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Application of reinforcement learning for integrating project risk analysis and risk response planning: A case study on construction projects

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C H R O N I C L E

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A B S T R A C T

Project Risk Management contains processes ranging from planning to control. It is applied to identify risks, analyze them, and design responses to change the occurrence rate and/or the effect of project risks. It is important for project managers to analyze the effects of the risks in projects and also consider project risks in their decisions. If project risks are not addressed during the risk management process, issues such as schedule delays, cost overruns, and even project failure may occur. This paper aims to introduce a Markov method to integrate project risk analysis and risk response planning. This method is applied to forecast the following status of the project when limited information about the project is available. Moreover, earned value management (EVM) methods were used to include various types of project risks through the project lifecycle. The model also offers the capability to choose the most effective risk response for managing project risks through the application of the Markov decision process (MDP). Eventually, we introduce a case study to demonstrate functionality and effectiveness of the presented approach. Solving the model allows for identifying the best set of risk response strategies tailored to each specific project state. The computational results illustrate that the current state of the project has a significant impact in the process of risk response planning. Since uncertainty is the inherent characteristic of projects, the use of the project's current state is more reliable than the previous status of projects, and the Markov method is applied in this research because it uses the current state for its modelling. Using this method, managers can predict the future state of projects and find the best response in each status of projects.

1. Introduction

Today, projects face constant pressure due to the challenges of globalization and their inherent innovation (Alhawary et al., 2012). Many projects are not terminated according to desired results today. In other words, small numbers of projects can be found completed at the time and cost defined at the beginning of the project. The growing size and complexity of projects make uncertainties and risks during projects increase significantly. For example, construction costs in the Channel Tunnel Project increased 80 percent higher than the forecasted costs (Aljohani et al., 2017). Moreover, a 2017 report by the Project Management Institute (PMI) indicated that 14 percent of IT projects fail entirely. However, this figure only accounts for complete failures; among the remaining projects, 31 percent fell short of their objectives, 43 percent went over budget, and 49 percent were delayed. companies use enterprise risk management to identify, assess and monitor risks to increase organizations' value (Zhang et al., 2016). A key challenge in projects is how their unique and evolving characteristics create risks, making it difficult for management to fully comprehend or conceptualize them (Brookfield et al., 2014). A project risk refers to an unpredictable event or situation that, if it happens, can influence the project and hinder its objectives (Project Management Institute, 2017). Examining the impact of risks that alter the distribution of outcomes is crucial not only for theoretical purposes but also for its practical implications (Bonilla et al., 2022). Risks can manifest in various aspects of a project, such as budget overruns, timeline delays, or compromised quality, if not properly addressed during the project

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management process (Zhang and Fan, 2014). Given the high cost of most projects, even a single one can pose significant challenges for the largest companies across various industries (Jensen et al., 2012).

The use of risk management systems is widespread in contemporary companies, primarily because of the potential of risk management to improve organizational performance (Marc et al., 2023). Project performance is continuously influenced by risks, making the implementation of effective risk management crucial to the overall success of the project (Luko, 2013). Project risk management is a structured method that involves identifying, analyzing, addressing, and controlling risks to enhance the likelihood and effect of positive risks while reducing the occurrence rate and effect of negative risks (Project Management Institute, 2017). In other words, managing project risk is necessary for ensuring project success (Wu et al. 2016). It ensures that most issues are identified early enough, allowing for recovery without jeopardizing the schedule or exceeding the budget (Tamak and Bindal, 2013). In other words, Risk management aims to minimize the likelihood and severity of losses. By reducing these losses, the overall value of the project is enhanced (Ford and Lander, 2011). Various standards have been established related to risk management, particularly concerning project risk management (Association for project management, 2010 & Project Management Institute, 2017 & International Organization for Standardization, 2002 & IEEE Standards Association, 2002 & International Organization for Standardization, 2017). Developed risk management methods mainly focus on two components: risk occurrence rate and its impact on a project objective, evaluated through either qualitative or quantitative methods (Fang et al., 2012). Projects are exposed to continuous environmental changes due to their inherent characteristics, such as extended execution timelines, complex processes, significant financial demands, and evolving organizational structures (Sujiao, 2009). Hence, the employment of quantitative approach is more applicable for risk management. One of the best methods to evaluate project performance during its lifecycle is the EVM approach. Earned Value Management method allows project managers to address schedule and cost deviations by implementing corrective measures (Chen et al., 2016). This method uses indicators to compare the current status of a project with its baseline. In traditional project management, project performance is evaluated based on only its activities, durations and costs. Whereas there are many types of risks affecting a project duration or cost. These risks are important factors leading to deviation in EVM indicators compared with a project baseline. In other words, considering project risks, designing and executing appropriate risk responses can result in EVM indicators and the project baseline convergence and finally the project performance improvement. EVM can be enhanced by integrating it with the risk assessment tools. This allows for the simultaneous consideration of a project's past, present, and future states with regard to the work accomplished, expenses incurred, and overall project progress (Muriana and Vizzini, 2017). Moreover, project risks change continuously due to the rapid changes in project environment (Smith et al., 2014). Besides, on the grounds that the advancement of projects mainly relies upon the venture circumstances, the risks within projects have the qualities of the stochastic phenomenon (Obare and Muraya, 2019). Thus, project risks should be modeled in a dynamic framework, and it tends to be modeled by Markov chains analogy.

This paper introduces a model for assessing project risks that utilizes EVM method and Markov chain during the project lifecycle for predicting the future state of projects, and authorizing managers to apply the optimized risk response strategies for managing project risks. Since almost all risks have impacts on a project duration and cost, the impacts of any type of risk are determined using EVM indicators (SPI and CPI). Furthermore, the Markov chain does not need historical data and uses current information. Hence, it is possible to perform the proposed approach even when we face limited information about a project performance. Given that EVM can depict project performance from the start of the project, using EVM indicators embedded in the Markov model leads to considering all project risks during the project lifecycle. After identifying and analyzing the project risks, suitable risk response strategies should be implemented to manage them during project execution (Zou et al., 2007). Hence, we use MDP to ensure that the best risk response strategies are selected in all of the project states. Markov Decision Processes (MDPs) are frameworks grounded in decision theory and the principles of discrete-time Markov processes. In a Markov Decision Process (MDP), at each time step, the decision maker observes the current state of the controlled Markov process and selects an action from a finite set of possible actions based on the current state. Therefore, since the transition matrix (P) of the Markov method at any time depends on the last action, MDP is led to evolve along a driven trajectory (Magni et al. 2000).

