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Modelling Risk Interdependencies to Support Decision Making in Project Risk Management: Analytical and Simulation-based Methods

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Abstract

Project risks are mostly considered to be independent, ignoring the interdependencies among them, which can lead to inappropriate risk assessment and reduced efficacy in risk treatment. The purpose of this research is to investigate how cause-effect relationships among project risks influence risk assessment results and to develop comprehensive network-based risk indicators which allow project managers to identify critical risks and important risk interdependencies more effectively. This study establishes three analytical methods-based project risk assessment models, namely, a Fuzzy Bayesian Belief Network-based risk assessment model, an Interpretive Structural Modeling-MICMAC analysis-based risk assessment model, and a Social Network Analysis-based risk assessment model. In addition, one simulation-based project risk assessment model, i.e., the Monte Carlo Simulation-based risk interdependency network model, is developed to capture the stochastic behavior of project risk occurrence when modeling risk interdependencies. Case studies are provided to illustrate the application of the proposed project risk assessment models. The research findings have highlighted the importance of considering risk interdependencies in project risk assessment and verified the performance of the proposed models in practical use.

Keywords: Project risk assessment, Risk interdependency, Fuzzy Bayesian Belief Network, Interpretive Structural Modeling, Social Network Analysis, Monte Carlo Simulation.

1. Introduction

The successful delivery and operation of projects remains a critical issue for contemporary project-driven organizations. As projects are potentially plagued with diverse risks and face a growing complexity from both internal (e.g., organizational, and technical aspects) and external (e.g., economic, social, and environmental aspects) (Fang & Marle, 2012), effective project risk management is of great importance for creating a proactive environment and achieving project objectives, such as to avoid budget overruns, schedule delays, quality deficiencies, and lower reputation (Guan, Abbasi, et al., 2020). Risk management is a formal and fundamental process to improve project performance by mitigating or controlling the consequences of risks associated with project objectives (El-Sayegh, 2008; Islam et al., 2017), usually including risk assessment (involving risk identification, risk analysis, and risk evaluation), risk treatment, and risk monitoring and review throughout a project life cycle (BSI, 2018). Among these phases, risk assessment is a very essential activity that allows project decision makers to have an overall risk perception of a project (at an early phase or during its implementation) and therefore to make appropriate risk response decisions proactively.

In real-world situations, project risks are interdependent, meaning there are cause-effect relationships among risks, where an identified risk is likely to trigger the occurrence of one or more other risks (Guan, Abbasi, et al., 2020; Marle & Vidal, 2008; Wang et al., 2019). These project risk interdependencies can result in a propagation from one upstream risk to numerous downstream risks, or a situation that one downstream risk arises from the occurrence of several upstream risks. If the effects of risk interdependencies are not considered and treated in project risk management, the occurrence of one risk can aggravate the probability or impact of other related risks over the course of a project lifecycle, even leading to domino effects which can threaten the final project results (Hwang et al., 2016).

The classical Probability–Impact (P–I) risk model, assessing project risks purely through their probability of occurrence and corresponding impact on project objectives (if the risks occur) with the assumption that risks are independent from their environment, has been gradually extended and incorporated additional parameters to reflect the complexity of projects (Aven, 2016; Taroun, 2014). Researchers have investigated various theories, tools, and techniques for aiding project risk assessment. Network-based risk assessment methods, where nodes and directed edges represent project risks and risk interdependencies, respectively, are more capable of modeling complex interdependencies among project risks than the classical P–I risk model (Marle et al., 2013; Yang & Zou, 2014). In such methods, the evaluation of a given risk is based on the risks which can trigger it directly or indirectly within a risk interdependency network (RIN). However, the existing studies into applying the RIN to project risk management are still limited and needs to be improved by analyzing multiple characteristics of risks (e.g., stochastic behavior, risk loops, and risk position within a network). Therefore, developing effective risk assessment methods is pivotal to better reflect actual project risk conditions and to provide decision makers with more objective, repeatable, and visible decision-making support for project risk management.

The main objective of this research is to develop comprehensive and effective risk assessment indicators that can better reflect actual project risk conditions to provide project risk management practitioners with more objective, repeatable, and visible decision-making support for project risk management. To achieve this objective, three main questions should be solved –– Q1: How to represent cause-effect relationships among project risks (i.e., risk interdependencies)? Q2: How to consider the risk stochastic behaviour, risk loops, and risk position in network-based project risk assessment? Q3: What risk indicators considering risk interdependencies can be developed using analytical methods and simulation-based methods, respectively?

The remainder of this paper is structured as follows. Section 2 provides an overview of the existing research on modeling project risks. Section 3 introduces the research methodology of developing project risk assessment models based on analytical and simulation-based approaches. Case studies of the applications of proposed risk assessment models and corresponding computational results are demonstrated in Section 4. The implications of this study are discussed in Section 5. Section 6 presents conclusions and future work.

2. Literature Review

According to whether or not risk interdependencies are considered in project risk assessment, existing project risk assessment methods can be classified into two main groups: assuming risks are independent and considering risk interdependencies (as shown in Table 1).

Table 1. Examples of existing project risk assessment methods.

	Existing project risk assessment methods	References
Assuming risks are independent	Classical *P–I* risk model	BSI, 2018; PMI, 2017
	Analytical Hierarchy Process (AHP)	Wang et al., 2016
	Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)	Zavadskas et al., 2010
	Fuzzy Synthetic Evaluation (FSE)	Islam et al., 2017; Zhao et al., 2016
	Monte Carlo Simulation (MCS)	Sadeghi et al., 2010
Considering risk interdependencies	Fault Tree Analysis (FTA)	Shoar et al., 2019
	Bayesian Belief Network (BBN)	Hu et al., 2013; Ojha et al., 2018
	Structural Equation Modeling (SEM)	Ahmadabadi & Heravi, 2019
	Design Structure Matrix (DSM)	Marle & Vidal, 2008
	Social Network Analysis (SNA)	Yang et al., 2016; Yang & Zou, 2014
	Interpretive Structural Modeling (ISM)	Kwak et al., 2018

In most cases, project risk management practitioners usually develop a two-dimensional risk matrix given the classical P–I risk model as a tool to assess and categorize individual project risks (BSI, 2018; PMI, 2017). Gradually, many complex methods have been developed to improve the classical P–I risk model in assessing project risks. For example, Multi-criteria Decision Making (MCDM) methods are introduced such as Analytical Hierarchy Process (AHP) (Wang et al., 2016) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Zavadskas et al., 2010). The Fuzzy Set Theory (FST), first introduced by Zadeh (1965), is usually combined with the MCDM methods during the project risk assessment to handle the uncertainties of risk data due to the imprecision, vagueness and subjectivity of human thoughts. As an application of the FST, the Fuzzy Synthetic Evaluation (FSE) method can deal with complicated risk evaluations with multiple levels and attributes and is able to represent empirical knowledge of practitioners (Islam et al., 2017; Zhao et al., 2016). However, the main limitation with adopting these analytical methods during project risk assessment is that they just assess project risks individually while ignoring their interdependencies, which can lead to the inevitable underestimation of project risks to some extent.

