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A FRAMEWORK OF PROJECT RISK SIMULATION WITH EVENT KNOWLEDGE GRAPH

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ABSTRACT

Risk simulation is crucial for effective project management, yet conventional methods often fail to capture the complex interdependencies and interactions among risk events. This paper proposes a novel approach to project risk simulation by integrating event knowledge graphs, fuzzy logic techniques, and game theory principles. Event knowledge graphs provide a structured representation of project events and their relationships thereby facilitating the simulation of risk events and pathways; fuzzy logic enables the assessment of uncertain events; and game theory aids in identifying high-risk events and elucidating risk pathways. A methodology is outlined encompassing the construction of event repositories, establishment of event knowledge graphs, and simulation of project risks. Following, a case study of wind farm projects demonstrates the practical application of the proposed approach, highlighting its effectiveness in simulating and analyzing project risks.

1 INTRODUCTION

In the realm of project management, a project manager contends with a myriad of occurrences daily encompassing tasks, jobs, work, activities, and requisite actions. Particularly for a novice project manager or when embarking on a new project, navigating uncertain events can prove to be formidable. Routine operation endeavors inherently harbor significant uncertainties and trials, which may arise and trigger risks by causal inference such as deviations, issues, problems, errors, mistakes, changes, modifications, variations, urgencies, emergencies, incidents, and accidents (Figure 1). These uncertain events require a detailed explanation using risk simulation. Thus, it is important to consider the following question: is there a method by which a project manager can ascertain comprehensive awareness of all potential events and interrelated logical dependencies, along with the ability to simulate such risk events and anticipate monetary loss?

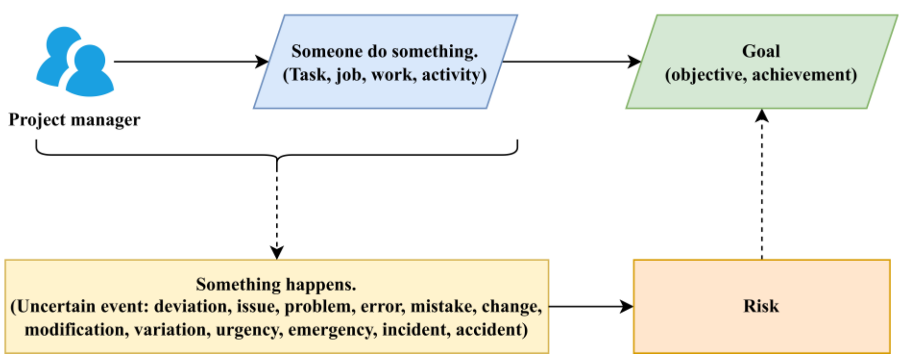

Figure 1: Events in project management.

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To answer this question, we can begin with risk simulation itself. Indeed, risk simulation is pivotal in bolstering decision-making within project management and has garnered significant attention in research. Conventional approaches to risk simulation—predominantly reliant on Monte Carlo simulation—typically assume a Gaussian distribution for risk probabilities, resulting in excessively wide probability distributions (Williams 2004). Enhanced methodologies involve adapting Gaussian distributions to more complex skewed distributions (Rezaie et al. 2007; Bodea and Purnus 2012) or employing fuzzy functions (Sadeghi, Fayek and Pedrycz 2010) such as triangular fuzzy distributions. However, Monte Carlo simulations often overlook interdependencies and interactions among risk factors (Rezaie et al. 2007). Consequently, a subsequent improvement entails constructing network models (Fang and Marle 2012; Guan, Abbasi and Ryan 2021), an innovative concept to refine probability estimation. Despite these advancements, risk simulation techniques integrating statistical methods (Senthil and Muthukannan 2021) and machine learning (Gondia et al. 2020) are continually evolving, and progress in this area has been hindered by the predominance of project data in textual form, which impedes direct utilization for statistical analysis and data mining.

Interestingly enough, the integration of network models appears to offer insights into knowledge graphs, while the utilization of natural language processing (NLP) suggests the potential to employ knowledge graphs to identify risk events. Theoretically, all actions within construction projects can be seen as events, allowing for the creation of an event knowledge graph to model potential risks. Generally, an event knowledge graph is a type of knowledge graph organized by the logic of events (Guan et al. 2022). It often includes causal and temporal relationships between events (Liu et al. 2021; Knez and Žitnik 2023). It can be inferred that such an event knowledge graph for a construction project initially encompasses tasks and sequential jobs, work, and activities. It is also worth noting that risk events may disturb normal operation and enlarge the event knowledge graph.

