a]					IGDP (%)[b]		
		R1	R2	R3	R4	R5	Green	Yellow	Red
RT1 - Project execution should take place in 36 months	Restrictions	15.0	13.0	13.0	15.4	43.7	39.3	15.9	44.8
RT3 - Minimum value per equipment 100 thousand	Restrictions	32.4	23.9	23.9	14.2	5.55	29.0	13.8	57.2
R3 - Scientific team containing at least 5 productivity fellows	Restrictions	20.5	15.5	15.5	15.5	33.0	36.7	15.3	47.9
R4 - Average CAPES evaluation of graduate programs with a minimum score of 4	Restrictions	38.0	16.7	16.7	16.7	11.8	34.9	15	50.1
R5 - Research Multiuser Lab	Restrictions	35.3	14.6	14.6	14.6	20.8	38.0	15.6	46.3
T1 - Equipment requisition (6 months)	Time (Deliveries)	8.92	9.59	23.3	49.3	8.92	18.9	11.8	69.3
T3 - Request to bid for work (3 months)	Time (Deliveries)	12.4	28.8	38.7	7.64	12.4	22.4	12.5	65.1
T5 - Temporary rendering of accounts (1 month)	Time (Deliveries)	23.4	25.2	13.6	14.4	23.4	33.4	14.7	51.9
T6 - Final rendering of accounts (1 month)	Time (Deliveries)	20.7	34.6	11.3	12.7	20.7	30.7	14.1	55.1
P1 - Compliance with the financial schedule (FINEP)	Premises	28.3	25.9	17.1	10.2	18.4	33.4	14.7	52.0
P2 - Work projects delivered on time (Infrastructure)	Premises	20.0	18.3	12.1	37.1	12.5	26.3	13.3	60.5
P3 - Quotation of equipment by researchers on schedule	Premises	10.6	15.4	33.1	9.84	31.0	30.8	14.2	55.0

Note. [a] The abbreviations for Project Scratchs (%) have the following meanings: R1 - Project not fully approved (FINEP); R2 - Delay in financial disbursement or partial release (FINEP); R3 - Delay in equipment acquisitions (FUNPEC/PROPESQ); R4 - Delay in delivery of architectural projects (Infra); and R5 - Change in the team (researchers). [b] the acronym IGDP refers to the General Project Performance Indicator.

The second simulation, also referring to the Restrictions node, idealized the scenario where the minimum value of 100,000 per piece of equipment not reached, triggering the RT3 parameter. With the RB projection, there is a probability that the project will not fully approve by FINEP in approximately 32.4%, directly interfering with the R1 risk of the project, in addition to the project having a lower performance expectation of 57.2% (red IGDP). Delay in funding and inadequate assessments of project management mentioned as the main reasons for project delays (Shaktawat & Vadhera, 2020). Proper monitoring of risk management in projects can supply considerable benefits for complex projects. Accommodating the maximization of planned costs, mitigating costs with scratchs, reducing threats to rational decision-making (Firmenich, 2017).

Among the simulations conducted in the Requirements node, in a first scenario there is not a minimum of 5 productivity fellows in the scientific team, triggering parameter R3. The results point to a probability of 33% of change in the research team, focusing on the R5 risk of the project. It estimated that the project has a probability of 47.9% for an inferior performance, with this scenario (red IGDP). The next simulated scenario presents a perspective where the CAPES evaluation average of the graduate programs does not present a minimum score of 4, triggering the R4 parameter. There is a possibility of 38% of non-approval of the project in full by FINEP, intervening in risk R1 of the project. With this scenario, the project would underperform in a perspective of 50.1% (red IGDP). The last simulation of the node says the non-availability of the Research Multiuser Laboratory, triggering parameter R5. There is an expectation of 35.3% of non-approval of the project in full by FINEP, resulting in risk R1 of the project. This simulation points to a probability of 46.3% of an underperformance of the project (red IGDP). Scratchs relevant to the team in a project must addressed as they can compromise the performance of the project since they involve aspects such as changes among team members, accumulation of personnel, limitation of knowledge among team members, motivation, cooperation and communication among members (Poursoltan et al., 2020).

Regarding the simulations obtained through the Tempo node, a first scenario warns against requesting equipment within a period of 6 months, triggering parameter T1. This episode could generate a 49.3% chance of delay in the delivery of architectural projects, causing the R4 risk of the project. Also noteworthy is a high estimate of 69.3% of lower performance of the project (red IGDP). Another scenario shows the non-occurrence of the request to bid for the work within a period of 3 months, triggering parameter T3. This simulation shows that there is a probability of 38.7% of delays in the acquisition of equipment from FUNPEC and PROPESQ, causing risk R3 for the project. Also in this case, a high probability (65.1%) of poor project performance (red IGDP) seen.

A third simulated scenario in the Time node shows the fact that the temporary rendering of accounts does not happen within a period of 1 month, triggering parameter T5. This episode implies a probability of 25.2% of delay in the financial disbursement or partial release by FINEP, affecting the R2 risk of the project. Note, in this case, a probability of 51.9% of an inferior project performance (red IGDP). The last simulation with this node makes up a non-rendering of final accounts occurring in 1 month, triggering parameter T6. In this case, there is a probability of 34.6% of delay in the financial disbursement or partial release by FINEP, risk R2 occurrence. There is also a 55.1% probability of underperforming the project (red IGDP). The project execution phase considered the most critical and corresponds to cost and schedule overloads. Proactive project monitoring, in all spheres of the project, can reduce cost overruns and the execution schedule (Shaktawat & Vadhera, 2020).