To incorporate risk interdependencies in project risk assessment, many researchers have proposed more sophisticated approaches and frameworks, including Fault Tree Analysis (FTA) (Shoar et al., 2019), Bayesian Belief Network (BBN) (Hu et al., 2013; Ojha et al., 2018), Structural Equation Modeling (SEM) (Ahmadabadi & Heravi, 2019), Design Structure Matrix (DSM) (Marle & Vidal, 2008), Social Network Analysis (SNA) (Yang et al., 2016; Yang & Zou, 2014), and Interpretive Structural Modeling (ISM) (Kwak et al., 2018). For instance, Shoar et al. (2019) proposed a Fault Tree (FT)-based approach for quantitative risk analysis in the construction industry that can consider both objective (aleatory) and subjective (epistemic) uncertainties; Hu et al. (2013) proposed a BBN-based model with causality constraints to discover the causality between risk factors and project outcomes in software projects; Ahmadabadi and Heravi (2019) developed a risk assessment framework in public private partnership megaprojects based on SEM method to rank risks focusing on risk interactions and to identify critical risk paths that can be used to offer proper risk responses; Marle and Vidal (2008) explored the DSM principles and defined a binary risk structure matrix to represent project risk interactions; Yang et al. (2016) built an SNA-based risk model that is capable of analyzing stakeholder associated risks and their interrelationships in complex green building projects; and Kwak et al. (2018) investigated the interactions between international logistics risks within the prevailing structures of international supply chains and highlighted how these risks may be inter-connected and amplified using the ISM method. These analytical methods are all based on a network structure to assess risks instead of viewing risks independently, but they still have several limitations in practice. Specifically, the FTA, BBN, and SEM methods cannot model complex risk interdependencies with loops. Simply using the measures in SNA cannot quantitatively evaluate to what extent the risks will influence project objectives. The ISM method is unable to evaluate the strengths of interdependencies among interrelated risks.

In the context of project management, comprehensive experimental studies on projects are costly and infeasible. Thus, simulation is proposed as an alternative tool for empirical research in decision support systems (Law, 2007). Some researchers have applied simulation-based methods to project risk assessment. For example, Sadeghi et al. (2010) proposed a fuzzy Monte Carlo Simulation (MCS) framework for risk assessment and cost-range estimation in construction projects. To further investigate project risk interdependencies using simulation-based models, Fang and Marle (2012) analyzed project risk networks through a simulation using ARENA software and re-evaluated project risks; and Wang et al. (2019; 2020) developed RIN simulation models to support the evaluation of project risk response decisions and proposed new network indices using the SNA method to quantify the significance of risks and risk interactions. Although simulation-based methods tend to be popular in project risk assessment, related studies on assessing the influence of project risks on project objectives considering risk interdependencies and analyzing the risk propagation phenomenon in an RIN with risk loops have been quite insufficient.

Overall, based on the literature review, the identified research gap is that there is no systematic study that investigates project risk management process considering multiple additional characteristics of risks, such as the risk stochastic behavior, complex risk interdependencies with loops, and risk position within a network. This work tries to fill this gap by developing appropriate project risk assessment models based on analytical and simulation-based methods for managing project risks considering their interdependencies in a project RIN.

3. Research Methodology

3.1. Identification of project risks and risk interdependencies

As the first phase for project risk assessment, risk identification is a process to find, recognize and describe potential risks that might help or prevent achieving project objectives (BSI, 2018; PMI, 2017). When identifying individual project risks, three main sources can be referred to: (1) previous academic research on relevant project risks; (2) historical risk data of completed projects; and (3) expert opinions on potential project risks. It is important to identify project risks according to relevant, appropriate and up-to-date information. Then, the interdependencies (i.e., the cause-effect relationships) among project risks need to be further identified. To increase the accuracy of the identification of risk interdependencies, the interrelations among project objects such as work-packages, tasks, or product components can help to determine the causal relationships among the risks related to these objects (Fang & Marle, 2012). Additionally, risk interdependencies can be identified across different contexts or domains of a project because risks associated with quality, cost or schedule may be linked. As a result, developing a proper project risk list and determining the cause-effect relationships among identified risks are the basis of structuring a project RIN in the next stage.

3.2. Representation of project risk interdependency network (RIN)

This research explores a FT-based BBN method and an ISM method to present interdependencies among project risks. In these two methods, nodes and directed edges represent the project risks and involved interdependencies, respectively. The FT-based BBN method is used in the development of FBBN-based project risk assessment model (in Section 3.3.1), while the ISM-based method is employed in the development of ISM-MICMAC analysis-based project risk assessment model (in Section 3.3.2), SNA-based project risk assessment model (in Section 3.3.3), and MCS-based RIN model for project risk assessment (in Section 3.4).

In the FT-based BBN method, FT analysis and BBN are merged to present risk interdependencies (Kabir et al., 2016; Wilson & Huzurbazar, 2010). As shown in Fig. 1, an FT structure can be set up in a top-down fashion based on the preliminary results of identified project risks and risk cause-effect relationships. Furthermore, a BBN structure can be constructed based on the FT transformation for fully presenting cause-effect relationships among identified risks. The events and vertical links in an FT structure should be directly transformed into corresponding nodes and fundamental links of a BBN structure according to conversion algorithms (basic (BEn), intermediate (IEn) and top (TE) events of an FT structure are mapped into root (RNn), intermediate (INn) and leaf (LN) nodes of a BBN, respectively). Further, overlapping nodes are combined into one node, and supplementary links can be inserted into the BBN structure according to experts' opinions. The edges in the BBN-based RIN structure, directed from a parent node (e.g., RN2) to a child node (e.g., IN1) through probabilistic gates, denote the interdependencies among project risks.

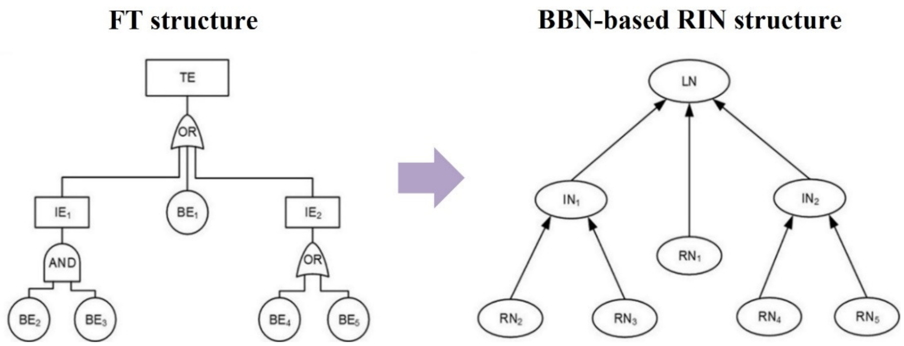

Fig. 1. Example of a BBN-based RIN structure transformed from an FT structure.

The ISM method, first introduced by Warfield (1974), has proven to be a practical tool for representing and analyzing relations and interdependencies among complex factors within a system. Based on the results of project risk identification, the ISM method can be used to develop an RIN and then to classify the nodes into levels, considering both direct and indirect relationships (Kwak et al., 2018). Firstly, a binary structural self-interaction matrix (SSIM) is established to represent the interactions among identified project risks. Contextual relationships between each pair of risks can be determined through existing studies or expert opinions via Delphi-based approaches. Secondly, indirect relationships between two risks are identified by transforming the SSIM into a reachability matrix (RM), where the transitivity among risks is taken into consideration. Then, the identified risks can be partitioned into levels in the RM using judging rules according to each risk's reachability set and intersection set (i.e., the overlap of the risk's antecedent set and reachability set). After removing the indirect links added in the RM and reviewing the conceptual inconsistency of risk interactions, a directed graph, i.e., an ISM-based network, is constructed to illustrate the hierarchical structure of complex project risk interdependencies. Fig. 2 shows an example of the developed ISM-based RIN structure with four hierarchical levels.