This paper is structured as follows. Firstly, previous studies related to project risk modeling are reviewed. Next, the novel method is explained. The efficiency of the method is discussed using a case study. Finally, the paper outlines the conclusions and suggests some topic for future study.

2. Literature Review

Risk management has consistently been a priority for managers, and researchers have devoted significant attention to this topic, developing frameworks, methods, and techniques to aid in the identification, assessment, and management of project risks (Arena et al., 2013). Project managers and executives have realized that the process of detecting, evaluating, and assessing potential risks significantly aids in formulating contingency plans for intricate projects (Kwak and Ingall, 2007). Both industry professionals and scholars broadly acknowledge project risk management as an essential process for ensuring the success of a project. Given that risk management is a vital aspect of project management, extensive research has been conducted on project risk management from various perspectives in recent years. The approaches discussed in existing studies are typically divided into three main categories: 1) project risk identification and classification, 2) project risk analysis, and 3) project risk response selection (Fan et al., 2015). In the following, a comprehensive description of these approaches is explained.

2.1 Project Risk Identification and Classification

The first step in risk management is risk identification and classification, in which potential project risks are identified. In this step, firstly, applying one of the risk management tools related to risk identification such as brainstorming and interviews, significant negative and positive risks with their sources and characteristics are identified. Secondly, using qualitative tools, the frequency of occurrence and the effect of each identified risk are estimated. Then, the identified risks are ranked and compared with each other. It is required to be mentioned that the purpose of this step is not only to prioritize risks but also to identify the characteristics and importance of the identified risks. There are many techniques for risk identification and classification like checklists, nominal group technique (NGT) (Mojtahedi et al., 2010), failure mode and effect analysis (FMEA) (Yan et al., 2019). Rolik (2017) presented the application of SWOT analysis and McKinsey matrix as two useful tools for project risks identification and classification. To identify risks of brownfield remediation projects in China, Han et al. (2019) gathered an initial list of risks from literature, then they used a Delphi method to revise and merge risks. Khodeir & Nabawy (2019) used risk breakdown structure (RBS) and project work breakdown structure (WBS) to classify an infrastructure project risk and subsequently generated a full risk register. Barghi and Shadrokh (2020) identified and categorized project risks using expert opinions throughout a fuzzy Delphi technique, and ranked them using DEMATEL and analytic network process (ANP) techniques. Since There is no single optimal method for risk identification and classification, it is required to select appropriate methods considering project type and context. Furthermore, no single method cannot be used for identifying all risks, so it seems that applying hybrid methods may result in a better result.

2.2 Project Risk Analysis

In recent years, risk analysis has assumed a more prominent role within the broader scope of project management (Cango et al., 2007). The primary purpose of this process is to evaluate the effect of the project risks. Many scholars are trying to develop risk assessment models using mathematical tools (Gupta, 2018). These models were developed to increase risk management accuracy (Muriana and Vizzini, 2017). Among proposed models, one can refer to Acebes, Pajares et al. (2013), who introduced a method to incorporate the EVM approach and risk management. The proposed model allows the project manager to detect any project performance deviations from its planned value. They also developed their previous research and proposed a model categorizing the project deviations into acceptable and unacceptable deviations (Acebes et al., 2014). Gładysz et al. (2015) using a hybrid method of PERT and linear programming model, manage risks throughout a project lifecycle. Applying this model, the authors introduced two main classes of risk treatment strategies comprising risk acceptance and avoidance. They also expressed that applying this method can result in project cost reduction. Zhao et al. (2016) introduced a fuzzy- base risk assessment model that used the likelihood of occurrence, the impact, and risk importance degree. They used the effect of risk on project success to measure risk importance. However, in their model, the authors did not link risk factors to project tasks. Furthermore, the risk impacts on project activities network were not analyzed. Another stream of research on project risk management focused on analyzing the correlation between risk factors and project deliverables. Kumar and Yadav (2015) proposed a Bayesian network to identify and estimate significant risks of software projects. Furthermore, Mousavi (2015) proposed a new approach to assess risks in highway projects based on the Markov chain. He classified highway project risks into five levels. Initial risk probability distribution function and transition probability matrix were calculated by using expert judgment. Then by using the limiting probability, the probabilities related to the final status of risk were calculated. Shyang et al. (2018) introduced a model to assess project risk using multi-criteria decision making (MCDM) and DEMATEL methods. In that research, the relationship between project risks, project management, and organization performance was investigated throughout interviews with experts in project management. In a published paper by Baylan (2020), a new MCDM method which ranks project risks is presented. He prioritized work packages considering relative importance of project output quality, project time, and project cost. Chakrabortty et al. (2019) developed a scheduling risk assessment framework (SRAF) to model uncertainties in duration and resources and to observe their impact on project objectives. Their model provided appropriate information by incorporating uncertainties and risks. Liu et al. (2019They developed a hybrid model combining a neural network with particle swarm optimization to assess risks in large-scale projects. In other research, Soltan and Ashrafi (2020) proposed a method to predict the project duration and cost using control charts considering the EVM method. In all of these researches, large scale data are needed for proper risk modeling. Besides, these models consider a specific type of risk, such as construction risks. Moreover, they were not accompanied by a model for the best risk response selection.

2.3 Project Risk Response Selection

Risk response selection is a pivotal element of risk management. This phase is always considered to have a direct influence on reducing the risk exposure. In other words, if risk response selection is not performed, the effect of the risk identification and the risk analysis will be diminished (Zhang et al., 2020). Some scholars paid attention to this topic. According to the classification proposed by Zhang and Fan (2013), the zonal- base method, the work breakdown structure-based (WBS) method, the tradeoff method, and the optimization-based methods are examined as the four types of methods used for risk response selection. The zonal-based method applies two-dimensional charts based on two selected criteria concerning risks to determine the region of the response action (Zhang and Fan, 2013). The WBS-based method relates risk response selection to activities based on the WBS of the project (Wu et al., 2018). The Trade Off method makes tradeoffs between the time, cost, and quality to introduce a set of risk response actions based on the project's objectives (Zhang et al., 2020). The optimization-based methods are used to develop an optimization model to optimize the risk response strategy selection. This approach can avoid other methods limitations, and is the most relevant approach to our study. In this regard, Zhang and Fan (2013) developed an optimization model, which integrates the project schedule, the project cost, and project quality. Their integer programming model maximizes the impact of all the estimated responses. Zhang (2016) proposed a mathematical model considering the expected risk loss. He investigated the impact of the risk interdependence on its response. Wu et al. (2018) introduced an optimization model with two objective functions. Their model provided risk response plans. Zuo and Zhang (2018) proposed an optimization method that aims to minimize the total risk costs regarding the project duration as a constraint. In other research, Zhang et al. (2020) proposed a fuzzy model to find the best response. The formulation of risk responses and the calculation of the best set of risk responses are the two main steps of the proposed model. Since these methods use mathematical models, it is required a complex calculation to solve these models. All of the aforementioned branches of research concentrate on a particular sub-process of project risk management, such as risk analysis. These methods applied static approaches focusing on a certain time slice of the project. However, there are many risks involved in the project lifecycle, and the risk management method should be updated periodically. Moreover, a vast amount of data is needed for risk modeling in these methods. Hence, we aim to propose a dynamic method that integrates risk analysis and risk response planning. This method includes different types of project risks during the project lifecycle. Besides, this method does not need large-scale data for modeling, and it is applicable throughout a project lifecycle. Hence, the major novelties of this study are provided as follows:

