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INTELLIGENT PROJECT MANAGEMENT TOOLS

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The application of Artificial Intelligence (AI) in Project Management (PM) is a current research field with a growing demand from companies and organizations, interested in applying these technologies to get the most out of their data and expertise. Many organizations use software tools that allow automating the status of projects (situation analysis). These tools also provide predictions on the evolution of projects, using classic techniques such as Earned Value Management (EVM). However, the standard tools do not have many advanced functionalities, based on AI, which would allow to take much better advantage of the knowledge acquired by the organization. This fact is especially important in Risk Management (RM), which is one of the most complex aspects of PM. The objective of this work is to propose a methodology for research and development of tools based on AI technologies that allow organizations to analyze information from projects already developed (historical information) and to use it to improve RM in the planning of future projects.

Keywords: risk management; artificial intelligence; project management software

HERRAMIENTAS INTELIGENTES PARA LA GESTIÓN DE PROYECTOS

La aplicación de la Inteligencia Artificial (IA) en la Gestión de Proyectos (GP) es un campo de investigación actual y además existe una demanda creciente por parte de empresas y organizaciones para aplicar estas tecnologías. Muchas organizaciones utilizan herramientas de software que permiten automatizar el estado de los proyectos (análisis de situación). Estas herramientas también proporcionan predicciones sobre la evolución de los proyectos, utilizando técnicas clásicas como la Gestión del Valor Ganado (EVM). Sin embargo, estas herramientas, en general, no disponen de muchas funcionalidades avanzadas, basadas en la IA, que permitirían aprovechar mucho mejor los conocimientos adquiridos por la organización. Este hecho es especialmente importante en la Gestión de Riesgos (GR), que es uno de los aspectos más complejos de la GP. El objetivo de este trabajo es proponer una metodología para la investigación y el desarrollo de herramientas basadas en las tecnologías de la IA que permitan a las organizaciones analizar la información histórica de los proyectos ya ejecutados (información histórica) y utilizarla para poder mejorar la GR en la planificación de los proyectos futuros.

Palabras clave: gestión de riesgos; inteligencia artificial; sofware de gestión de proyectos

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INTELLIGENT TOOLS FOR PROJECT MANAGEMENT

1. Introduction

The application of AI in the field of Project Management is a field of research that has attracted the attention of the scientific community in recent years (Magaña, D. et. al, 2015) (Hanchate & Bichkar, 2016) (Wauters, M., 2016) (Auth, g., et. al. 2019) (Mohagheghi, V., et al, 2019) (Munir, M., 2019) (Ong, S., & Uddin, S., 2020). Nowadays there is a growing demand from companies and organizations to start applying these technologies in their project management tasks. According to the report presented by Gartner "Top 10 Strategic Technology Trends for 2017"[1], AI is the main strategic technology trend for most organizations". In the field of Project Management, these technologies are also considered to be of great importance; for example in the website "ProjectManagement"[2] we find many (non-scientific) opinion articles, in which experts analyse this topic. As discussed in this forum, investments related to IA applications in Project Management will increase significantly over the next few years. These technologies will reduce human errors and biases in budgeting, allow prediction of cost overruns and help develop project schedules. However, IA will not replace project managers but will allow them to monitor projects in a more automated way and allow them to focus on other, higher value areas. For instance, IA tools can help the project manager improve quantitative risk management and make the right decision to mitigate or avoid risks.

A project risk is an event that when it occurs, has a positive or negative effect on one of the project's objectives (time, cost, resources, scope or quality). Risk management is carried out by the Project Manager with the help of his/her team, and based on his/her experience. Risk is caused by the uncertainty present in any project. *Known risks* are those that have been previously identified and analyzed, and therefore can be managed and planned for. *Unknown risks* are more difficult for organizations to manage. The reliable estimation of the risks of a project undoubtedly improves the management of the projects.

The literature shows that risk was originally modelled as the variance in budget estimate and/or project duration (Hertz, 1964). It is now modelled as the multiplication of the "Probability of Occurrence" of the risk by its "Impact on the project", the so-called P-I models (Taroun, 2014). For years, some proposals have been made to try to improve risk modelling, for example by incorporating new variables into the models, such as the predictability of risk (Charette, 1989), the interdependence of risks (Cervone, 2006), the degree of exposure to risk (Jannadi & Almishari, 2003), or the significance of risk as a third dimension of P-I models (Han, Kim, Kim, & Jang, 2008). Other proposals incorporate factors such as the organization's risk management capacity (Aven, Vinnem, & Wiencke, 2007) and risk control (Cagno, Caron, & Mancini, 2007).