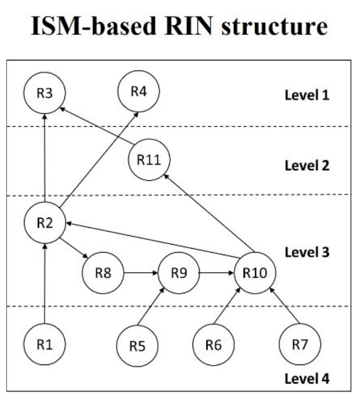

Fig. 2. Example of an ISM-based RIN structure.

3.3. Development of project risk assessment models using analytical methods

Three new project risk assessment models using advanced analytical methods are introduced respectively as follows: an FBBN-based risk assessment model, an ISM-MICMAC analysis-based risk assessment model, and an SNA-based risk assessment model.

3.3.1. Proposed FBBN-based risk assessment model

There are three major phases in the proposed FBBN-based risk assessment model, as shown in Fig. 3, and they are explained in detail as follows.

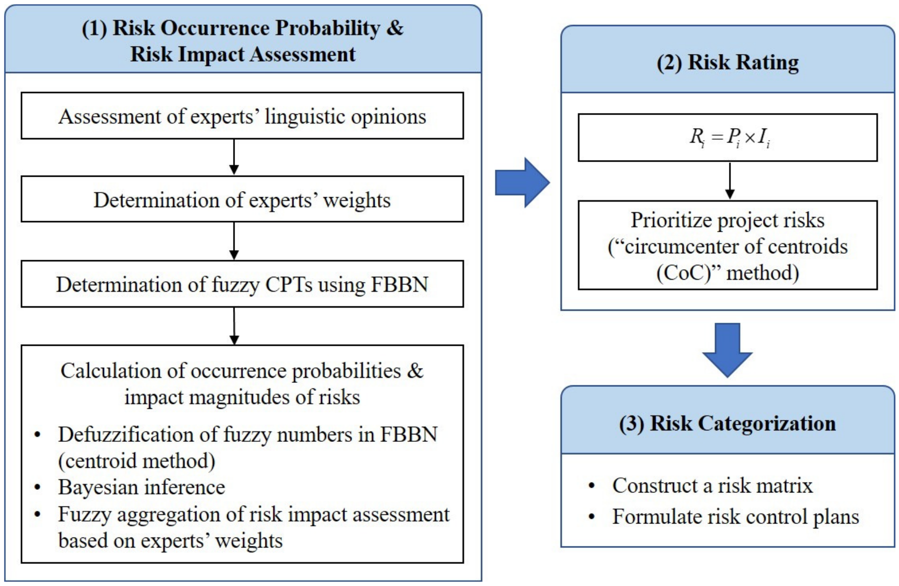

Fig. 3. Three major phases of the proposed FBBN-based risk assessment model.

(1) Risk occurrence probability and risk impact assessment: Experts estimate the occurrence probability and impact of all identified project risks in form of fuzzy linguistic scales. When experts are making judgments based on their knowledge and experience, it would be much easier for them to use qualitative descriptors than to provide crisp numerical values directly. The concept of linguistic variables allows for ambiguities, uncertainties or incomplete information of experts' judgments (John et al., 2014). Fuzzy linguistic scales can be designed with a set of linguistic variables, and each linguistic variable is represented by a fuzzy number and a corresponding fuzzy membership function that covers the universe of discourse (Samantra, Datta, & Mahapatra, 2017). In addition, the determination of experts' weights on their judgments' confidence to conduct fuzzy aggregation of their judgments can increase the reliability of data acquired from questionnaire surveys. The link between any two project risks in a BBN structure can be evaluated by means of a conditional probability distribution. Before the determination of fuzzy conditional probability tables (CPTs), fuzzy prior and conditional probabilities of risks should be estimated at first based on experts' judgments. Through the Bayesian inference (i.e., causal and diagnostic inference), different types of risk occurrence probabilities (i.e., prior and marginal occurrence probability, and posterior occurrence probability) can be calculated and the final results are in the form of crisp values after defuzzification. From the causal inference, risk occurrence probabilities are predicted considering existing cause-effect relationships. However, the diagnostic inference can provide reliable references for fault diagnosis and risk probability updating analysis when risk data are updated during the project implementation. In terms of calculating each risk's impact on project objectives, the experts' judgments represented by linguistic variables are transformed into trapezoidal fuzzy numbers according to a presumed fuzzy scale and then, a fuzzy aggregation of the judgments of risk impact based on experts' judgment weights is conducted. Therefore, an average preference fuzzy set is obtained to represent the impact magnitude of each project risk.

(2) Risk rating: This is a process for assessing severities of undesired events, which helps developing risk control and mitigation strategies. This phase rates project risks by multiplying their occurrence

probability and impact magnitude. Due to the application of FBBN method to occurrence probability assessment of risks, different types of risk ratings can be obtained. As a result, corresponding fuzzy risk ratings are calculated by multiplying the fuzzy impact magnitude of risks with different types of risk occurrence probabilities. Finally, critical project risks having a significant effect on project objectives will be identified by prioritizing risks based on the crisp values of risk ratings.

(3) Risk categorization: This phase categorizes project risks based on the concept of risk matrix, where horizontal and vertical axes represent risk occurrence probability and risk impact, respectively. A referential risk matrix can be constructed through the product of the linguistic scale of occurrence probability and that of impact magnitude. Every project risks will be distributed in the referential risk matrix with a certain value of risk rating from the FBBN method, and different risk levels of the identified risks can also be divided. Based on the results of risk categorization, project risk management practitioners can devise appropriate risk control plans to maximize the project success.

3.3.2. Proposed ISM-MICMAC analysis-based risk assessment model

After developing an ISM-based RIN, the importance of project risks associated with project objectives can be calculated based on the influence transmission from risks to objectives through network paths, as shown in Eq. (2). The weight of different levels (W_l) in the ISM-based RIN calculated using Eq. (1), are also considered.

$$W_l = \frac{1/l}{\sum_1^m (1/l)}, \quad l = 1, 2, \cdots, m \tag{1}$$

where, l is the numerical order of the partitioned levels (the smaller the l, the higher the level in a hierarchy), and m is the total number of levels.

$$I_{S_\sigma, O_\varphi} = W_l \left(\frac{1}{N_1+1} + \frac{1}{N_2+1} + \cdots + \frac{1}{N_i+1} + \cdots + \frac{1}{N_t+1}\right), \quad \sigma = 1, 2, \cdots; \varphi = 1, 2, \cdots; t = 1, 2, \cdots \tag{2}$$

where, S_σ represents project risks, O_φ represents project objectives, I_{S_σ, O_φ} denotes the importance of S_σ to O_φ, t denotes the number of network paths from S_σ to O_φ, and N_i is the number of intermediate nodes on the ith path excluding two endpoints.

In this proposed risk assessment model, the Matrice d'Impacts Croisés Multiplication Appliquée á un Classement (MICMAC) analysis is used to complement the ISM method in the aspect of analyzing the drive and dependence degree of each element in the risk assessment model. The values of drive/dependence powers can be calculated based on the RM which is obtained from the ISM method. Moreover, the MICMAC analysis can classify project risks into four clusters through a drive-dependence diagram, i.e., autonomous factors (Ⅰ), dependent factors (Ⅱ), linkage factors (Ⅲ), and independent factors (Ⅳ) (Chandramowli et al., 2011; Tavakolan & Etemadinia, 2017), which helps clarifying how each risk will behave interactively in a project. Through the MICMAC analysis, critical project risks can be identified as those have very strong drive power which fall into the category of independent or linkage factors.