- A new quantitative method named Markov model is developed to integrate project risk analysis and risk response selection.
- This model can be applied when limited information about projects is available.
- EVM indicators are used to include various types of project risks throughout the project lifecycle.
- Both short term and long-term prediction for the future status of the project is provided simultaneously.
- Optimal risk response framework is provided and can be updated dynamically based on the project's current status.

3. Developing a Markov Chain Model of a Project Risks

Traditional methods that assess project risks in a static manner have been criticized for not adequately reflecting the true nature of projects. In a more realistic risk model, project risks should be evaluated dynamically. The Markov method, a technique used to analyze the behavior of dynamic systems, offers a quantitative approach to performing project risk analysis within a dynamic framework. Since only the last data from the model is used in Markov method, project risk assessment can be made based on only the last status of projects without the need for extensive historical data. This paper introduces a Markov method to analyze project risks. As mentioned before, the presented method is based on a Markov property and EVM indicators. The structure of this section is as follows. First, the EVM indicators of the proposed model are identified and selected. Subsequently, to define project states, the control limits for selected indicators are calculated and the Markov model is constructed. Finally, the process of optimized risk response strategy selection is explained. Fig. 1 delineates the details of the proposed model steps.

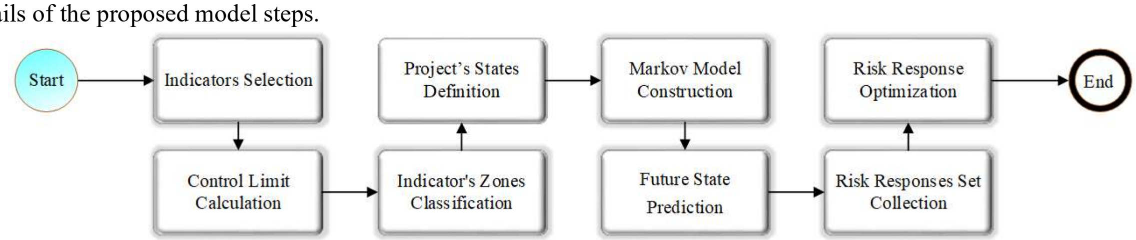

Fig. 1. Main steps of presented Model

3.1 Appropriate Indicators Selection for Risk Assessment

The first step for risk modeling is the selection of appropriate indicators to define Markov model states. Assuming that all the project risks affect a project duration or cost, SPI and CPI as two measurable factors can be used for the representation of a project duration and cost performance respectively. These two indicators are calculated using Eq. (1) and Eq. (2) (Project Management Institute, 2011):

$$CPI = \frac{EV}{AC} \tag{1}$$

$$SPI(t) = \frac{ES}{AT} \tag{2}$$

where *EV*, *AC*, *ES* and *AT* represent earned value, actual cost, earned schedule and actual time respectively. Also, *SPI* and *CPI* is the schedule performance index and cost performance index and. A vast amount of research is conducted on the application of statistical methods in EMM. For example, Leu and Lin (2008), constructed control charts for SPI, CPI, CPI^{-1}, $Ln\ CPI$ and $Ln\,CPI^{-1}$ to evaluate a project performance. Since control charts are only applied for normally distributed variables, it is required to identify its probability distribution function before using control charts. The distribution function of EVM indicators and also earned schedule indicators were investigated by Lipke (2002). The author of the aforementioned study used some statistical tests named Anderson-Darling, Chi-squared, Kolmogorov–Smirnov, and Shapiro–Wilk test to investigate the distribution function of CPI^{-1}, $Ln\,CPI^{-1}$, CV (Cost Variance), SPI^{-1}, $Ln\ SPI^{-1}$ and $Ln\ SPI(t)^{-1}$ (Lipke, 2002). Finally, these tests showed that $Ln\ SPI(t)^{-1}$ and $Ln\,CPI^{-1}$ follow normal distribution.

3.2 Dynamic Control Limit Calculation for Risk Classification

The general structure of the statistical control limit for normal variable is as $\mu \pm Z_\alpha \times \sigma$ where μ is the average of the variable, Z_α is the normal standard distribution value with α confidence level (the confidence level is determined based on risk-taking and risk tolerance threshold) and σ indicates the standard deviation of the normal distribution. It is worth mentioning that control charts are developed and applied to control a process, not a project. In other words, the population used to establish control limits is assumed to be infinite, and the activities are assumed to have a repetitive nature. However, projects are unique and have specific start and finish dates. Furthermore, due to the unique nature of projects, static control limits are not suitable for assessing project performance throughout its lifecycle. Thus, it is required to adjust control limits for a project. To encounter and answer the mentioned challenges, we applied the coefficients introduced by Lipke et al. (2009) as the adjustment factors for project schedule and cost which are multiplied by the standard deviation to calculate control limits. These adjustment factors are defined in Eq. (3) and Eq. (4):

$$AF_S = \sqrt{\frac{PD - ES}{PD - \frac{ES}{n}}}, \tag{3}$$

$$AF_C = \sqrt{\frac{BAC - EV}{BAC - \frac{EV}{n}}}, \tag{4}$$

where AF_s represents the adjustment factor for the project schedule, *PD* is the planned duration, *ES* is the earned schedule, and *n* represents the current period of the project. Also, AF_c is the adjustment factor related to the project cost, *EV* is the earned value, *BAC* represents the budget at completion, and *n* represents the current period of the project. According to these factors, we set up control limits for $Ln\ SPI(t)^{-1}$ and $Ln\,CPI^{-1}$. Based on the current status of project, these control limits can be calculated especially. The control limits are calculated using Eq. (5) and Eq. (6):