The latest simulations took place at the RB Premises node. One of the simulations evaluated FINEP's non-compliance with the financial schedule, triggered by parameter P1. There was a probability of 28.3% that the project would not fully approve by FINEP, which is risk R1 of the project. It noted that the P1 premise and the R1 risk are antagonistic in the project, being interesting the detection of this antagonism by the RB. This simulation signaled a 52% probability of underperforming the project (red IGDP). Another simulated scenario examined a possible non-delivery of infrastructure work projects within the expected time, triggering parameter P2. The results point to a probability of 37.1% of delay in the delivery of infrastructure architecture projects, focusing on the R4 risk of the project. There is an antagonism between the P2 premise and the R4 risk, once again detected by the RB. It also estimated that the project presents a high probability of 60.5% for an inferior performance, with this scenario (red IGDP). The last simulated scenario presents an eventual non-quotation of equipment by the researchers within the schedule, triggering parameter P3. There is a possibility of a 33.1% delay in the acquisition of equipment by FUNPEC and PROPESQ, intervening in the project's R3 risk. With this scenario, the project would underperform in a 55% perspective (red IGDP). From the probabilities presented by the RB, it is possible to recognize uncertainty, providing a better organization of the project, perfecting it in relation to financing with investors (Firmenich, 2017).

Another observation of the simulations focuses on the strength that the scratchs present with the IGDP. Project risk R1 has the highest number of parameters, four in all, with the highest probability of interference when compared to the probabilities of the other scratchs . However, the parameter that has the greatest strength among the four, in the IGDP, is RT3 with 57.2%. All other scratchs appear with two parameters with the highest probability in each. The project's R2 risk has the T6 parameter with the greatest strength next to the IGDP, with 55.1%. The R3 risk of the project has the T3 parameter with the greatest strength next to the IGDP, with 65.1%. The project's R4 risk has the T1 parameter with the greatest strength next to the IGDP with 69.3%, this is the highest probability against all scratchs . The R5 risk of the project has the R3 parameter of the Requirements node with greater strength next to the IGDP with 47.9%, this is the lowest probability compared to all the scratchs.

From the generated RB, it is possible to measure and analyze the project scratchs, pondering which scratchs absorb a greater number of parameters in the simulation, so in the project, as well as those scratchs that present the highest or lowest probability of inferior performance in relation to the IGDP . Such information can become an essential asset for project managers to make rational decisions, based on a metric capable of probabilistically measuring uncertainty, as RB provides. For Firmenich (2017), risk assessments by experts are decisive for the project, so that the adoption of risk control methods can minimize or prevent threats to irrational decision-making.

Dantas (2020) recalls that the use of risk management in projects serves to create and protect value. Although there is little research on the subject in the context of segments. For Bezerra (2019), risk control, in addition to other factors, is essential for the success of projects. A good risk management strategy should develop in the first phase of project planning, thus supplying greater support for project monitoring during the other stages (Shaktawat & Vadhera, 2020).

An increase in the project's risk indexes will increase the chances of it not delivered on time. These variations increase the alert status of the project flow (Silva et al., 2021). Time control is one of the essential factors for the success of projects (Bezerra, 2019). Good risk management, with a tool capable of monitoring occurrence estimates, can directly help control not only time, but other project factors. Changes in the parameters that are part of the RB cause changes in other project factors, such as scratchs and status (Silva et al., 2021). Risk analysis can deal with uncertainties about various aspects of a project, presenting a better and more reliable scenario (Poursoltan et al., 2020). Finally, the last topic of this research will present the final considerations on the results obtained so far.

4. Discussion

The present study looked to measure and analyze the scratchs of a project developed using the LCC method based on a model developed in Bayesian Networks. The research developed a probabilistic model that supplied the quantification of scratchs in the project, based on the belief of a project specialist. Based on generated simulations, the developed RB allowed project managers to measure, and so deliberate on eventual problem solutions that directly affected by project scratchs, based on parameterized analyses.

Although the RBs use probabilistic mathematical equations in their parameterization structure, it was possible to display an RB model with a visual representation of the network, both by illustration and by the probability table, helping the understanding by project managers who do not present determined intimacy with mathematical equations. The probabilities presented can supply interactive discussions among members of the project risk management team, eventually promoting better decision-making.

Based on the generated simulations, it seen which scratchs affected by a greater number of parameters in the project, as well as the scratchs that present a high or moderate probability of inferior performance in relation to the General Project Performance Indicator. With this information in hand, the project management team will be able to predict the impacts of these scratchs, mitigating threats that may compromise the satisfactory execution of the project. A good risk management anchored in an RB model will, in a certain way, provide better control over the possible incidence of scratchs, as well as over the probabilistic power that each one will present together with a lower performance of the project.

Among the limiting factors of the study, the construction of the RB based on information from only one project specialist stands out. It believed that the participation of more specialists in the project would promote estimates and parameterizations with different results from those provided by the responses of a single specialist. Another limitation is due to the number of simulations performed in the study. Due to the scope of the article, it was not possible to implement and analyze all simulations available in the RB. It believed that with a greater number of simulations, it will be possible to find new inferences of the project parameters along with the scratchs .

Innovative studies focusing on a larger number of specialists, as well as with a scope capable of supporting a larger number of simulations, would present new perspectives along with the RB models developed for risk management in projects. It would also be interesting to implement an RB model for risk management that could check, in parallel, the evolution of a project under development, confronting and/or converging with the findings of this research.

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