Why is studying event knowledge graphs crucial for construction projects? Although seasoned project managers often encounter similar events across projects and can effectively leverage their past experiences during new projects, new or inexperienced project managers may find this challenging as they do not have the same sufficient experiential support. Indeed, effectively utilizing past experiences for new projects becomes paramount in this scenario, which is where knowledge graphs come into play. The challenge with this concept centers on the extraction of events and the establishment of logical connections between them as those events mentioned above—task, job, work, activity, uncertain event—are typically documented as text data with nuanced meanings. Although there have been numerous efforts (Hogenboom et al. 2016; Song 2021), effectively extracting events and discovering knowledge continues to pose a major challenge. Nonetheless, the event knowledge graph itself holds practical applications, such as in supply chain management (Deng et al. 2023).

There have been recent and substantial advancements made in event-driven risk simulation, as well (Mohamed, Seresht and AbouRizk 2023), suggesting potential future directions that involve integrating it with knowledge graphs and fuzzy evaluations. Mature software for fuzzy risk simulation has already been developed. For example, the Fuzzy Risk Analyzer (FRA) (Fateminia et al. 2020) has recently been developed and has been innovated by researchers at the University of Alberta. Unfortunately, current risk simulations often suffer from a lack of interpretability in practical applications. Even when a project manager acknowledges the potential existence of a risk, the logical sequence leading to that risk is frequently unclear. This gap in knowledge and application opens up an opportunity to identify risk paths through event knowledge graphs and elucidate them using algorithms capable of explainable artificial intelligence (XAI). Therefore, the purpose of this study is to address some of the following related issues:

1. How can we effectively harness previous project experience through event knowledge graphs?
2. How can event knowledge graphs be employed for simulating and predicting project risks?
3. How can we interpret the simulated risk reasonably?

In addition to event knowledge graphs and fuzzy logic techniques, game theory might also contribute to a potential solution in this context. As noted earlier, conventional risk simulations often overlook interdependence among events (Rezaie et al. 2007). In game theory, risk events can be viewed as participants in a cooperative game, collectively contributing to the overall risk. By assessing the marginal risk contribution of each event, a logical and justifiable explanation can be derived. The application of the Shapley value can serve as a useful reference in this regard (Narbaev, Hazır and Agi 2022). Therefore, the proposed solution in this study entails constructing an event knowledge graph by extracting events from similar past projects, followed by the application of fuzzy logic methods to simulate event risks. Afterward, the Shapley value from game theory is utilized to expound risk pathways and pinpoint high-risk events.

The remainder of this paper is organized as follows: Section 2 describes the methodology in detail; Section 3 is a case study of wind farm projects; Section 4 summarizes the discussion; and Section 5 offers remarkable conclusions.

2 METHODOLOGY

2.1 General Framework

The risk simulation framework proposed in this study is shown in Figure 2. It consists of three parts: constructing event repositories, establishing an event knowledge graph, and simulating the risk. In the subsections, 10 steps are introduced. It is noted that all data storage and calculations in this study were completed in Jupyter Notebook based on Python.