$$Ln\ SPI(t)^{-1}: \begin{cases} UCL = \overline{Ln\ SPI(t)^{-1}} + Z.\sigma.\sqrt{\frac{PD-ES}{PD-\frac{ES}{n}}} \\ CL = \overline{Ln\ SPI(t)^{-1}} \\ LCL = \overline{Ln\ SPI(t)^{-1}} - Z.\sigma.\sqrt{\frac{PD-ES}{PD-\frac{ES}{n}}} \end{cases} \tag{5}$$

$$Ln\ CPI^{-1}: \begin{cases} UCL = \overline{Ln\ CPI^{-1}} + Z.\sigma.\sqrt{\frac{BAC-EV}{BAC-\frac{EV}{n}}} \\ CL = \overline{Ln\ CPI^{-1}} \\ LCL = \overline{Ln\ CPI^{-1}} - Z.\sigma.\sqrt{\frac{BAC-EV}{BAC-\frac{EV}{n}}} \end{cases} \tag{6}$$

Next, to achieve a more effective classification of project states, each indicator is divided into four zones labeled A, B, C, and D, as shown in Table 1:

Table 1
Indicators zones definition based on the control limits

Zone	$Ln\ SPI(t)^{-1}$	$Ln\ CPI^{-1}$
A	$(-\infty\ ,\ \overline{Ln\ SPI(t)^{-1}} - Z.\sigma.\sqrt{\frac{PD-ES}{PD-\frac{ES}{n}}}]$	$(-\infty\ ,\ \overline{Ln\ CPI^{-1}} - Z.\sigma.\sqrt{\frac{BAC-EV}{BAC-\frac{EV}{n}}}]$
B	$(\overline{Ln\ SPI(t)^{-1}} - Z.\sigma.\sqrt{\frac{PD-ES}{PD-\frac{ES}{n}}}\ ,\overline{Ln\ SPI(t)^{-1}}]$	$(\overline{Ln\ CPI^{-1}} - Z.\sigma.\sqrt{\frac{BAC-EV}{BAC-\frac{EV}{n}}}\ ,\ \overline{Ln\ CPI^{-1}}]$
C	$(\overline{Ln\ SPI(t)^{-1}}\ ,\ \overline{Ln\ SPI(t)^{-1}} + Z.\sigma.\sqrt{\frac{PD-ES}{PD-\frac{ES}{n}}}]$	$(\overline{Ln\ CPI^{-1}}\ ,\ \overline{Ln\ CPI^{-1}} + Z.\sigma.\sqrt{\frac{BAC-EV}{BAC-\frac{EV}{n}}}]$
D	$(\overline{Ln\ SPI(t)^{-1}} + Z.\sigma.\sqrt{\frac{PD-ES}{PD-\frac{ES}{n}}}\ ,+\infty)$	$(\overline{Ln\ CPI^{-1}} + Z.\sigma.\sqrt{\frac{BAC-EV}{BAC-\frac{EV}{n}}}\ ,\ +\infty)$

When the project status of each defined indicator is outstanding, the indicator falls within the *A* zone, and in the same way, the indicator falls within the *D* zone if the project status is terrible. Hence these zones help us for better categorization for project status.

3.3 The Markov Model Construction for Project Risks Analysis

Let $\{X_n\ ,\ n=1,2,...\}$ be a stochastic process that presumes values in a discrete state space *S*. If $P\{X_{n+1}=j\,|\,X_n=i\,,X_{n-1}=i_{n-1},...,X_1=i_1\}=P\{X_{n+1}=j\,|\,X_n=i\}$ for all state $i_1\,,...,i_{n-1},...,i,j$ and all $n\geq 1$, it is to be said that $\{X_n\ ,\ n=1,2,...\}$ is a Markov chain. Then, $P_{ij}=P\{X_{n+1}=j\,|\,X_n=i\}$ are referred as a single-step transition probability of X_n. If *P* denote the one-step transition probabilities P_{ij}, such that,

$$P=\begin{bmatrix} P_{1\,1} & P_{1\,2} & \cdots & P_{1\,j} & \cdots \\ P_{2\,1} & P_{2\,2} & \cdots & P_{2\,j} & \cdots \\ \cdots & \cdots & & \cdots & \\ P_{i\,1} & P_{i\,2} & \cdots & P_{ij} & \cdots \\ \cdots & \cdots & & \cdots & \end{bmatrix}$$

Table 2
Definition of model states is based on the zones of selected indicators

State	$Ln\ CPI^{-1}$	$Ln\ SPI(t)^{-1}$
Perfect	*A*	*A*
Normal	*B*	*A*
	A	*B*
Low Risk	*B*	*B*
	A	*C*
	C	*A*
High Risk	*C*	*B*
	B	*C*
	D	*A*
	A	*D*
Critical	*D*	*B*
	B	*D*
	C	*C*
	D	*C*
	C	*D*
	D	*D*

Since the project status can be categorized based on the indicators' zones, and the future status of projects depends only on their current status, a Markov chain is developed to model project risks. It represents the current state of the project concerning its risk level. In this model, project states are divided into five classes: "Perfect," "Normal," "Low Risk," "High Risk," and "Critical." These states are defined based on the zones of project performance indicators. As mentioned earlier, the defined zones of each indicator represent the project status. Thus, we can define the "Perfect" state as occurring when both indicators fall within zone A. Similarly, the model states are defined in Table 2. Accordingly, the Markov chain of the presented method is shown in Fig. 2.

