Evaluating Risk Response Strategies on Construction Projects Using a Fuzzy Rule-Based System

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Abstract – The development and implementation of risk response strategies contributes to effective risk management processes in construction organizations. Risk response strategies need to be developed and implemented as follows: first, all possible risk responses for each given risk event of a project are identified; next, each risk response is evaluated to determine its effectiveness; then, for each risk event of the project, the optimal risk response is identified and implemented; and finally, the risk events and responses are consistently monitored. The existing literature confirms that there is a lack of research on evaluation criteria for risk responses, making it difficult to determine their effectiveness. This paper presents research that fills this gap by developing a way to evaluate the effectiveness of risk response strategies using a fuzzy rule-based system (FRBS) that consists of three inputs and one output. The inputs of the FRBS are the affordability and the achievability of risk responses and the controllability of risk events; the output is the effectiveness of the risk response. The application of fuzzy ranking methods instead of crisp ranking methods allows the model to mimic three human attitudes towards risk: risk averse, neutral, and risk taking. The proposed model lays the foundation for an automated evaluation of risk response strategies and provides a decision support tool for experts in the field.

Keywords – Risk management; risk response; fuzzy logic; FRBS

1 Introduction

Risk management is vital for achieving business objectives on construction industry projects. Current trends in the construction industry are towards bigger and more complex projects, which can result in a greater amount of risks and uncertainties [1]. These risks can cause failures in terms of cost overruns, schedule delays, environmental damages, and fatal injuries. In general, risk management processes include identification, qualitative analysis, quantitative analysis, risk response planning, and monitoring and control [2]. First, risk events need to be identified and documented. These risk events should be analyzed by qualitative methods so they can be prioritized based on probability and impact. Next, quantitative risk analysis must be performed to model the combined effects of randomly occurring risk events and to develop a synthesized view of the overall effects of risk events on the project. Then, risk responses should be identified, evaluated, and implemented to mitigate occurrence probability and/or the negative impacts of risk events. Finally, the overall effectiveness of the risk management process needs to be monitored, reviewed, and controlled on a regular basis. The effectiveness of the risk response is the extent to which the risk events' probabilities and/or impacts are reduced as a result of implementing the risk responses.

A large amount of the research on risk management acknowledges the importance of risk response planning [3]. Hillson [4] argues that identifying and analyzing risks and uncertainties is clearly vital for the risk management process, as it is not possible to address risks that are not identified or that are poorly analyzed. Risk response planning is considered an important step for effective risk management; it is a process that is complementary to risk identification and analysis; and without risk response planning, only limited benefits can be had from the risk management process [4]. Risk response strategies need to be developed and implemented as follows: first, all possible risk response strategies for each given risk event of the project are identified. Next, each risk response strategy is evaluated to determine its effectiveness. Then, for each risk event, the optimal risk response strategy is identified and implemented. Finally, the risk events and the response strategies are consistently monitored.

Although some researchers have developed optimization-based methods for selecting an optimal set of risk responses [5], the application of these methods on real projects can be a complex and costly process due to the effort and amount of data that are required. Moreover, these models account for only a limited number of criteria, namely time, cost, and quality, which can lead to the selection of risk responses that are cost effective but unfeasible in terms of technology, environment, and achievability. Optimization-based approaches have low transparency (i.e., they operate in such a way that it is not easy for others to see what actions are performed) during the process of selecting the optimal set of risk responses. Employing approaches with the ability to address the abovementioned weak points can result in more realistic, applicable, and feasible risk responses—a fuzzy ruled-based system (FRBS) is just such an approach. The existing literature confirms that there is a lack of research on evaluation criteria for risk response strategies, making it difficult to determine their effectiveness. The objectives of this paper are to (1) identify appropriate criteria for evaluating risk responses; (2) develop an FRBS to determine the effectiveness of risk responses; and (3) develop a fuzzy ranking method for selecting the most effective risk responses.

This paper is organized as follows. First, a brief literature review of risk management and risk response planning in construction projects is presented, followed by a discussion about the application of fuzzy logic methods in the risk management process. Second, evaluation criteria for risk responses are identified and an FRBS is developed for determining the effectiveness of risk responses; a fuzzy ranking method is then applied to rank the risk responses based on their effectiveness (determined by the FRBS) on construction projects. Third, a hypothetical example is provided to illustrate the proposed framework. Finally, conclusions are presented and future extensions of the current research are discussed.