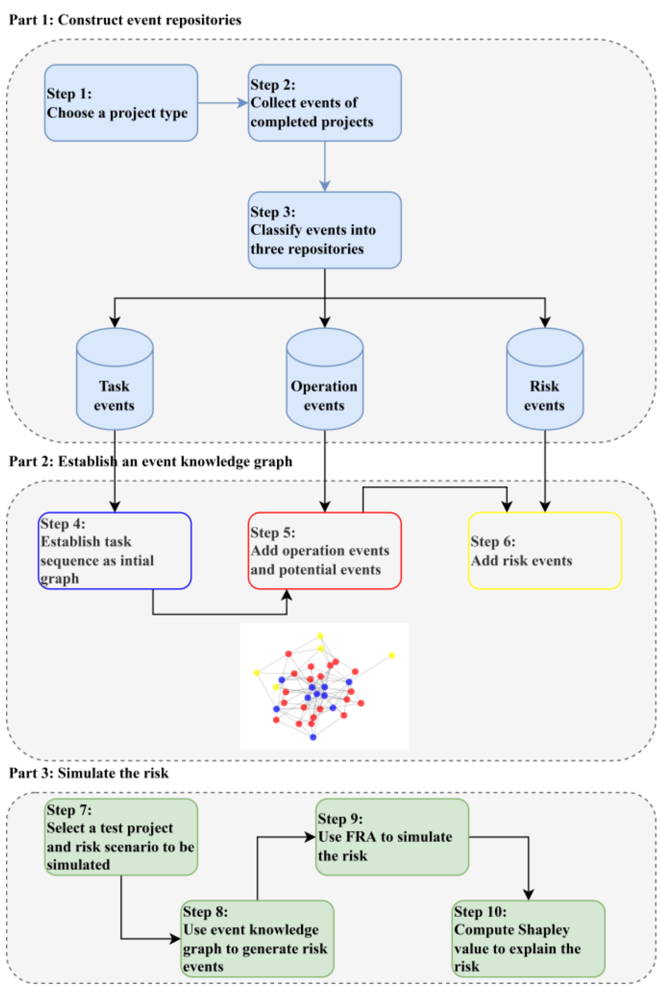

Figure 2: Framework of project risk simulation with an event knowledge graph.

2.2 Part 1: Construct Event Repositories

This part includes three steps to construct event repositories (Figure 3).

Step 1: Select a type of construction project.

Step 2: Collect all events of completed projects of the same type.

Step 3: Classify and generalize the events into three categories—construction tasks, operation events, and risk events—and establish three corresponding event repositories.

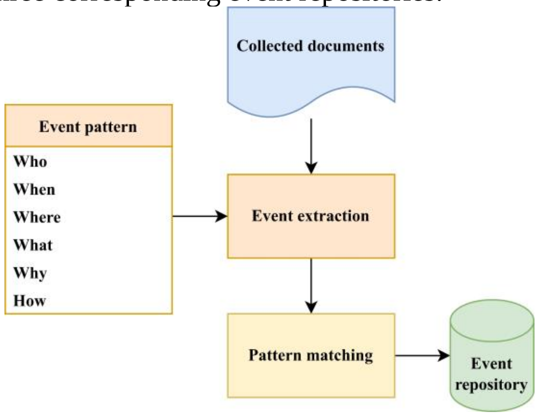

Figure 3: Process of constructing event repositories.

Here, the construction tasks include activities, jobs, and work to complete the construction project. The operation events consist of anything happening in the process including work progress, communications, environmental situations, change requests, and others. The risk events are deviations, issues, problems, errors, mistakes, modifications, changes, variations, urgencies, emergencies, incidents, accidents, and corrections. Each event is described in the pattern of "who, when, where, what, why, and how" as complete as possible.

2.3 Part 2: Establish an Event Knowledge Graph

This part includes three steps to establish an event knowledge graph.

Step 4: Draw a construction sequence diagram for construction tasks as the initial event knowledge graph (Figure 4).

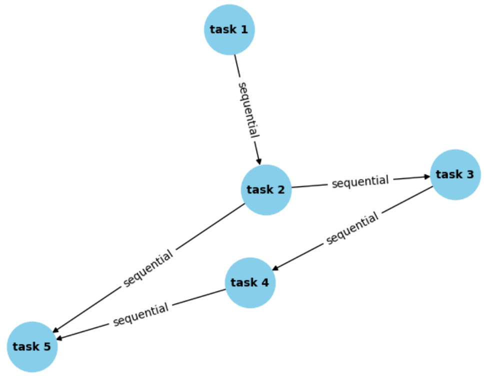

Figure 4: Example of construction project sequence.

Step 5: Add all operation events on construction tasks to build an event knowledge graph.

This step is based on the observation and inference from an object event. Generally, there may be casual, sequential, hierarchical, and simultaneous relationships between events (Figure 5). Therefore, one event can trigger at least four potential events in each type, and it grows geometrically in the following levels. Events may also correlate with each other at any level and in any relationship.

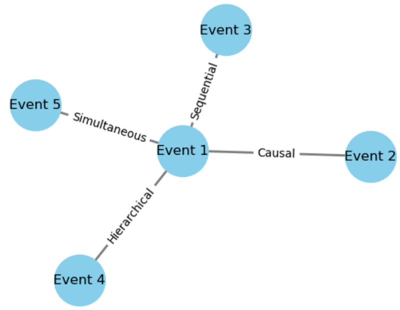

Figure 5: Relationships between events.

Step 6: Locate and identify potential risk events.