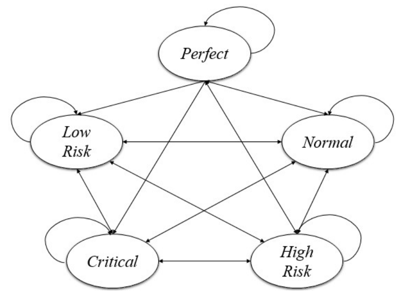

Fig. 2. The Markov chain of the proposed method

Then applying the large numbers law (Ross, 2014), the transition probabilities are calculated as Eq. (7):

$$P_{ij} = \frac{N_{ij}}{\sum_k N_{ik}} \tag{7}$$

where N_{ij} appears the transition number from the status i to status j observed in similar projects implemented in the same area or industry such as construction, energy or information technology, $\sum_k N_{ik}$ indicates the overall number of transitions from the status i to another status, and P_{ij} is the single-step transition probability from the status i to status j. For example, the transition probability from the "Perfect" status to the "Normal" status is equal to the transition number from the "Perfect" status to the "Normal" status divided by the sum of total transition number of from the "Perfect" status to another states. When SPI = 1 and CPI = 1 for a project, and a significant improvement in the project indicators is observed, the future state of the project should be changed from "Normal" to "Perfect". Therefore, the project's future state can be predicted by the two-step transition matrix derived by multiplying the one-step transition matrix by itself two times as illustrated in Eq. (8):

$$P^{(2)} = \begin{bmatrix} P_{11} & P_{12} & P_{13} & P_{14} & P_{15} \\ P_{21} & P_{22} & P_{23} & P_{24} & P_{25} \\ P_{31} & P_{32} & P_{33} & P_{34} & P_{35} \\ P_{41} & P_{42} & P_{43} & P_{44} & P_{45} \\ P_{51} & P_{52} & P_{53} & P_{54} & P_{55} \end{bmatrix} . \begin{bmatrix} P_{11} & P_{12} & P_{13} & P_{14} & P_{15} \\ P_{21} & P_{22} & P_{23} & P_{24} & P_{25} \\ P_{31} & P_{32} & P_{33} & P_{34} & P_{35} \\ P_{41} & P_{42} & P_{43} & P_{44} & P_{45} \\ P_{51} & P_{52} & P_{53} & P_{54} & P_{55} \end{bmatrix} \tag{8}$$

For an irreducible ergodic Markov chain, there are probabilities which is defined as the long-term proportion of time the Markov chain remains in a particular state (Ross, 2014). These probabilities, which are independent of preliminarily system status, called limiting probability and calculated by Eq. (9):

$$\begin{cases} \pi = \pi \, . \, P \\ \sum_{j=0}^{\infty} \pi_j = 1 \end{cases} \tag{9}$$

Since Eq. (9) has a unique solution for each project states, these states are aperiodic and positive recurrent. Hence, the proposed Markov chain is irreducible and ergodic. After solving the equation, the final probabilities of the project states in the Markov model can be determined.

3.4 Risk response selection

As discussed in the previous subsections, we developed a Markov chain to model and analyze project risks. However, if risk response is not performed well, the impact of risk analysis will be diminished. Hence, based on the project risk management process, project risks should be responded. Moreover, Due to limited resources in projects, an accepted tool for selecting the best risk response strategies is needed. Hence, we used the MDP to choose the best risk response strategy.

MDP is a discrete-time stochastic process which is shown as $M = \{S, A, P, R\}$, which *S*, *A*, and *R* are sets of states, actions, and rewards and *P* represents the transition probability matrix which is defined as Eq. (10) (Sigaud & Buffet, 2013):

$$P(s,s',a) = P(s_{t+1} = s' \mid s_t = s \ , \ a_t = a) \qquad \forall \ s,s' \in S \ , a \in A(s) \tag{10}$$

$P(s,s',a)$ is the transition probability from status s to s', when action *a* is selected. Moreover, based on this action, a reward or penalty is assigned. The main difference between a MDP and a Markov model is the concept of reward or penalty. The main issue in MDP is finding an optimal policy so that the total expected discounted rewards are maximized. According to Bellman's equation, optimal policy is obtained as Eq. (11) (Puterman, 2014):

$$V_{n+1}(s) = \max_{a \in A(s)} \ \{ r\ (s,a) + \lambda \sum_{j \in S} P(j \mid s,a)\ .\ V_n(j) \} \tag{11}$$

where $V_n(j)$ represents the value of status *j* at the time of *n*. and $r\ (s,a)$ is the reward of state *s*, when the action *a* is selected. Moreover, $\lambda \in (0,1]$ is a positive constant that represents the discount factor. Regarding the Markov model for selecting the best risk response, we can consider project costs reduction or time as the reward.

4. Conducting a Case study on Construction Projects

4.1 Data Selection

The data from projects used in this research are part of a large real-life construction project database introduced by Batselier and Vanhoucke (2014). The proposed database is publicly available at (OR-AS, 2020) and has been used in several studies in project management (Batselier & Vanhoucke, 2015, 2017; Colin & Vanhoucke, 2016; Martens & Vanhoucke, 2018). The database includes a wide range of construction projects, such as dam projects, bridge building projects, industrial projects, information technology projects, and R&D projects. It contains different types of information, such as Gantt charts, project baseline data, and tracking information. The database consists of 150 projects, 111 of which have complete baseline and tracking information. We needed periodic project tracking information containing EVM indicators for the Markov modeling. After investigating several segments of the database, we chose apartment building projects that contained the most complete project tracking information. Since there are 22 similar apartment building projects with complete baseline and tracking information, they have been used to examine the validity of the risk modeling and response selection using the proposed method in this paper.

4.2 Markov Model Development for the Case Study

The first step in developing the Markov model is the selection of appropriate indicators. As mentioned previously, we used functions of EVM indicators that follow a normal distribution for the Markov model. Therefore, we applied the Chi-Square test, Normal Probability Plot (NPP) method, Anderson-Darling (A-D) method, and Shapiro-Wilk (S-W) method. The results of these tests on the distribution function of earned value management indicators related to the 22 similar apartment building projects are shown in Table 3.

Table 3
The Normality tests conducted for the functions of EVM indicators

Data Representation	Expected Accept	NPP Accept	A-D Accept	S-W Accept	Chi-Square	Probability
$Ln\ CPI^{-1}$	22	20	20	21	0.258	**0.884**
CPI^{-1}	22	11	13	15	5.321	**0.342**
CV	22	11	11	11	9.546	**0.012**
$Ln\ SPI(t)^{-1}$	22	22	22	22	0.00	**1.000**
SPI^{-1}	22	7	9	7	9.924	**0.015**

If an EVM indicator is normally distributed, it is expected that the hypothesis test (the indicators follow the normal distribution) is accepted for all of 22 apartment building projects. In Table 3, the frequency reported for each test is the number of projects for which the hypothesis of normality is accepted. Moreover, the probability of Chi-Square distribution for each indicator was calculated. So, following the normal distribution probability for each indicator was approved obtained. Since $Ln\ SPI(t)^{-1}$ and $Ln\ CPI^{-1}$ follow normal distribution, these indicators can be used to estimate control limits of the model. Then, according to the proposed model, the control limits for the two selected indicators were calculated. Firstly, one of the

22 apartment building projects was selected, and based on the data from a specific time period within the selected project's lifecycle shown in Table 4, adjustment factors for time and cost indices were obtained using Eqs. (3) and (4). The time and cost indices were 0.265 and 0.473, respectively.