3.3.3. Proposed SNA-based risk assessment model

In the proposed SNA-based risk assessment model, an ISM-based RIN is first developed, and then, a series of path-based network risk indicators are tailored based on general SNA measures and classical P–I risk model. Fig. 4 displays the commonly used three node measures (i.e., degree, closeness, and betweenness) and one edge measure (i.e., betweenness) in traditional SNA method, which are further improved in proposed risk indicators.

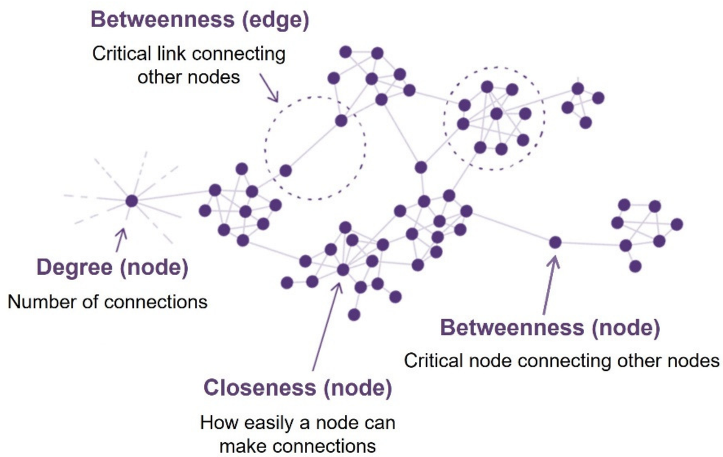

Fig. 4. General measures for node/edge in traditional SNA method.

In traditional SNA, the shortest path between any pair of nodes in a network is a key factor in most of node/edge measures. The "distance" is employed to measure the length of a path between any pairs of nodes in the network, i.e., the number of edges between the two nodes in a binary network or the sum of the values of edges in a weighted network (Scott, 1991; Wang et al., 2020). Considering the edge values in the project RIN are probabilities between 0 and 1, in such case, the use of "distance" is not appropriate. Therefore, we use the term "path probability strength" to replace the "distance", i.e., the product of transition probability (TP) values of all the edges in that path. Then, the weighted edge betweenness centrality is proposed to evaluate the significance of risk interdependencies. Four indicators, namely, out-degree centrality of node, betweenness centrality of node, out-closeness centrality of node, and hybrid structural centrality of node (developed based on the weighted edge betweenness centrality), are devised to evaluate risk significance from the perspective of SNA method. In addition, another two indicators, i.e., risk local and global significance, are proposed based on the concepts of risk probability and risk impact from the classical P–I risk model to evaluate risks. As a result, project risk rankings based on different risk indicators can be obtained, which support the determination of critical project risks and related risk interdependencies from different aspects.

3.4. Development of project risk assessment model using simulation-based methods

Monte Carlo method is used in the proposed simulation-based RIN model to capture the stochastic behavior of project risk occurrence and then to generate numerous risk scenarios during a project life cycle. We make the following assumption in the proposed simulation model: the status of risk occurrence (i.e., occurred or not) for each project risk in the RIN is determined once in each simulation run (Guan et al., 2021). In the Monte Carlo method, random numbers (RNs) representing occurrence probabilities of a risk are generated in the interval (0, 1) following a certain probability distribution. To improve the traditional MCS, this work proposes calculated occurrence probability (COP) of each risk as a dynamic threshold to evaluate a risk's occurrence status by comparing the generated RNs with its COP. A risk's COP is calculated based on the spontaneous probability (SP) of the risk and TPs from other related upstream risks (varied with the dynamic change of RIN in each simulation run) using probability theory. Therefore, if a generated RN of risk R_i in the t^{th} simulation run (i.e., $RN_{i,t}$) is no more than its calculated COP (i.e., $COP_{i,t}$), then R_i occurs in this simulation run and its occurrence status $mc_{i,t} = 1$, otherwise R_i does not occur and $mc_{i,t} = 0$. In addition, a "hypothesis-test" process is designed and incorporated in the proposed MCS-based RIN model to solve risk loops which could appear in a project RIN, and related four major steps are presented in Fig. 5. As shown in Fig. 6, the inputs of the proposed

MCS-based RIN model for project risk assessment includes: an ISM-based project risk interdependency network, each risk's spontaneous probability (SP), transition probability (TP) among interrelated risks, and each risk's impact on project objectives. To evaluate individual project risks and the overall project risk level, the outputs of the proposed model can be classified into two groups, where the simulated occurrence probability (SOP), simulated local influence (SLI), and simulated global influence (SGI) are related to each risk, while the total risk loss (TRL) and total risk propagation loss (TRPL) are related to the overall project. The obtained project risk assessment results can be used for planning and evaluating risk treatment actions, including planning appropriate risk treatment actions, testing them using the proposed risk indicators, and finally making a decision on the selection of the best risk treatment action among alternatives.

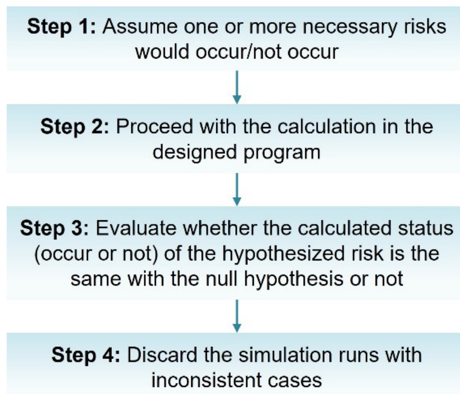

Fig. 5. A flow diagram of the "hypothesis-test" process in the proposed MCS-based RIN model.

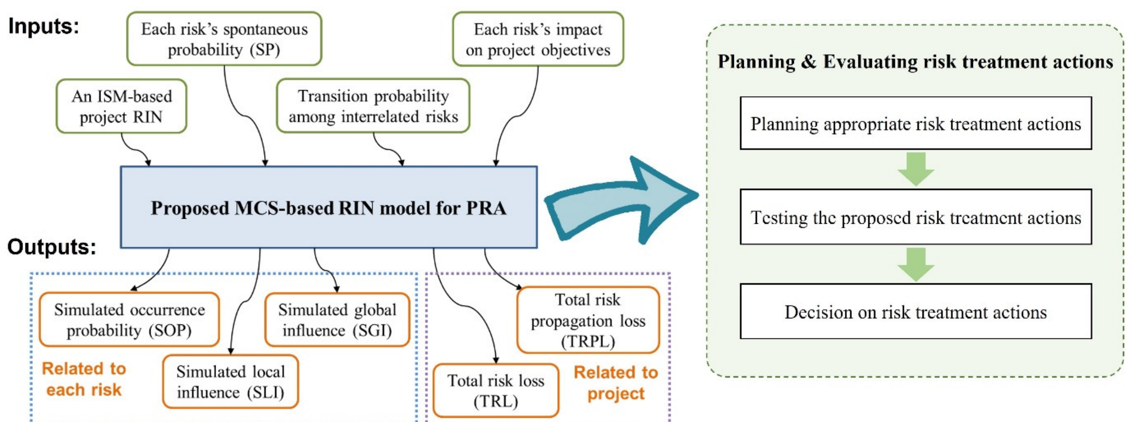

Fig. 6. The inputs and outputs of the proposed MCS-based RIN model for project risk assessment (PRA).