In event propagation, once it generates a risk event that is selected from the established risk event repository, corrections should be taken and the generating process could be terminated promptly. In Figure 6, the blue nodes are initial events (e.g., construction tasks), the red nodes are the generating of potential events including risk events, and the yellow nodes are risk correction measurements.

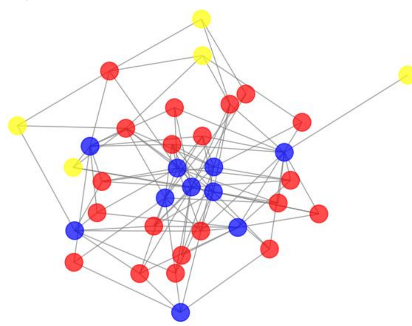

Figure 6: Example of an event knowledge graph.

2.4 Part 3: Simulate the Risk

This part is the application of the event knowledge graph for risk simulation.

Step 7: Select a test project and define the timepoint to simulate project risk with specific events and scenarios.

Step 8: Use the event knowledge graph to output all possible next-level events including risk events.

Step 9: Use FRA to simulate risk loss for all risk events.

This research employed the academic software Fuzzy Risk Analyzer (FRA) version 2.0.9 (Fateminia et al. 2020) for simulating project risks. FRA utilizes fuzzy logic to estimate the likelihood and impact of risk events. To conduct a thorough simulation, users are required to define the project and its tasks, identify relevant risk events, and specify fuzzy probability and severity descriptions. FRA is then capable of generating a comprehensive project risk report.

Step 10: Calculate the Shapley value and marginal risk loss of each risk event, and sort them; then explain various risks faced and risk response measures. This is a structural procedure to help achieve the goal and can be performed by following the steps outlined below.

1. Identify the players (risk events), and suppose n risk events.
2. Determine the cooperation value function (the risk loss by FRA).
3. Determine all possible cooperation sets: For n risk events, there are $2^n - 1$ non-empty cooperation sets.
4. Calculate the contribution margin for each cooperative set: Run FRA with the $2^n - 1$ sets and obtain the corresponding risk loss.
5. Calculate the Shapley value for each risk event using the formula for the Shapley value
$$\phi_i = \sum_{S \subseteq N\{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!}\big(v(S \cup i) - v(S)\big), \tag{1}$$
where ϕ_i represents the Shapley value of player i, N is the set of all players in the game, $v(S)$ represents the worth of coalition S, and $|\cdot|$ denotes the cardinality of a set.
6. Find the highest Shapely value and corresponding risk event.
7. Interpret risk event path.

3 CASE STUDY

3.1 Part 1: Construct Event Repositories

Step 1: Select a type of construction project.

We selected wind farm construction projects as the study object because they are highly repetitive, the main task (turbine assembly) is relatively unified, and the events encountered are highly similar and repetitive, which is conducive to the application of event knowledge graphs.

Step 2: Collect all events of completed projects of the same type.

We collected construction reports of 25 wind farm projects on the public Internet, totaling 218 documents which include construction plans, completion reports, handbooks, best practices, and others.

Step 3: Classify and generalize the events into three categories—construction tasks, operation events, and risk events—and establish three corresponding event repositories.

This study used text-mining technology to find all tasks and events. Specifically, we wrote programs in Python Jupyter Notebook to analyze the collected documents. The major steps are outlined below.

1. Use pdfminer.six to extract text;
2. Use spaCy for named entity recognition;
3. Define the event description method as "who, when, where, what, why, and how" to extract the event and description;
4. Manually correct the acquired events.

The construction tasks of tiers 1 and 2 are shown in Table 1.

Table 1: Example of construction task in wind farm project.

Tier 1	Tier 2
Pre-construction activities	Clearing
	Stripping and removal of topsoil
	Site preparation
Turbine foundation	Excavating
	Formwork construction
	Transport of concrete
…	…

Additionally, an example of operation events is shown in Table 2. Due to the data privacy of the wind farm projects, it is difficult to obtain and disclose real data. Therefore, we compiled a part of the operation events based on public papers and materials, and 100 operation events were collected and then categorized into objective, scope, deliverable, timeline, resource, budget, cost, stakeholder, quality, communication, and change request.

Table 2: Example of operation events.