Table 4
Input data about the case study in a particular track

Parameter	Value
Planned Duration	**732.38 day**
Budget At Completion	**21369835.51 $**
Number of time track	**104**
Earned Value	**16633732.12 $**
Earned Schedule	**681.33 day**

Then, the control limits for $Ln\ SPI(t)^{-1}$ and $Ln\,CPI^{-1}$ at 90% confidence level as an indicator of decision-makers level of risk-taking were calculated using Eq. (5) and Eq. (6) as shows in Es. (12) and Eq. (13):

$$Ln\ SPI(t)^{-1}: \begin{cases} UCL = 0.2117 + (1.65 \times 0.4564 \times 0.265) = 0.411 \\ CL = 0.2117 \\ LCL = 0.2117 - (1.65 \times 0.4564 \times 0.265) = 0.012 \end{cases} \tag{12}$$

$$Ln\ CPI^{-1}: \begin{cases} UCL = 0.042 + (1.65 \times 0.2381 \times 0.473) = 0.228 \\ CL = 0.042 \\ LCL = 0.042 - (1.65 \times 0.2381 \times 0.473) = -0.144 \end{cases} \tag{13}$$

Next, as mentioned in Table 1, the zones for both indicators are depicted in Table 5. To develop the Markov model, firstly, the selected project states considering their risk status were defined using the following zones. The project state definition is shown in Table 6.

Table 5
Indicators zones calculation for the case study

Zone	$Ln\ SPI(t)^{-1}$	$Ln\ CPI^{-1}$
A	$(-\infty\ ,\ 0.012]$	$(-\infty\ ,\ -0.144]$
B	$(0.012\ ,\ 0.2117]$	$(-0.144\ ,\ 0.042]$
C	$(0.2117\ ,\ 0.411]$	$(0.042\ ,\ 0.228]$
D	$(0.411\ ,\ +\infty)$	$(0.228\ ,\ +\infty)$

Table 6
Project states definition

State	$Ln\ CPI^{-1}$	$Ln\ SPI(t)^{-1}$
Perfect	$(-\infty\ ,\ -0.144]$	$(-\infty\ ,\ 0.012]$
Normal	$(-0.144\ ,\ 0.042]$	$(-\infty\ ,\ 0.012]$
	$(-\infty\ ,\ -0.144]$	$(0.012\ ,\ 0.2117]$
Low Risk	$(-0.144\ ,\ 0.042]$	$(0.012\ ,\ 0.2117]$
	$(-\infty\ ,\ -0.144]$	$(0.2117\ ,\ 0.411]$
	$(0.042\ ,\ 0.228]$	$(-\infty\ ,\ 0.012]$
High Risk	$(0.042\ ,\ 0.228]$	$(0.012\ ,\ 0.2117]$
	$(-0.144\ ,\ 0.042]$	$(0.2117\ ,\ 0.411]$
	$(0.228\ ,\ +\infty)$	$(-\infty\ ,\ 0.012]$
	$(-\infty\ ,\ -0.144]$	$(0.411\ ,\ +\infty)$
Critical	$(0.228\ ,\ +\infty)$	$(0.012\ ,\ 0.2117]$
	$(-0.144\ ,\ 0.042]$	$(0.411\ ,\ +\infty)$
	$(0.042\ ,\ 0.228]$	$(0.2117\ ,\ 0.411]$
	$(0.228\ ,\ +\infty)$	$(0.2117\ ,\ 0.411]$
	$(0.042\ ,\ 0.228]$	$(0.411\ ,\ +\infty)$
	$(0.228\ ,\ +\infty)$	$(0.411\ ,\ +\infty)$

Then, using the tracking information of the 22 apartment building projects, the transition probability matrix of the selected project concerning the law of large numbers for a specific time was formed as Table 7.

Table 7
One-Step transition probability Matrix

	Perfect	Normal	Low Risk	High Risk	Critical
Perfect	0.28	0.28	0.14	0.17	**0.13**
Normal	0.05	0.73	0.14	0.05	**0.03**
Low Risk	0.01	0.15	0.68	0.13	**0.03**
High Risk	0.02	0.06	0.16	0.60	**0.16**
Critical	0.00	0.03	0.04	0.11	**0.82**

Now, using the one-step probability transition matrix, future states of the project can be predicted. Considering the data given in Table 4 as the selected project's current status, the project's next status was calculated using a two-step transition probability matrix as shown in Table 8.

Table 8
Two-step transition probability matrix

	Perfect	Normal	Low Risk	High Risk	Critical
Perfect	0.09	0.31	0.21	0.20	**0.19**
Normal	0.05	0.56	0.22	0.10	**0.07**
Low Risk	0.02	0.22	0.50	0.17	**0.09**
High Risk	0.02	0.12	0.22	0.40	**0.24**
Critical	0.00	0.07	0.08	0.16	**0.69**

Using the row involving the project's current state in the above matrix, the probability of the future state of the project is obtained. For instance, given that the current status of a project in this case study is "Low Risk", the future state of this project is predicted will be in "High Risk" with the probability of 0.17. In the same way, the future state of this project is predicted to be in "Perfect", "Normal", "Low Risk" and "Critical" with the probabilities of 0.02, 0.22, 0.50 and 0.09 respectively. Besides, since the current status of this project is "Low Risk", it is most likely that the future state of the project to be "Low Risk" too. However, as depicted in Table 8, the probabilities of the future state of the project are different for other states.

The final state of the project is obtained using limiting probability. As depicted in Table 9, the final state of this project is predicted to be in "Perfect", "Normal", "Low Risk", "High Risk" and "Critical" with the probabilities of 0.03, 0.24, 0.25, 0.20 and 0.28 respectively. Since the current state of the project is "Low Risk", if any risk response is not considered, deviation from the project's baseline may increase, and the future state of this project will be more likely than other states to be "Critical".