The project management methodologies themselves propose different methods for managing risks. Especially important are the quantitative methods, that is, those that allow for the estimation of numerical values related to the uncertainty that may affect the main objectives of the project (scope, time and cost), on the deviations from these magnitudes, and on the probabilities associated with these objectives. In the context of this paper we will understand that predicting the risk of a project consists of making estimates on the future value of this type of numerical variables. These amounts are measurable and are also related to the concept of risk. However, risk management professionals prefer to perform

[1] Gartner Inc. is one of the world's leading IT consulting firms http://www.gartner.com/technology/home.jsp
[2] The ProjectManagement website is one of the leading professional forums in the field of project management worldwide https://www.projectmanagement.com/

these tasks in a more personalized manner, using simpler techniques rather than complex quantitative models, and are also not very much in favor of incorporating Decision Support Systems (DSS) or AI technologies (Taroun, 2014). Nor do the methodologies and guides for project management contemplate the use of this type of tools (Laryea & Hughes, 2008). However, to reach a new evolutionary level in risk prediction, the incorporation of new technologies that make use of AI techniques should be the next natural step.

Project management software tools generate a lot of data and information about the project life cycle (historical information). This data is the basic source of information to be able to estimate the variables of interest in risk management. These tools allow statistical analysis of historical data and provide a great deal of information about what has happened in projects that have already been carried out. However, they do not allow reliable predictions to be made about current projects for various reasons, related to the statistical models and probability functions they implement, the reliability of the calculations, the data used, etc. When these data are used to try to model and predict risk, errors are propagated and amplified, and estimates about the variables are unrealistic.

In general, predicting the risks of a project is a very complex problem. Estimates depend not only on the specific variables of the project itself, but also depend on what happens in other projects of the organisation, on the organisation's economic and financial data, and even on external socio-economic variables. Many of these "hidden" variables could be important in order to correctly estimate risk-related parameters, but they are not taken into account. Although it is unrealistic to try to include all possible variables in the models, at least all the historical data related to the organization's own project management should be used.

Machine Learning techniques, for example the different types of artificial neural networks (Multilayer Perceptron, TDNN, FIR Networks, Recurrent Networks, SOM, etc.) are quite adequate tools to try to build reliable predictive models from the data (Mitchell, 1997). Although these techniques are hardly used in the professional field, we do find scientific works in which their application has been investigated for risk management. Therefore, the main objective of this paper is twofold:

1. To review current AI systems and tools for the intelligent management of project risks (section 3).
2. To discuss the state of the art and analyse open issues in this area (section 4).

3. AI Systems for Risk Management

AI techniques, and specially Machine learning, have been applied in projects focused on software development (Hu, et al., 2013), software analysis (Emam, Benlarbi, & Goel, 2001) (Ezawa, Singh, & Norton, 1996), finance and investment (Trippi, 1995), and construction (Gaarslev, 1992), among others. There are also relatively recent references in which AI has been applied in risk management. In this work, we focus on AI systems and techniques applied to manage risks as uncertain events that may occur during the project life cycle. The application of AI (mainly big data analytics) to other conceptions of risks, such as managing financial risks[3], risks in stock markets (Pham, Cooper, Cao, & Kamei, 2014), Business Intelligence (Wu, et. al., 2014) (Choi, T.M., 2016), or enterprise risks management (Sohrabi, et. al. 2018) have been also reviewed in the literature.

Therefore, in this section we focus on the Project Risk Management (PRM) area and review the state of the art of AI systems for risk management, do not focusing on a concrete

[3] The State of AI in Risk Management. Infopro Digital Services Limited & Tata Consultancy Services 2019: https://www.tcs.com/content/dam/tcs/pdf/Industries/Banking%20and%20Financial%20Services/State-of-AI-in-Risk-Management.pdf

application domain, but classifying them as focused on a specific process of the risk management area as proposed in the Project Management Body of Knowledge (PMBOK, 6th Ed.[4]). In what follows, some processes are grouped together in the same section, since they are very related and can be managed simultaneously by the AI system.