2 Overview of Risk Response Evaluation and Selection Approaches

Risk response planning involves reducing the negative impact and probability of occurrence of risk events to ensure project success. Identified risk responses need to be evaluated, and the optimal risk response needs to be implemented for each risk event. Several researchers have developed decision support systems for evaluating and selecting risk responses using different approaches, including the trade-off approach [4, 6, 7], the zonal-based approach [8, 9], mathematical modeling and optimization [5, 3, 10–13], and a combination of these approaches and fuzzy logic [14].

The trade-off approach makes trade-offs between parameters—such as cost, time, and quality—that are either risk event-related or risk response-related in order to evaluate a set of risks. Kujawski [6] makes trade-offs that account for a project's objective requirements and project stakeholders' subjective preferences. Risk responses are selected based on the cost of implementing each risk response compared with the probability of project success when the risk response is implemented. Hillson [4] argues that the effectiveness of proposed risk responses must be assessed based on appropriateness (i.e., the correct level of risk response according to the severity of the risk event, ranging from a crisis response to a "do nothing" response), affordability (i.e., the cost effectiveness of the risk response), achievability (i.e., how realistically achievable or feasible the risk response is, either technically or in terms of a respondent's capability and authority), agreement (i.e., the consensus and commitment of stakeholders), and allocation (i.e., the responsibility of and accountability for implementing the risk response). Qazi et al. [7] develop a model for selecting a set of optimal risk responses by measuring the impacts of different combinations of risk responses on the objective function of a project. In zonal-based approaches, two-dimensional diagrams are applied to assess the regions of the risk responses using one of two common assessment tools: (1) a matrix that features different factors in a two-dimensional diagram and (2) a two-axis graph that maps risk responses based on the values of the two dimensions.

Using an optimization-based approach, Fan et al. [5] suggest a model for assessing the effectiveness of risk responses based on three criteria: risk event controllability, risk response costs, and project characteristics. Kayis et al. [10] employ five heuristic algorithms to minimize the cost of implementation within the constraints of the implementation budget and acceptable risk effects for new product development. Zhang and Fan [11] maximize the sum of estimated risk response effects (i.e., they reduce the expected loss of the risk event) after risk response strategy implementation using a method for selecting risk responses with an integer linear programming (ILP) model. Zhang [12] uses an ILP model that accounts for the cost of implementation and the determined budget for risk responses. Wu et al. [13] propose a multi-objective decision-making model for the selection of risk responses that minimize total expected losses, total expected schedule delays, and total expected quality reduction. An optimization model is used to minimize expected time loss, expected cost loss, and expected quality loss. To calculate the coefficients of the objective function, a fuzzy analytic hierarchy process (FAHP) is employed as a technique to guide the risk analysts [14].

3 Developing the Risk Response Evaluation and Selection Approach

In order to develop the proposed FRBS for the evaluation of risk responses, appropriate evaluation criteria are identified, which are the inputs of the FRBS. The output of the FRBS is the effectiveness of the risk responses. Based on the output of the FRBS, the risk responses are then ranked using a fuzzy ranking method that allows the model to mimic the three human attitudes towards risk: risk averse, neutral, and risk taking.

3.1 Evaluating Risk Responses: Identifying Inputs and Outputs

This study uses three criteria to evaluate risk responses: affordability of the risk response, achievability of the risk response, and controllability of risk events. These criteria make up the three inputs of the FRBS, and its output is the effectiveness of the risk response strategy. There is a positive correlation between the controllability of a risk event and the effectiveness of its risk response. For example, even if you implement a risk response with high affordability and high achievability, the risk response will not be effective in addressing a risk event with low controllability. Therefore, the FRBS developed for the evaluation of risk responses needs to evaluate both risk events and their identified risk responses in order to identify the most effective risk responses. Subjective system variables (evaluation criteria) are represented by triangular fuzzy membership functions, which are commonly used in engineering applications.