4. Results of Case Studies

4.1. Risk assessment results using FBBN-based risk assessment model

An international construction project in Turkey, i.e., the Ankara-Istanbul high-speed railway project, was used to demonstrate and verify the application of the proposed FBBN-based risk assessment model. This project was commenced in 2008 by a consortium of four companies (two from China and two local) through the Engineering, Procurement and Construction agreement. It was into operation in 2014. The total length of the high-speed railway is around 158 kilometers. The project scope mainly insists of railway beds and tracks, bridges, tunnels, electrification and communication infrastructure. Based on a thorough literature review, a generic network structure of potential project risks from the perspective of contractors was preliminarily built. Then, seven domain experts were invited to take part in separately organized exploratory interviews and gave their opinions on the cause-effect relationships among the existing project risks of the generic network structure, which led to the addition of several other project risks and risk interdependencies. A BBN risk structure of the project was therefore developed, involving a total of 91 project risks and 111 risk interdependencies. In addition, a questionnaire survey for the collection of project risk data (i.e., conditional probability tables of potential risks for occurrence probability assessment, and the magnitudes of risk impacts for impact assessment) was conducted. Seven distributed questionnaires were all retrieved from the experts and then analyzed as the input data for risk assessment using the proposed FBBN-based method (as explained in Section 3.3.1).

The risk degrees of potential project risks considering risk interdependencies were assessed, and critical risks were therefore determined. According to a six-level referential risk matrix, the project risks were categorized into four risk levels (Categories 2–5) within corresponding sub-ranges of risk ratings from the FBBN method, and the results are shown in Table 2. Category 5 represents the highest risk level while Category 0 is the lowest risk level.

Table 2. Risk categorization for the Ankara-Istanbul high-speed railway (Guan, Liu, et al., 2020).

Risk level	RFs	
	Causal inference	Diagnostic inference
Category 5 (Risk rating: 0.70929 – 0.96028)	R_{34}, R_{42}	R_{34}, R_{42}; I_3, L
Category 4 (Risk rating: 0.54975 – 0.70928)	R_{41}, R_7, R_2, R_{11}, R_{23}, R_6, R_{33}, R_{13}, R_{20}, R_{45}, R_{25}, R_{22}, R_{54}, R_{16}; I_{26}, I_2, I_{24}, I_8, I_{25}, I_5, I_4, I_{30}, I_{28}, I_{10}, I_{16}, I_{14}, I_7, I_1, I_{12}, I_{35}, I_{11}, I_9, I_{22}, I_{29}, I_3, L	R_{41}, R_7, R_2, R_{11}, R_{23}, R_6, R_{33}, R_{13}, R_{20}, R_{45}, R_{25}, R_{22}, R_{54}, R_{16}; I_{26}, I_{24}, I_2, I_{25}, I_8, I_5, I_4, I_{30}, I_{28}, I_{10}, I_{16}, I_7, I_{14}, I_{12}, I_1, I_{11}, I_9, I_{35}, I_{22}, I_{29}
Category 3 (Risk rating: 0.46600 – 0.54974)	R_{53}, R_9, R_{39}, R_{35}, R_4, R_{36}, R_{19}, R_{21}, R_{52}, R_5, R_{15}, R_{30}, R_{28}, R_{12}, R_{43}, R_{55}, R_{26}, R_{51}, R_{17}, R_{14}, R_{27}, R_{38}, R_{18}, R_{37}, R_3; I_{19}, I_{27}, I_{32}, I_{13}, I_{15}, I_{34}, I_{18}, I_{21}, I_{17}, I_{23}, I_{31}, I_{33}, I_6, I_{20}	R_{53}, R_9, R_{39}, R_{35}, R_4, R_{36}, R_{19}, R_{21}, R_{52}, R_5, R_{15}, R_{30}, R_{28}, R_{12}, R_{43}, R_{55}, R_{26}, R_{51}, R_{17}, R_{14}, R_{27}, R_{38}, R_{18}, R_{37}, R_3; I_{19}, I_{27}, I_{32}, I_{13}, I_{15}, I_{34}, I_{18}, I_{21}, I_{17}, I_{23}, I_{31}, I_{33}, I_{20}, I_6
Category 2 (Risk rating: 0.42399 – 0.46599)	R_{48}, R_{31}, R_{10}, R_{47}, R_8, R_1, R_{40}, R_{44}, R_{50}, R_{29}, R_{24}, R_{46}, R_{49}, R_{32}	R_{48}, R_{31}, R_{10}, R_{47}, R_8, R_1, R_{40}, R_{44}, R_{50}, R_{29}, R_{24}, R_{46}, R_{49}, R_{32}
Category 1 (Risk rating: 0.41708 – 0.42398)	Not identified	Not identified
Category 0 (Risk rating: 0.00000 – 0.41707)	Not identified	Not identified

The project risk categorization results in Table 2 show that from both causal inference and diagnostic inference, "different construction standards and measurement system (R_{42})" and "variations in design (R_{34})" are the top-two critical root risks, and "project implementation risk (I_3)" is the most critical intermediate risk of the project. The overall project risk, i.e., the leaf node "ICP failure (L)", is located in the risk level of Category 4 after the causal inference, denoting that the project risk level is relatively high. The project risk manager should pay more attention to the risks located in Category 5 and Category 4 and formulate risk control and mitigation plans at the commencement of the project.

By comparing the results calculated using the proposed FBBN-based risk assessment model with the real risk situations of the investigated project, many identified risks appeared during the implementation of the project and mostly complied with the obtained critical risks. For example, variation in design was one of the most serious problems due to the project owner's multiple requirements and inaccurate geological prospecting documents. In addition, the project contractors had a higher pressure to master the required standards and specifications of the implementation process of the project. Furthermore, the contract risk, in terms of unclear contract clauses and excessive contract variations, caused difficulties in coordination among project participants. Language barrier and information asymmetry also raised challenges to achieve the project objectives. Given the above analyses, the proposed FBBN-based risk assessment model has manifested its effectiveness to be applied in practical projects.

4.2. Risk assessment results using ISM-MICMAC analysis-based risk assessment model

Using the proposed ISM-MICMAC analysis-based risk assessment model, the general green building (GB) project risks were investigated and assessed. Firstly, a systematic literature review was conducted for differentiating the GB project constraints from the GB project risks, in which 16 constraint factors (C) and 22 risk factors (R) throughout a GB project life cycle were identified. Then, 11 GB project objectives (O) were selected based on related existing researches. In this work, four types of relationships among constraint factors, risk factors and objectives in GB projects were considered, as illustrated in Fig. 7. These contextual relationships were determined based on the relevant literature and domain knowledge of the authors. Therefore, based on the steps of the ISM method to present risk interdependencies (mentioned previously in Section 3.2), a hierarchical ISM-based RIN of GB projects was developed. Further, the importance of constraints and risk factors associated with GB project objectives was calculated based on Eq. (1) and Eq. (2). Table 3 shows the sample results of the importance of identified critical GB project constraints and risks which can highly affect the GB project objectives. In addition to the determination of critical factors (i.e., constraints and risks), the GB project objectives which are highly affected by risks and constraints can also be identified. For example, "O2 Completed on time", "O8 Anticipated return on investment & payback period", and "O1 Completed within budget" are easily to be affected by all the GB project risks and constraints. GB Project risk managers should constantly monitor the risks especially related to these three project objectives and try to mitigate their negative effects.