Related work is exponentially growing in recent years, so we have concentrated our review in highly cited references (around 50+), references that deal with less common tasks (e.g. most AI systems have been applied to identification, qualitative analysis and risk responses planification), or promising recent contributions.

3.1. Risk Management Planning

Risk Management Planning is the process by which the risk management activities for a project are defined. Planning for risk management processes is important to ensure that the level, type and visibility of risk management is consistent with the risks as well as the importance of the project to the organization. It is also important to provide sufficient resources and time for risk management activities and to reach an agreement for a common risk assessment procedure.

With this aim, (Forbes et. al. 2010) uses Case-Based Reasoning (CBR) to suggest the most appropriate risk management technique for a becoming risk, reusing the information of previous risk management problems represented in cases as a combination of political, economic, social, technological, legal and environmental factors.

3.2. Risk Identification

Risk Identification is the process by which the risks that may potentially apply to the project are determined and their characteristics are reported. Risk identification is an iterative process since new risks may be discovered or may evolve as the project proceeds through its life cycle.

Focused on this area, (Vijayakumar, K., et. al., 2017) uses natural language processing techniques (LSI+LDA) and deep learning to automate the risk identification process based on the findings or outcome of static code analysis software development projects.

(Goh, Y. M., et. al. 2009) applies CBR techniques for construction safety risk management and uses past knowledge in the form of past hazard identification and incident cases to improve the efficiency and quality of new hazard identification.

Following a similar approach, (Lu et. al. 2013) makes use of semantic networks which contain sub-concepts to describe all the possible precursors of project risks, from workers, physical system and environment, and hence help with the risks identification. This information is stored in cases to perform latter a CBR cycle to analyse risks.

3.3. Risk Analysis

Risk Analysis is divided into two different processes in the PMBOK guide. Qualitative Risk Analysis is the process of prioritizing risks for subsequent quantitative analysis, if required, assessing and combining the probability of occurrence and impact of those risks. Performing Qualitative Risk Analysis is usually a quick and inexpensive means of setting priorities for risk response planning. Subsequently, Quantitative Risk Analysis is the process of numerically assessing the effect of identified risks on the overall objectives of the project.

[4] Project Management Body of Knowledge (6th Edition): https://www.pmi.org/pmbok-guide-standards/foundational/pmbok

The process of Performing Quantitative Risk Analysis applies to risks that can have a potentially significant impact on the project requirements.

In this area, AI systems that deal with qualitative risk analysis are the common approach. (Tang et. al. 2008) proposes a fuzzy-Genetic Algorithm (GA) intelligent framework to assess the level of risk level caused by discrepancy between different supply chain parties, enabling the identification of the best set of decision variables.

(Abbass et. al., 2009) created MEBRA, a Multi-objective Evolutionary-Based Risk Assessment quantitative framework that makes use of the search capabilities of evolutionary computation to evaluate the effect of uncertainty on multiple conflicting objectives to analyse the level of risk.

(Feng, Jiannan, & Li, 2014) proposes the use of Bayesian Networks (BNs) to qualitatively analyse risk from observed cases and expert opinion, identifying the causal relationships among risk factors and analyzing the complexity and uncertainty of vulnerability propagation in information systems (IS) projects.

(Abolghasemi et. al. 2015): combines the Supply Chain Operation Reference (SCOR) standard model and Bayesian Networks to manage supply chain risks and improve supply chain performance.

In contrast, performing a more comprehensive quantitative analysis, (Badurdeen et. al., 2014) uses Bayesian networks to create a risk network map to represent the interrelations among risks and other driving factors, and hence, the system is able to quantitatively analyse risks by computing the probabilities of specific risks.

3.4. Risk Response Planification and Implementation

Risk Response Planning is the process by which options and actions are developed to improve opportunities and reduce threats posed to the project objectives. Planned risk responses must be tailored to the importance of the risk, be cost-effective in relation to the underlying risk challenge, realistic within the context of the project, agreed by all stakeholders, and managed by a person in charge. Commonly, the best response to risks needs to be timely selected from several options. Afterwards, the agreed risk response plans must be implemented and managed in accordance to the plan.