Event	**Description**
Excavation Delay	Heavy rainfall causes a delay in excavation work for the foundation.
Material Shortage	Supplier fails to deliver rebar on time, causing a delay in concrete pouring.
Equipment Breakdown	Concrete mixer malfunctions, halting concrete pouring for half a day.
Change Order Request	The client requests a modification to the building layout.
Safety Incident	The worker sustains minor injuries due to a fall from scaffolding.
Payment Dispute	The subcontractor raised a dispute over payment for additional work.

The risk events in this study follow the previous research results from the University of Alberta (Fateminia et al. 2020) and are directly adopted. Examples of risk events are shown in Table 3.

Table 3: Example of risk events.

Risk event	**Event type**
Lack of experience and project management skills of the project team	Global
Poor coordination and communication among various parties	Global
Inadequate project organization structure	Global
Interdependencies with other projects	Local
Poor or incomplete definition of project scope	Local
Loss of productivity due to inadequate site facilities planning	Global

3.2 Part 2: Establish an Event Knowledge Graph

Step 4: Draw a construction sequence diagram for construction tasks as the initial event knowledge graph (Figure 7).

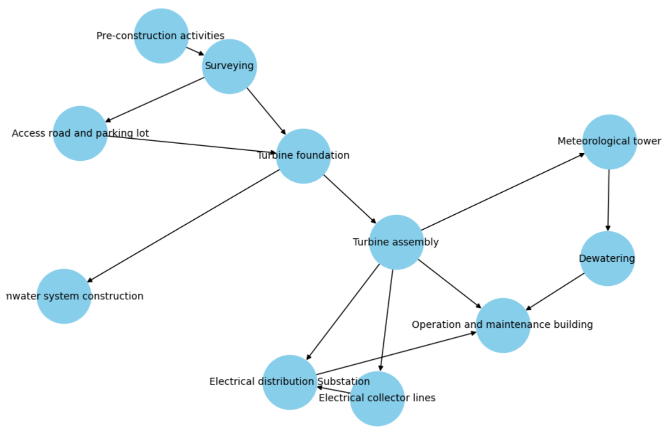

Figure 7: Example of construction project sequence.

Steps 5 and 6: Add all operation events on construction tasks to build an event knowledge graph; locate and identify potential risk events.

Based on the collected 100 operation events, we inferred potential events and risk events with the four types of relations—casual, sequential, hierarchical, and simultaneous—and then stopped the event generating once a risk event and its corrections were generated and there were no more than three levels of inference. Following, 309 head-tail relation sets were constructed. The established event knowledge graph is shown in Figure 8.

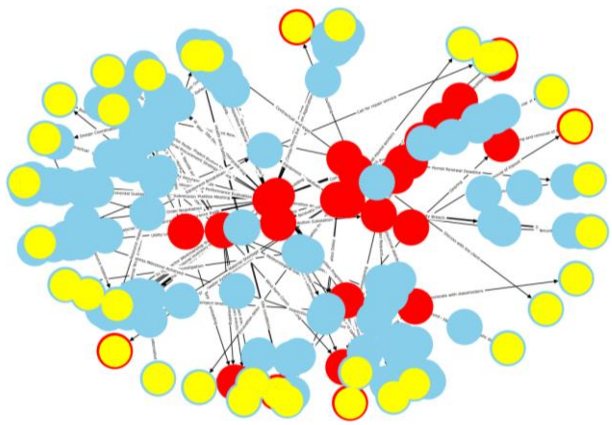

Figure 8: The established event knowledge graph.

3.3 Part 3: Simulate the Risk

Step 7: Select a test project and define the timepoint to simulate the project risk with specific events and scenarios.

We assumed one of the wind turbine assembly tasks in a wind farm construction project involves blade lifting work on a certain day. The blade lifting process is briefly shown in Figure 9, demonstrating the cooperation of two cranes. The wind speed on that day was 6-15m/s. The auxiliary crane failed to raise the blade in time, resulting in extrusion deformation and damage to the ground. Moreover, one worker was bruised.

Figure 9: The blade lifting process.

Step 8: Use the event knowledge graph to output all possible next-level events including the risk events.

According to the above scenario, we used keywords match to extract the events from the established event knowledge graph and construct a new sub-graph (Figure 10).