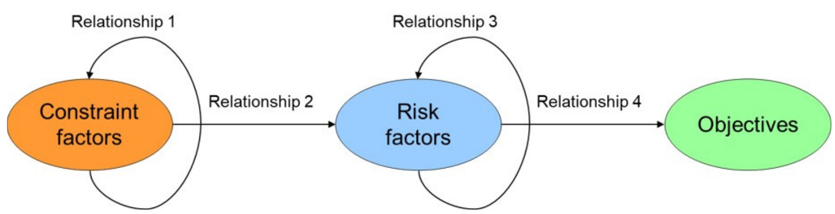

Fig. 7. The investigated relationships among GB project constraints, risks and objectives (Guan, Abbasi, et al., 2020).

Table 3. The importance of critical project risks and constraints associated with GB project objectives (Guan, Abbasi, et al., 2020).

	Top-ten critical GB project risks and constraints										Total influence
GB project objectives	C7	C4	C13	C6	C12	R1	C16	R2	C9	C14	
O1 Completed within budget	1.71	1.69	1.26	0.90	0.54	0.46	0.46	0.31	0.28	0.28	11.43
O2 Completed on time	2.92	2.86	2.15	1.51	0.90	0.79	0.55	0.52	0.28	0.47	17.26
O3 Comfort & artistry	0.74	0.72	0.56	0.41	0.27	0.25	0.16	0.18	0.11	0.13	4.33
O4 Long-term performance	0.39	0.39	0.30	0.23	0.14	0.15	0.09	0.11	0.04	0.06	2.26
O5 Safety in construction	1.07	1.07	0.78	0.58	0.32	0.26	0.18	0.18	0.25	0.15	7.10
O6 Safety in operation & maintenance	1.02	1.02	0.75	0.55	0.31	0.26	0.18	0.18	0.21	0.15	6.56
O7 Green certification	0.37	0.36	1.02	0.75	0.45	0.36	0.25	0.25	0.28	0.22	8.58

O8 Anticipated return on investment & payback period	2.50	2.49	1.84	1.28	0.78	0.67	0.49	0.45	0.28	0.44	15.96
O9 Customer satisfaction	0.93	0.93	0.67	0.50	0.26	0.20	0.15	0.13	0.21	0.15	5.96
O10 Promotion of brand image	0.98	0.98	0.71	0.53	0.28	0.20	0.15	0.13	0.25	0.15	6.42
O11 Promotion of new technologies & materials	0.93	0.93	0.67	0.50	0.26	0.20	0.15	0.13	0.21	0.15	5.96
GB project success (O1–O11)	14.54	14.42	10.71	7.74	4.49	3.82	2.67	2.58	2.38	2.34	-
No. of influenced objectives	11	11	11	11	11	11	11	11	11	11	-

In addition, the MICMAC analysis was further used to analyze the drive and dependence power of each element of the GB project constraints, risks, and objectives. A drive-dependence diagram was then constructed in Fig. 8, and all the elements were classified into three groups. In this work, drive power is more important than dependence power. Thus, in the independent cluster (Ⅳ), "R1 Unclear requirements of a project implementation", "R2 Ambiguity in contracts", and "R7 Design errors" are the top-three critical GB project risks from the overall network perspective, which should be controlled early to decrease the occurrence probability of the risks that they will influence; while "C7 Inadequate experienced designers/contractors/suppliers for GB projects", "C4 Limited GB benchmarks & shared information", and "C13 Inadequate communication & cooperation among project stakeholders" are the top-three critical GB project constraints which should also be paid more attention to by project risk managers. In contrast, "R3 Inaccurate estimate of project ROI (return on investment) & payback period", "R20 Not getting materials/equipment on approved period/phase", and "R22 Injuries and accidents" are the risks located in the dependent cluster (Ⅱ), which means they have weak drive power but strong dependence power. For such risks, they should also be controlled in a timely manner to reduce the influence of dependent risks on certain objectives through risk paths. In addition, if risk/constraint factors have the same drive power (e.g., "R18 Equipment breakdown" and "R21 Unlawful disposal of waste"), the factor with the higher dependence power should be addressed earlier. From the above analysis results, the critical GB project risks and constraints with higher drive power also have stronger influence on project objectives, which tend to be located in the lower levels of the ISM-based GB project RIN.

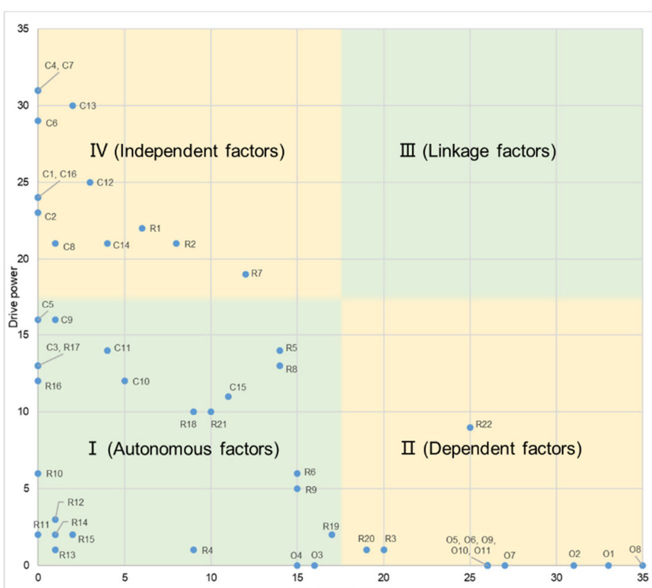

Fig. 8. A MICMAC diagram for GB project constraints, risks and objectives (Guan, Abbasi, et al., 2020).

4.3. Risk assessment results using SNA-based risk assessment model

The proposed SNA-based risk assessment model model was applied to a specific project to verify its feasibility and applicability in project risk assessment. The sample project (from Wang et al. (2020)) concerns employing artificial intelligence technology for predicting medical items, which belongs to a program related to logistics and healthcare. There are 16 risks and 26 direct risk interdependencies of the sample project originally identified by Wang et al. (2020). In addition, the evaluated values of risk spontaneous probability (SP) and risk impact on the project objectives (denoted by cost) are also provided. These risk-related data were initially collected by a primary member of the project who was in charge of the project plan, implementation, and risk management.

Based on these risk data, we first developed a two-level hierarchical ISM-based RIN of the project using the ISM method. Several risk loops can be identified in the project RIN due to complex risk interdependencies. Then, the project risk assessment process was performed by calculating the values of six proposed risk indicators, respectively. Critical project risks which can highly affect the project objectives were therefore determined based on the local and global risk measures from the network perspective. The obtained results are presented in Table 4. Locally, “R08 Building and training the model repeatedly”, “R06 Poor selection of the medical items”, and “R05 Poor analysis of the factors regarding medical items” are the top-three risks which have the highest values of the out-degree centrality; and “R03 Unclear milestone and technical route”, “R16 Too much rework for the team in charge of the modeling”, and “R09 Interfaces problem among the software platforms of different terms” are the the top-three risks which have the highest values of the risk local significance. Globally, “R13 Tense partnerships among the teams”, “R02 Communication problems between the teams”, and “R03” are ranked highest in the betweenness centrality; “R06”, R05”, and “R03” are the top-three risks which have the highest values of out-closeness centrality; “R08”, R06”, and “R05” are highly ranked in the hybrid structural centrality (the same with the top-three risks evaluated by the out-degree centrality); and “R03”, “R04 Lack of professional medical knowledge”, and “R06” are ranked highest in the risk global significance. These identified risks from six different aspects of risk positions in a network are essential to the project, specific risk mitigation measures need to be formulated in advance and the project risk manager should pay more attention to these critical risks during the project implementation.