Related to this area, (Micheli et. al. 2014) provides a decision support system to select appropriate mitigation measures for supply chain risks. The system applies stochastic integer linear programming approach and fuzzy logic to model the expected impact of alternative sets of mitigation measures on supply chain risks.

(Lu et. al. 2013) uses CBR to retrieve similar cases from a case-base, which represent precursors of previous risks that occurred in similar projects and the responses applied to them to automate the selection of responses in view of the precursors of a current project.

(Fan et. al. 2015) relies again on CBR to develop a risk response strategies generation system for subway projects, retrieving and reusing information and knowledge of the similar historical cases.

3.5. Risks Monitoring

Risk Monitoring is the process by which identified risks are tracked, residual risks (risks that remain after the implementation of a contingency plan) are identified, new risks are identified, and the effectiveness of the risk management process is evaluated throughout the project. The process applies techniques, such as variance and trend analysis, that require the use of performance information generated during project implementation. Other purposes of this process include determining whether project assumptions remain valid, whether analyses show that an assessed risk has changed or can be discarded, whether risk management policies and procedures are being followed, or whether contingency provisions for cost or schedule should be modified to be aligned with the current risk assessment.

Dealing with this risk management tasks, (Bansal et. al., 2005) proposes a decision support system based on an intelligent agent that monitors risks, detecting deviations from Key Performance Indicators (KPIs), identifying rectification strategies, finding the optimal rectification strategy and rescheduling operations.

Finally, (Giannakis et. al., 2011) develops a MAS that features several agents that control the appearance of risks and uses a CBR module to adapt past successful risk mitigation strategies to be used in a current situation. Thus, the CBR module also helps the PM to plan the best risk response mitigation strategy.

4. Discussion and Open Issues

Risk is associated with the uncertainty that always exists around projects. That is to say, they are events that may or may not occur. But when risks materialize then so-called "corrective actions" need to be applied to mitigate their impact on the organization. One of the most important activities in project management is to plan adequately the response to project risks. In general, organizations can only plan responses to the highest priority risks. P-I models are the most commonly used to prioritize project risks. As pointed out before, risk probabilities are still calculated with unreliable techniques in many cases, and the accuracy of the whole calculation hardly depends on the project nature and on the expertise and knowledge of the project manager and his/her risk expert consultants. In order to plan the response to risks, it is necessary to know a priori (in the planning phase) the possible risks that could affect the project.

In all projects, and especially in large projects, developed in multinational companies, among multidisciplinary teams, in very different areas, working in different countries, with different legislation, high budgets, etc., the possible risks that could occur are very difficult to know a priori. One must take into account the risks related to the international economic situation, the specific risks of a certain sector, the risks that are particular to the organization itself, which may be related, for example, to the project team, to the clients, etc.

Organizations such as PMI regularly publish guides on different aspects of project management, and in particular on risk management. These publications include and characterize many of the most common project risks (PMI, 2009). We can also find many sector-specific publications that cover the most common and specific risks that usually occur in a given sector (e.g. banking, insurance, construction, software, etc.). Finally, each organization has information about the risks that usually occur in their own projects. In organizations that use project management tools, they even have data on the risks that have occurred previously in projects that have already been executed (historical information).

Table 1 summarises the related work reviewed in the previous section. As shown in the table, technologies such as CBR (Kolodner, 1993) are a common approach to design DSS that help find the best corrective actions by reusing the experience acquired by the organization, the form of the cases, to solve current problems based on the solution used in previous similar problems. This is particularly useful in risk management, identification and planning areas, and as expected, CBR related work focus on them.

Regarding analysis, advanced stochastic models based inspired by biological evolution, such as evolutionary computation and genetic algorithms, and statistical models, such as

Bayesian Networks have been successfully applied to qualify the level of risk and quantify its expected impact.

Multi-Agent Systems (MAS) with multiple interacting intelligent agents is a powerful paradigm to simulate the reality by means of these agents, their behaviour, their interaction rules and their environment. This is therefore especially suitable for monitoring tasks, allowing for the simulation of the appearance of risks and for the study of the dynamics of the system when this occurs, providing decision support.

In line with the current AI trendy technologies, NLP and deep learning have already been applied for risk identification, and we foresee a future increase in work that follows this approach, especially in the areas of identification and analysis, due to its strength in classification and prediction tasks.