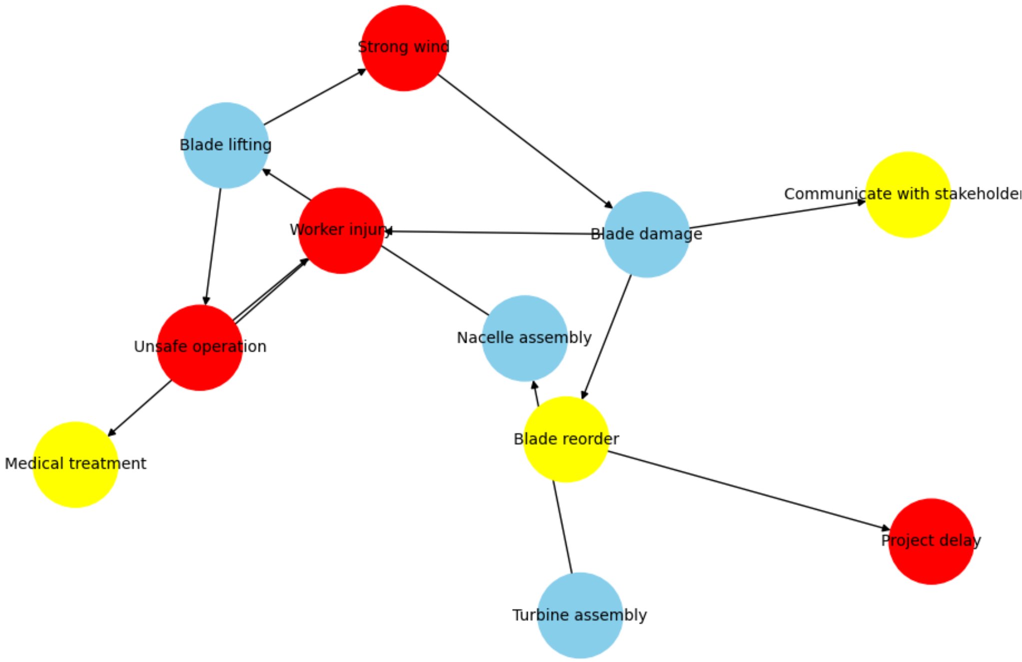

Figure 10: Sub-event graph for the selected scenario.

Steps 9 and 10: Use FRA to simulate the risk loss for all risk events; calculate the Shapley value and marginal risk loss of each risk event and sort them; then explain the various risks faced and risk response measures.

Four risk events were identified and imported to FRA to simulate the risk loss as the cooperation value function. Since four events would have 15 combinations, we ran FRA 15 times accordingly. The results of the simulation are shown in Table 4 and one screenshot of examples is shown in Figure 11. Subsequently, the Shapley value of each risk event could be computed (Figure 12).

Table 4: Risk loss.

Set	**Risk loss ($)**
{strong wind}	2,566.81
{unsafe operation}	2,861.27
{worker injury}	3,550.93
{project delay}	66,580.54
{strong wind, unsafe operation}	95,621.13
{strong wind, work injury}	95,872.64
{strong wind, project delay}	96,630.52
{unsafe operation, worker injury}	70,568.21
{unsafe operation, project delay}	76,582.67
{worker injury, project delay}	87,850.52
{strong wind, unsafe operation, worker injury}	110,684.56
{strong wind, unsafe operation, project delay}	110,567.34
{strong wind, worker injury, project delay}	111,058.92
{unsafe operation, worker injury, project delay}	98,126.82
{strong wind, unsafe operation, worker injury, project delay}	118,770.63

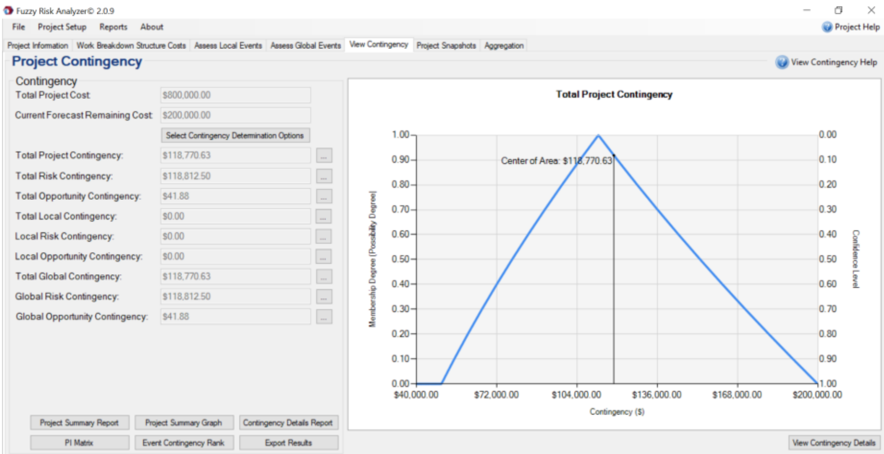

Figure 11: Example of risk simulation results by FRA.