Affordability refers to the cost-effectiveness of risk responses, where the amount of time, effort, and money spent on addressing a risk should not exceed the available resources for implementing risk responses. One way to measure the cost-effectiveness of risk responses is to use the risk reduction leverage (RRL) factor, which can be calculated by converting the impact of the risk event into a monetary value (for example, the cost of delay and/or the cost of negative impacts on quality) [4]. RRL represents the ratio of the increase in risk event exposure to the cost of risk response implementation. RRL can be calculated by dividing the difference between the risk responses' cost impacts before and after implementation by the implementation cost (see Equation (1)) [4].

$$RRL = \frac{(\text{Cost Impact})_{\substack{before \\ response}} - (\text{Cost Impact})_{\substack{after \\ response}}}{\text{Cost of response}} \tag{1}$$

Hillson [4] proposes that responses with high effectiveness in terms of affordability should have RRL values above 20. Responses with medium effectiveness have RRL values ranging from 1 to 20, and RRL values of less than 1 can be labelled as having low effectiveness (i.e., they are ineffective) because their implementation cost is more than what they might save later. Thus, the fuzzy membership functions for affordability are defined as low (less than 1), medium (between 1 and 20), and high (more than 20).

Achievability refers to the feasibility of a risk response in terms of three considerations: the technical complexity of the proposed risk response, the capability of the respondent, and the authority of respondent [4]. According to Fan et al. [5], the complexity of a risk response may stem from technical obstacles, political obstacles, limited access to information, or conflict resolution obstacles. Three fuzzy membership functions of achievability can be defined, namely low, medium, and high achievability.

Miller and Lessard [15] define *controllability* as the likelihood that the probability of occurrence of a risk event can be changed. This criterion describes the nature of the risk situation. Risk events with a low degree of controllability include occurrences such as natural disasters, while risk events with a high degree of controllability are caused by scheduling and budget problems. The latter can be addressed more effectively than the former by implementing an identified risk response [5]. Although the controllability value of a risk event is the same for all of its related risk responses, this criterion can be used to ascertain whether risk responses meet the threshold for effectiveness, which can be determined by risk decision makers. As with affordability and achievability, controllability can be categorized into three fuzzy membership functions, namely low, medium, and high.

3.2 Evaluating Risk Responses Using an FRBS

An FRBS is a methodology for modeling human logical thinking and decision-making. These systems use membership functions and fuzzy rules to make a decision [16]. An FRBS can be developed with either data or expert judgments using one of the few approaches proposed in the literature. Fuzzy c-means (FCM) clustering can be employed when there is access to historical data [17]. Expert judgments can be applied to develop an FRBS when historical data is unavailable [18, 19]. In this paper, the FRBS for the evaluation of risk responses is developed using expert judgments. The membership functions of three inputs and one output are determined based on documented literature using MATLAB® R2018b.

In this paper, a Mamdani fuzzy inference system is used to develop an FRBS for the evaluation of risk responses; by delivering fuzzy outputs, the Mamdani inference system facilitates the use of different defuzzification methods for fuzzy ranking. The membership functions of affordability are determined by RRL values between 0 and 20 as recommended by Hillson [4]. Figure 1 shows the membership functions of affordability.

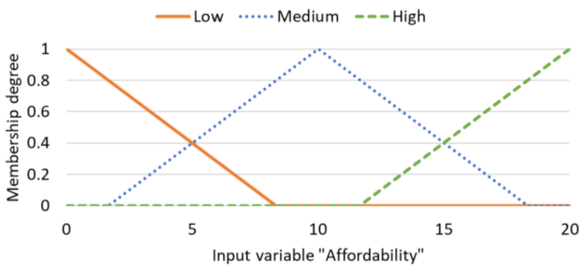

Figure 1. Membership functions of affordability.

For the achievability and controllability membership functions, the three linguistic terms *low*, *medium*, and *high* are used, as illustrated in Figure 2 and Figure 3, respectively.

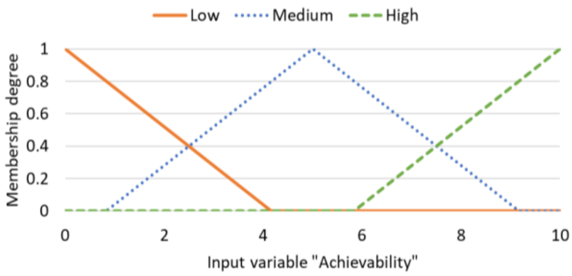

Figure 2. Membership functions of achievability.