Although the literature that reports application of AI in risk management has experienced a clear growth in the last decade, there are still many open issues to deal with in this area. The systems reviewed show a clear focus on machine learning techniques for risk assessment (Paltrinieri, N., et. al., 2019) and a clear focus on risk identification, analysis and response planification. This is obviously caused by the predictive nature of these techniques, but there are many other fields of AI that can be applied to these and other tasks. For example, as we have already mentioned, multi-agent systems and other related technologies (e.g. agreement technologies, decision support systems) can provide powerful what-if tools to simulate the project context and make appropriate decisions regarding the management, monitoring, design and implementation of risk response plans. With these technologies, for example, it is possible to observe in a totally secure way for the project what could happen if a risk or a combination of risks is presented, and specific contingency plans are implemented. Another area of research that is well established in AI and could have enormous advantages in the management and planning of risk response is recommendation systems. These systems could analyse the context of a project and use historical information and information from the project itself to ‘recommend’, for example, the most successful contingency plans or ad-hoc measures to deal with unexpected risks.

Furthermore, the literature review shows systems that apply specific AI techniques to specific systems or application domains (e.g. construction (Schwarz, I.J., et. al., 2015), software development (Vijayakumar, K., et. al., 2017), supply chain (Baryannis, G. et. al., 2019)). This is most likely to happen as these are 'classic' areas where project management methodologies are historically implemented and as the nature of these projects makes it possible to collect data on what happens in them. However, there is no generic tool (integrated into commercial risk management software, or a proprietary tool) that incorporates different AI techniques and covers the entire risk management cycle.

Finally, there are well established proposals that develop risk management frameworks. A risk management framework (RMF) is a structured process or methodology used to identify potential risks and to define the strategy for eliminating or mitigating their impact, as well as the mechanisms to effectively monitor and evaluate the contingency strategies. However, its relationship with intelligent systems design and development methodologies has not been investigated to date. However, the methodological design of intelligent frameworks and systems is an area widely studied in the field of AI (Bergenti, F., et. al., 2006), resulting in robust and more efficient systems. How can risk management frameworks integrate AI, especially as a source of new risks across the organisations is still an open issue[5].

[5] https://www.ferma.eu/publication/artificial-intelligence-ai-applied-to-risk-management/

Table 1: AI Systems for Risk Management

System	Domain	Risk Area	AI Technique	Objective
Abbass et. al. 2009	Multidomain	Quantitative Analysis	Evolutionary Computation	Model, understand, and reveal system level risk
Abolghasemi et. al. 2015	Supply Chain	Quantitative and Qualitative Analysis	Bayesian Networks	Manage risks and improve performance
Badurdeen et. al., 2014	Supply Chain	Quantitative Analysis	Bayesian Networks	Compute probabilities of risks
Bansal et. al., 2005	Supply Chain	Monitoring Response Planning	Agent-based DSS	Identify KPIs deviations and implement the rectification strategy
Fan et. al. 2015	Construction	Response Planning	CBR	Reuse successful risk response strategies of previous similar projects
Feng, Jiannan, & Li, 2014	Information Systems	Qualitative Analysis	Bayesian Networks	Determine the propagation paths with the highest probability and the largest estimated risk value.
Forbes et. al. 2010	Construction	Management	CBR	Suggest the most appropriate RM technique
Giannakis et. al. 2011	Supply Chain	Monitoring, Response Planification	MAS + CBR	Monitor risks and suggest mitigation strategies
Goh, Y. M., et. al. 2009	Construction	Identification	CBR	Identify new risks by reusing hazards and incidents of previous projects
Lu et. al. 2013	Construction	Identification, Response Planification	Semantic Networks + CBR	Identify potential risk pre-cursors and reuse and analyse previous risks and their responses
Micheli et. al. 2014	Supply Chain	Response Planification	DSS, Linear Programming, Fuzzy Logic	Model the impact of different mitigation measures
Tang et. al. 2008	Supply Chain	Quantitative Analysis	GA + Fuzzy sets	Asses level of risk caused by discrepancy
Vijayakumar, K., et. al., 2017	Software Development	Identification	NLP + Deep Learning	Identify code risks by analysing static code

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