Table 4. Project risk assessment results from the SNA-based risk assessment model.

Node No.	SNA-based indicators				P-I risk model-based indicators	
	Out-degree centrality	Betweenness centrality	Out-closeness centrality	Hybrid structural centrality ($*10^{-2}$)	Risk local significance ($*10^{-2}$)	Risk global significance ($*10^{-2}$)
R01	0.027	0	0.098	0.024	0.267	1.505
R02	0.053	0.552	0.178	0.107	0.533	1.348
R03	0.067	0.471	0.254	0.194	1.167	3.238
R04	0.047	0	0.227	0.077	0.400	2.696
R05	0.087	0.410	0.260	0.436	0.100	1.829
R06	0.113	0.467	0.359	0.312	0.480	2.635
R07	0.087	0.048	0.146	0.146	0.267	1.383
R08	0.140	0.190	0.181	0.324	0.600	1.198
R09	0.040	0	0.107	0.076	0.800	1.653
R10	0.053	0.224	0.135	0.257	0.187	0.694
R11	0.053	0.267	0.105	0.237	0.533	0.341
R12	0.040	0	0.079	0.030	0.133	0.133

R13	0.033	0.557	0.067	0.125	0.400	0.490
R14	0.027	0	0.047	0.112	0.267	0.228
R15	0.020	0	0.094	0.034	0.427	0.745
R16	0.027	0.162	0.053	0.137	0.800	0.349

4.4. Risk assessment and treatment results using MCS-based RIN model

The project case used here to illustrate the proposed MCS-based RIN model is the same with the sample project used in Section 4.3. Thus, the project RIN developed based on the ISM method is also the same. By inputting the original project risk-related data (i.e., each risk's spontaneous probability (SP), transition probability (TP) among interrelated risks, and each risk's impact on project objectives) into the proposed MCS-based RIN model in project risk assessment, evaluated values of the proposed risk indicators (i.e., simulated occurrence probability (SOP), simulated local influence (SLI), and simulated global influence (SGI)) were calculated. Table 5 shows the obtained project risk prioritization results, compared with those evaluated by spontaneous probability (SP) and risk criticality (RC) from the classical *P–I* risk model.

Overall, the project risk prioritization results have changed after using the proposed MCS-based RIN model. In respect to risk occurrence probability, "R14 Too many tests on the model", R05 and R16 have lower values of SP, while in terms of SOP, they are top ranked with the highest values, indicating that although this kind of risks are unlikely to occur spontaneously, they are highly affected by others due to direct and indirect cause-effect relationships. Some risks' occurrence probabilities may be evaluated as similar (e.g., R03 and "R15 Project scope spread") using the classical *P–I* risk model (SP_i) and the proposed simulation model (SOP_i), however, they are still underestimated to some extent. Except for the source risk "R01 Language problems and cultural conflicts", all the other risks have increased occurrence probabilities calculated by the proposed method, demonstrating that risk interdependencies can increase risk occurrence probability.

From the aspect of risk influence, the SLI of each risk (excluding R01) is higher than its evaluated RC from the classical *P–I* risk model due to the different values of risk occurrence probability, indicating that the risk propagation across the RIN has amplified the risk influence on project objectives. The SGI of a risk reflects to what extent the occurrence of this risk can increase other risks' influence on project objectives. Some risks have lower SLI, but their SGI may be higher, such as R05 and "R07 Poor selection of the existing database".

Table 5. Risk prioritization by different indicators.

Ranking	From the proposed MCS-based RIN model						From the classical P–I risk model			
	SOP_i		SLI_i (\$100)		SGI_i (\$100)		SP_i		RC_i (\$100)	
	Risk No.	Value	Risk No.	Value	Risk No.	Value	Risk No.	Value	Risk No.	Value
1	R14	0.895	R11	2.950	R05	18.574	R01	0.8	R03	1.75
2	R05	0.853	R16	2.516	R14	18.041	R03	0.7	R16	1.2
3	R16	0.839	R08	2.345	R07	17.256	R04	0.6	R09	1.2
4	R03	0.830	R03	2.074	R13	17.185	R09	0.6	R08	0.9
5	R13	0.825	R14	1.791	R01	17.095	R02	0.4	R01	0.8
6	R07	0.811	R02	1.321	R03	16.322	R06	0.4	R02	0.8
7	R01	0.799	R06	1.250	R16	16.243	R07	0.4	R11	0.8
8	R08	0.782	R09	1.246	R10	15.711	R13	0.4	R06	0.72
9	R11	0.737	R13	1.238	R08	15.546	R15	0.4	R15	0.64
10	R10	0.736	R10	1.031	R06	14.597	R16	0.4	R13	0.6
11	R06	0.694	R15	0.879	R11	14.049	R05	0.3	R04	0.6
12	R02	0.661	R07	0.811	R04	13.676	R08	0.3	R07	0.4

13	R04	0.651	R01	0.799	R02	13.442	R10	0.2	R14	0.4
14	R09	0.623	R12	0.746	R09	12.730	R11	0.2	R10	0.28
15	R15	0.549	R04	0.651	R15	11.423	R14	0.2	R12	0.2
16	R12	0.373	R05	0.427	R12	8.131	R12	0.1	R05	0.15

Moreover, the results of project level risk assessment indicators, i.e., the project total risk loss (TRL) and project total risk propagation loss (TRPL), were further calculated. Specifically, the obtained probability distribution of the project TRL was illustrated in Fig. 9. From the curve of cumulative distribution function (CDF), the project TRL in the interval value of $1500–$2820 accounts for around 79% of all the possible project risk scenarios, denoting that the project TRL caused by the project risks is highly possible to distribute in this range. Additionally, the expected (average) value of the project TRL was evaluated as around $2207 (locally), while the expected value of the project TRPL was calculated as $24002 (globally). These results can provide project risk managers with a holistic risk perception from the level of an overall project at its earliest stage.

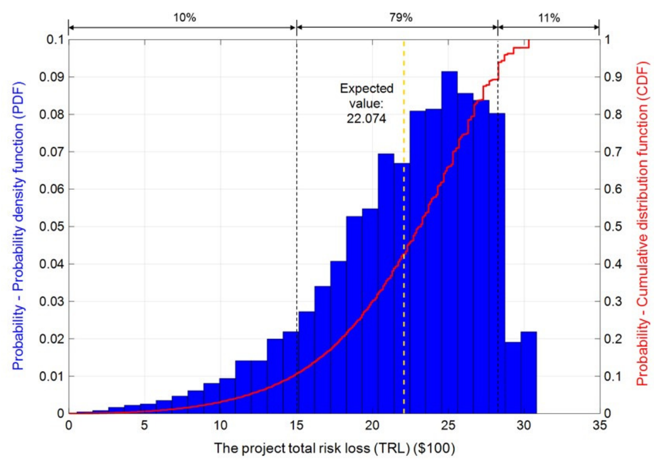

Fig. 9. Probability distribution of the project total risk loss (Guan et al., 2021).

Base on the above project risk assessment results, a series of risk treatment actions can be formulated, and their performance can be further evaluated using proposed five risk indicators. Fig. 10 shows the comparison of the values of the indicators related to each risk (i.e., SOP, SLI, and SGI) after four different risk treatment actions. The lower the line in the figures, the better the performance of risk treatment action. Therefore, the Action 4 outperforms the other three risk treatment actions. From the level of overall project, the performance of different risk treatment actions were evaluated by the reduced value of project TRL and the reduced value of project TRPL. As shown in Table 6, the Action 4 can reduce the highest values of both project TRL and TRPL among these four actions, so it also works the best in the project risk treatment.