Table 9
Project limiting Probability

State	Perfect	Normal	Low Risk	High Risk	Critical
Probability	0.03	0.24	0.25	0.20	**0.28**

4.3 Risk Response Selection for the Case Study

Although we can predict the future state and the final state of the project, since characteristics of project risks such as the likelihood and the effect of project risks may change during its lifecycle, we need strategies to respond to the project risks. Hence, a set of risk responses considering the various project risk levels is needed. Secondly, we need the transition probability matrix and transition reward matrix for each risk response to find the best risk response using the Markov decision process. Due to the different risk responses, a set of strategies were defined as follows:

1. Risk Exploitation: it means trying to enhance the occurrence rate or the effect of a positive risk to exploit the identified opportunity.
2. Risk Acceptance: this implies that no changes are made to the risk management plan, and the management is unable to choose any risk mitigation strategy.
3. Risk Transference: it means transforming the responsibility for the risk to another party.
4. Risk Mitigation: it means reducing the probability or consequences of a negative risk to an acceptable level.
5. Risk Avoidance: this means modifying the project plan to get rid of a negative risk.
6. Project redefinition: it means redefining the project scope or quality because of the risk impact.
7. Project Termination: it means closing-out the project because of the severity of a negative risk impacts.

Each risk response may be applicable and appropriate for some project states. Table 10 shows the appropriate risk response strategies for each state. It means that if the considering project is in the “Perfect” state, it is recommended to apply response strategies of “Risk Exploitation”, “Risk Acceptance”, or “Risk Transference”. Because the project performance is excellent, and the project is faced with positive risks or low impact risks.

Table 10
Available risk responses for states

State	Risk response number
Perfect	**1-2-3**
Normal	**1-2-3**
Low Risk	**2-3-4-5**
High Risk	**4-5-6-7**
Critical	**4-5-6-7**

To obtain unbiased information about the transition probability and transition reward for risk response strategies from multiple perspectives, several experts from construction project management, apartment building project management and project risk management were interviewed. Interviewees included project managers and risk team members. Hence, the transition probability matrices for risk response strategies were collected from experts' judgments, as illustrated in Table 11. The transition probability matrix was used as input data of the Markov decision process.

Table 11
Transition probability matrix for risk responses

Risk Response 1	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	0.73	0.23	0.01	0.02	**0.01**
Normal	0.09	0.78	0.07	0.04	**0.02**
Low Risk	0.20	0.20	0.20	0.20	**0.20**
High Risk	0.20	0.20	0.20	0.20	**0.20**
Critical	0.20	0.20	0.20	0.20	**0.20**
Risk Response 2	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	0.72	0.21	0.03	0.01	**0.03**
Normal	0.06	0.80	0.07	0.05	**0.02**
Low Risk	0.03	0.20	0.65	0.10	**0.02**
High Risk	0.20	0.20	0.20	0.20	**0.20**
Critical	0.20	0.20	0.20	0.20	**0.20**
Risk Response 3	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	0.77	0.20	0.02	0.01	**0.00**
Normal	0.08	0.83	0.06	0.02	**0.01**
Low Risk	0.04	0.22	0.63	0.09	**0.02**
High Risk	0.20	0.20	0.20	0.20	**0.20**
Critical	0.20	0.20	0.20	0.20	**0.20**
Risk Response 4	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	0.20	0.20	0.20	0.20	**0.20**
Normal	0.20	0.20	0.20	0.20	**0.20**
Low Risk	0.05	0.24	0.62	0.08	**0.01**
High Risk	0.04	0.07	0.16	0.63	**0.10**
Critical	0.01	0.06	0.07	0.15	**0.71**
Risk Response 5	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	0.20	0.20	0.20	0.20	**0.20**
Normal	0.20	0.20	0.20	0.20	**0.20**
Low Risk	0.06	0.26	0.60	0.07	**0.01**
High Risk	0.05	0.08	0.20	0.58	**0.09**
Critical	0.01	0.06	0.10	0.20	**0.63**
Risk Response 6	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	0.20	0.20	0.20	0.20	**0.20**
Normal	0.20	0.20	0.20	0.20	**0.20**
Low Risk	0.20	0.20	0.20	0.20	**0.20**
High Risk	0.06	0.10	0.25	0.51	**0.08**
Critical	0.02	0.09	0.12	0.24	**0.53**
Risk Response 7	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	0.20	0.20	0.20	0.20	**0.20**
Normal	0.20	0.20	0.20	0.20	**0.20**
Low Risk	0.20	0.20	0.20	0.20	**0.20**
High Risk	0.00	0.00	0.00	0.00	**1**
Critical	0.00	0.00	0.00	0.00	**1**

As discussed previously, based on the current state of the project, there should be a reward or penalty assigned to each available risk response in the MDP method. Using these rewards, the MDP method can determine the best policy that maximizes the total expected discounted rewards. Similar to the transition probability matrix, the transition reward/penalty matrix for risk responses was developed based on the judgments of several construction project experts, as shown in Table 12. This transition reward/penalty matrix is used as an additional input for the MDP method. The optimal risk response strategy was selected based on both the transition probability matrix and the transition reward matrix. Additionally, value iteration and policy iteration methods were applied to identify the best strategies in the MDP method, which were coded using MATLAB R2019. Both value iteration and policy iteration are exact methods: value iteration computes an optimal policy and its value, whereas policy iteration iteratively adjusts the policy and finds its reward (Hu & Yue, 2007). In this paper, both methods were used concurrently to assess prediction accuracy and to compare their results.

Table 12

Transition reward matrix for risk responses

Risk Response 1	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	12	8	8	2	**-7**
Normal	16	15	8	3	**-10**
Low Risk	-100	-100	-100	-100	**-100**
High Risk	-100	-100	-100	-100	**-100**
Critical	-100	-100	-100	-100	**-100**
Risk Response 2	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	14	7	6	1	**-8**
Normal	17	13	6	2	**-11**
Low Risk	21	17	7	3	**-10**
High Risk	-100	-100	-100	-100	**-100**
Critical	-100	-100	-100	-100	**-100**
Risk Response 3	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	10	9	5	3	**-6**
Normal	18	14	10	5	**-12**
Low Risk	20	15	8	4	**-9**
High Risk	-100	-100	-100	-100	**-100**
Critical	-100	-100	-100	-100	**-100**
Risk Response 4	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	-100	-100	-100	-100	**-100**
Normal	-100	-100	-100	-100	**-100**
Low Risk	19	13	9	5	**-8**
High Risk	23	20	14	5	**-4**
Critical	23	22	16	10	**-2**
Risk Response 5	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	-100	-100	-100	-100	**-100**
Normal	-100	-100	-100	-100	**-100**
Low Risk	18	12	10	6	**-7**
High Risk	22	18	12	3	**-5**
Critical	24	21	15	9	**-3**
Risk Response 6	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	-100	-100	-100	-100	**-100**
Normal	-100	-100	-100	-100	**-100**
Low Risk	-100	-100	-100	-100	**-100**
High Risk	21	16	10	1	**-6**
Critical	25	20	14	8	**-4**
Risk Response 7	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	-100	-100	-100	-100	**-100**
Normal	-100	-100	-100	-100	**-100**
Low Risk	-100	-100	-100	-100	**-100**
High Risk	0	0	0	0	**-15**
Critical	0	0	0	0	**1**
No Strategy	**Perfect**	**Normal**	**Low Risk**	**High Risk**	**Critical**
Perfect	7	5	3	1	**-20**
Normal	10	7	4	1	**-15**
Low Risk	10	7	4	1	**-15**
High Risk	15	11	8	2	**-10**
Critical	18	15	10	5	**-5**

Finally, an optimal risk response strategy for states using two aforementioned methods is shown in Table 13.