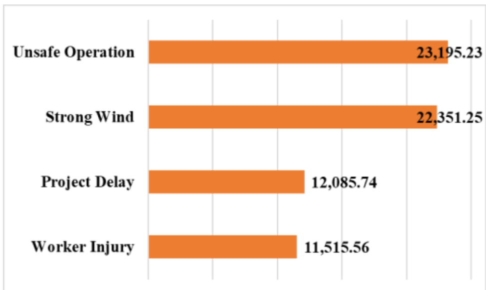

Figure 12: Shapley values.

Based on the Shapley value ranking, the primary factor contributing to risk losses presently could be identified as issues in crane cooperation, and a clear risk could be extracted (Figure 13). Short-term strong winds also significantly contributed to the situation. Overall, the lifting work process was not meticulously planned and rehearsed, and the team failed to promptly assess the increased construction difficulty brought on by worsening weather conditions.

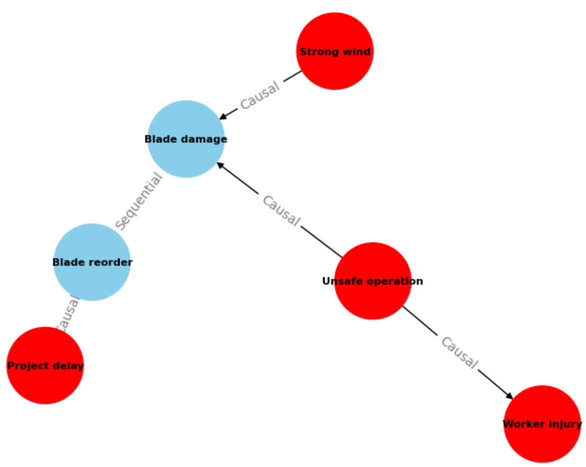

Figure 13: Risk path.

4 DISCUSSION

The results of the case study demonstrate the feasibility and effectiveness of the proposed approach in simulating project risks, and provide a detailed walkthrough of the proposed methodology, offering readers a comprehensive understanding of the entire process. While some may argue that there is little distinction between constructing an event knowledge graph in advance and detailing the event process retrospectively, the crucial aspect of this study lies in leveraging the event knowledge graph to minimize variations in risk responses among different project managers. This ensures that risk events are addressed rationally and professionally, regardless of individual managerial approaches.

Additionally, to address the need for verification and validation of our simulation results, potential methods could be implemented in future work. While direct validation of project risk simulations is challenging due to the complex and unpredictable nature of construction projects, future studies could compare our event knowledge graph and fuzzy logic-based approach with traditional risk assessment methods like Monte Carlo simulations.

The interpretation of data remains a challenge, particularly in extracting relevant events from textual data and establishing logical relationships. Effective approaches might include the utilization of synthetic data generation techniques, which can help in training models where historical data is sparse or inaccessible. In addition, there are some pioneering studies in automated operation process abstraction that complement similar work for addressing data scarcity in simulation modeling (Li, Ji and AbouRizk 2020).

Regarding explainability, this study employs the Shapley value, a concept derived from the SHapley Additive exPlanations (SHAP) algorithm within the realm of XAI, renowned for its efficacy in elucidating machine learning outcomes. The innovative aspect of our approach involves integrating the SHAP algorithm to directly calculate monetary losses. This adaptation enhances practicality and aids project managers in comprehensively understanding and utilizing the algorithm. Additionally, it addresses specific inquiries that arise when using risk simulation software, such as FRA, thereby improving the decision-making process in project management.

5 CONCLUSIONS

This study presents a novel approach to project risk simulation by integrating event knowledge graphs, fuzzy logic techniques, and game theory principles. By systematically capturing project events and their relationships, project managers can gain insights into potential risk occurrences and their implications. The proposed methodology provides a structured framework for simulating and analyzing project risks, enabling project managers to make informed decisions and implement proactive risk management strategies.

Future research could explore further refinements to the proposed approach and its application in diverse project contexts. Overall, the integration of event knowledge graphs, fuzzy logic, and game theory holds promise for advancing risk simulation and enhancing decision-making in project management.

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