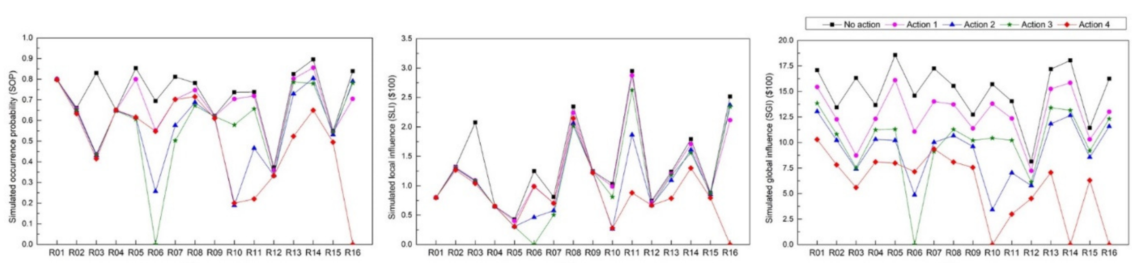

Fig. 10. Comparison of (a) the SOP, (b) the SLI, and (c) the SGI of risks after different project risk treatment actions (Guan et al., 2021).

Table 6. The performance of different risk treatment actions from the project level.

Performance	Risk treatment actions			
	Action 1 (Classical *P–I* risk model)	Action 2 (Wang et al., 2019)	Action 3 (Wang et al., 2020)	Action 4 (Proposed model)
Reduced value of project TRL	$217	$489	$412	$826
Reduced value of project TRPL	$3711	$9274	$7978	$14717

5. Discussion

Throughout this research, investigation of the influence of project risk interdependencies is based on both analytical and simulation methods, which improves the accuracy of project risk assessment results. A series of network-based risk indicators are proposed to quantify risk influence on project objectives and further to facilitate the formulation of effective risk treatment actions. Fig. 11 illustrates how multiple characteristics of project risks are analyzed by four proposed project risk assessment (PRA) models: the FBBN-based PRA model, the ISM-MICMAC analysis-based PRA model, the SNA-based PRA model, and the MCS-based RIN model for PRA. All these models have considered risk interdependencies during the project risk assessment. Further, the FBBN-based PRA model also uses the concepts of the classical *P–I* risk model; the ISM-MICMAC analysis-based PRA model additionally analyzes risk position in a network; the SNA-based PRA model also considers the classical *P–I* risk model, risk position, and risk loops in its analysis; and the MCS-based RIN model for PRA incorporates the classical *P–I* risk model, risk stochastic behavior, and risk loops as well. Based on the analysis of case studies, the proposed four project risk assessment models can provide more reliable risk assessment results and reflect more accurate project risk conditions than the methods only based on the classical *P–I* risk model.

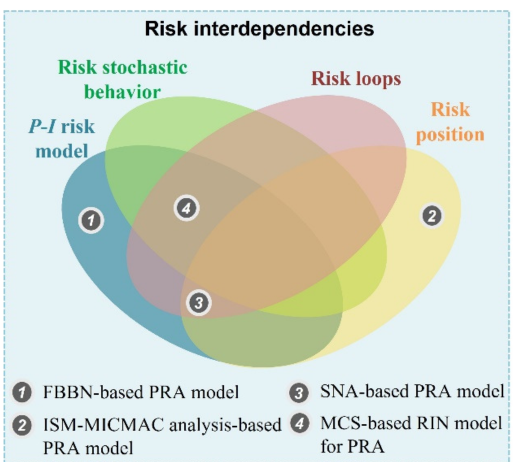

Fig. 11. The related project risk characteristics analyzed by proposed risk assessment (PRA) models.

This study makes some academic contributions to project risk management and in particular, to risk assessment. Firstly, effective analytical methods and simulation-based methods are investigated and designed to develop project risk assessment models considering the effects of risk interdependencies. Secondly, apart from involving the identification of cause-effect relationships among risks in the proposed decision-support system for project risk assessment, more aspects of the RIN complexity are taken into account, including the stochastic behavior of risk occurrence, risk loops, and risk position within a project RIN. Thirdly, proposed interdependency-based risk indicators can help planning of more appropriate project risk treatment actions.

Additionally, there are a number of managerial implications of our work, which are listed as follows:

(1) Project risk management practitioners can have more comprehensive perception of project risk through considering complex risk interdependencies in project risk assessment from a "network" perspective.

(2) The proposed risk assessment models try to mitigate the gap between theory and practice of the project risk management, so the basic concepts of the classical *P–I* risk model (i.e., risk's probability and impact), which are widely used by practitioners in managing project risks, are considered. Therefore, all related project risk management practitioners can engage their knowledge and experience in the risk assessment process. More importantly, the proposed risk assessment processes are easy to be conducted in practice because all complicated calculations are solved by program codes and/or software and practitioners only need to collect the project risk-related data as the inputs for project risk assessment.

(3) The proposed project risk assessment models have high universality and flexibility, which can be applied to projects in different fields (e.g., software, civil, or business), and even to large and complex projects. In particular, the proposed decision-support system for project risk assessment developed using the MCS-based RIN model outperforms many existing analytical project risk assessment methods which mainly rely on complicated calculations.

(4) The proposed project risk assessment models can be used at the commencement stage of a project when there is high uncertainty about project risks, and the project risk assessment results can update periodically to reflect risk conditions of the project over time when the new risk information is available.

6. Conclusions

This study has explored different project risk assessment models in the context of risk interdependencies using both analytical and simulation-based methods. The FT-based BBN and ISM methods were proposed to develop a project RIN based on identified project risks and their cause-effect relationships. The proposed FBBN-based risk assessment model, ISM-MICMAC analysis-based risk assessment model, and SNA-based risk assessment model are analytical methods-based models. In addition, the MCS-based RIN model is simulation-based model for project risk assessment. The corresponding risk prioritization results can support project managers in formulating appropriate risk treatment actions. The related results of different case studies highlight the importance of considering risk interdependencies in project risk assessment and verify the performance of the proposed models in practical use.

Compared with the proposed analytical methods-based risk assessment models, the proposed risk simulation model can address stochastic behavior of project risks as well as deal with risk loops in the complex project RIN. Through modeling the propagation behavior of risks in an RIN, the model enables project managers to gain innovative insights into interdependencies among project risks and possible risk influence on project objectives from a network perspective. However, the obtained risk assessment results from the simulation-based model do not consider the risk position in a project RIN. In order to obtain comprehensive risk assessment results, there is a need to integrate analytical methods-based and simulation-based risk assessment models.

There are a number of potential extensions of this research in the future, particularly: (1) the MCS-based RIN model for project risk assessment can be improved by integrating with SNA method to incorporate more analysis of risk position in the RIN; (2) as projects are time-related dynamic systems, project risks and risk interdependencies may vary with project phases, so the dynamic behavior of project RIN throughout a project lifecycle will be further investigated under current project risk assessment framework; (3) additional parameters, such as project budget and cost of risk treatment actions, will be involved to further optimize project risk treatment actions; and (4) an integrated practical tool for project risk assessment can be developed to incorporate the proposed models with the aim of further smoothing and reducing the workload of project risk management practitioners.

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