Table 13

Optimal risk response strategy

State	**Risk Response**	
	Value Iteration	**Policy Iteration**
Perfect	Risk Acceptance	**Risk Acceptance**
Normal	Risk Transference	**Risk Transference**
Low Risk	Risk Avoidance	**Risk Avoidance**
High Risk	Project Redefinition	**Project Redefinition**
Critical	Project Redefinition	**Project Redefinition**

Table 13 shows that there is no difference between the results obtained from the policy iteration and value iteration methods. Both methods yield the same result for each state. The optimal strategies for risk response planning indicate that "Project Redefinition" is recommended for both "High Risk" and "Critical" states, while "Risk Avoidance" is preferred for the "Low Risk" state. Similarly, "Risk Transference" and "Risk Acceptance" are identified as the best risk response strategies for the

"Normal" and "Perfect" states, respectively. The results suggest that when the project is in good condition and its state is "Perfect," the best strategy is "Risk Acceptance," as the impact of these risks on project performance is minimal. Additionally, this strategy has a higher expected reward compared to others in the "Perfect" state. Furthermore, since project goals may not be achievable in the "Critical" state, and project scope must be redefined to improve the chances of success, "Project Redefinition" is recommended for this state. It should be noted that these risk responses were derived specifically for the case study. In other words, these results were calculated based on the transition probability matrices and the transition reward/penalty matrices for the case study. It is evident that different results may be obtained for other projects.

4.4 Result and Discussion

Since we applied a comprehensive database of construction projects executed before, it provided complete access to all projects tracking data. So, it was possible to compare the results of Markov model prediction with the actual tracking information. Hence, using Mean of Square Error (MSE), the accuracy of the proposed method was investigated. The comparison between the results of the Markov model prediction about projected future states considering their current states with the actual project information in each track are shown in Table 14. Using these results, the accuracy of the proposed method which is modeled by MSE was calculated as . The accuracy shows that the proposed model is an effective tool for project managers to analyze project risks using prediction of the future states of projects.

Table 14
Comprison between the results of the Markov model and the actual information

Project ID	Track Number	EV (€)	ES (day)	Predicted State	Actual State
C2014-05	6 (Current State)	145523.33	58.38	Low Risk	**Low Risk**
	7 (Next State)	159700.67	75.88	Low Risk	**Low Risk**
	15 (Final State)	532410.28	277.21	Critical	**Critical**
C2015-32	4 (Current State)	420294.09	38.34	Perfect	**Perfect**
	5 (Next State)	519338.33	99.65	Normal	**Normal**
	15 (Final State)	2273753.27	403.12	Low Risk	**Low Risk**
C2014-08	10 (Current State)	1,558,030.00	251.55	High Risk	**High Risk**
	11 (Next State)	1,685,677.90	271.24	High Risk	**High Risk**
	12 (Final State)	1,937,660.41	292.48	Critical	**Critical**
C2011-13	105 (Current State)	17982925.88	687.38	Low Risk	**Low Risk**
	106 (Next State)	18130786.20	688.38	Low Risk	**High Risk**
	120 (Final State)	21369835.51	732.38	Critical	**Critical**

If we know the future states of the project, appropriate decisions to avoid cost overruns, schedule delays and even the project failure can be selected. In other hands, since project risks are analyzed and considering these risks, the best response strategies are selected to cope with the project risks using this method, the probability of project success can be improved. Besides, the proposed method provides the project manager with a decision support tool to integrate risk analysis and risk response planning, which helps the project manager to predict the future state of the project and also to select the best risk response considering the current state of the project.

5. Conclusion

One of the most critical issues in project management is project risk assessment and treatment. Numerous studies have been conducted on project risk management, with many proposing qualitative or quantitative models to evaluate project risk. All of the models proposed in the literature focus on specific types of risks, such as construction risks or human risks. Moreover, these studies generally lack an integrated method for simultaneous risk analysis and risk response selection. Additionally, these models use static approaches, and since project risks may change throughout the project lifecycle, they cannot be applied effectively at any stage of the project. Furthermore, these methods often require a vast amount of data for accurate risk modeling. While the application of Markov chains in risk modeling is not new, it is novel for the combined purpose of project risk assessment and treatment. In this paper, we introduce a quantitative model, the Markov model, for project risk assessment and treatment. This model provides short-term and long-term predictions of the future status of a project using its current data. By using the transition probabilities and transition rewards of risk responses, this model can also recommend the best risk response strategy based on the project's current state. Additionally, the model can be updated throughout the project lifecycle to reflect changes in project risks. A key characteristic of the Markov model is that it does not require large-scale data collection, as it is based on current information. Furthermore, Earned Value Management (EVM) is used to incorporate various types of project risks. The proposed method in this paper has three main advantages. First, by using EVM indicators, which determine the impact of various types of risks, this model can assess all risk types in projects more comprehensively than other risk assessment methods. Second, by relying on current project data at any time, the proposed method can be applied at any stage of the project lifecycle. Third, the model provides the ability to select an optimal risk response to manage project risks. Risk management is crucial to an organization, as it enables firms to define future objectives more accurately. Defining objectives without considering risks can lead to a lack of direction when risks materialize.

This method offers organizational managers a highly effective tool to identify and prioritize risks, track and measure performance, overcome challenges, address unforeseen risks, and achieve greater performance and success in each business endeavor. Managers can identify high-frequency events and work to reduce repetitive losses. Incidents are less likely to occur and have reduced impacts when they do, potentially saving the organization from significant losses. One of the main limitations of this research is that the project phase is not considered in predicting the future state of the project and in selecting the best risk response. As a result, the proposed model cannot provide phase-specific predictions and risk response recommendations. Future research could aim to address this limitation by using a time-dependent Markov process for modeling.

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