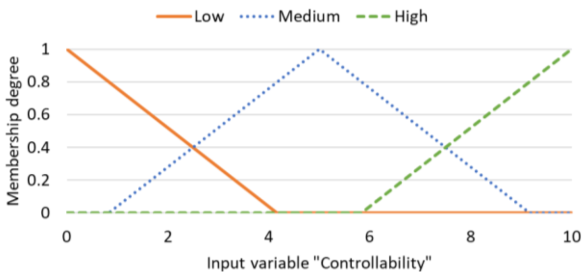

Figure 3. Membership functions of controllability.

The membership function of the FRBS output (effectiveness) is also between 0 and 1, as shown in Figure 4.

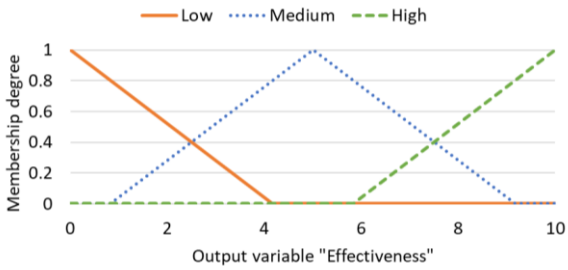

Figure 4. Membership functions of effectiveness.

Fuzzy rules are defined as "if-then" rules. In this system, 27 if-then fuzzy rules are defined. Some of these rules are presented in Table 1.

Table 1. Fuzzy rules used in the FRBS.

Rule	**If**			**Then**
	Affordability	Achievability	Controllability	Effectiveness
1	Low	Low	Low	Low
2	Low	Low	Medium	Low
3	Medium	Medium	Medium	Medium
4	Low	Medium	Medium	Medium
5	High	High	High	High
6	Medium	High	High	High

Figure 5 shows the three-dimensional curve that represents the mapping from inputs to output and the dependency of effectiveness on controllability and affordability.

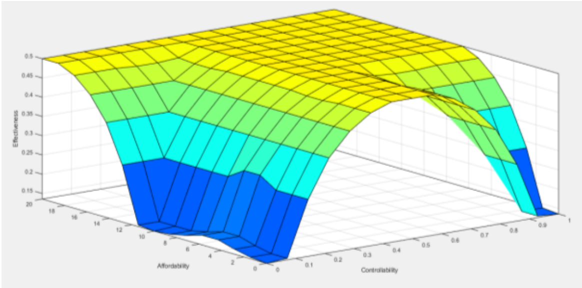

Figure 5. Three-dimensional representation of the proposed FRBS.

3.3 Selecting Effective Risk Responses Using the Fuzzy Ranking Method

In the next step, the risk responses need to be ranked based on their effectiveness, so that the most effective risk response can be selected for each risk event. In order to solve decision-making problems, fuzzy ranking methods are commonly used, wherein the evaluation scores (i.e., effectiveness) of decision alternatives (i.e., risk responses) are represented by fuzzy membership functions [20, 21]. There are various fuzzy ranking methods discussed in the literature, the majority of which can be grouped into three categories based on the approaches they use to rank fuzzy numbers. The first category of fuzzy ranking methods includes those methods that rank fuzzy numbers based on their α-cuts at a pre-specified level of α [22]; thus, these methods change the fuzzy ranking problem into an interval ranking problem. The second category of fuzzy ranking methods includes those methods that use fuzzy distance measures to rank fuzzy numbers [23]. The third category of fuzzy ranking methods includes those that rank the fuzzy numbers based on their defuzzified values [21]; these methods change the fuzzy ranking problem into a simple problem of ranking crisp numbers. The first two categories of fuzzy ranking methods (i.e., α-cut-based methods and fuzzy distance-based methods) usually require that fuzzy numbers be regularly shaped (e.g., triangular or trapezoidal fuzzy numbers) [21]. However, in this paper, the output of the FRBS (i.e., the effectiveness of the risk responses) is an irregularly shaped fuzzy membership function. Therefore, in this paper, the third category of fuzzy ranking methods (i.e., ranking methods based on the defuzzified value) is used to rank risk responses based on their effectiveness. To do this, the results of the FRBS need to be defuzzified. There are various defuzzification methods proposed in the literature; the smallest of maximum (SOM), largest of maximum (LOM), and center of area (COA) methods are commonly used in different engineering applications of fuzzy logic. Figure 6 presents the three aforementioned defuzzification methods implemented on a hypothetical example of risk response effectiveness. Moreover, Figure 6 also shows how different defuzzification methods can result in different defuzzified values for risk response effectiveness.

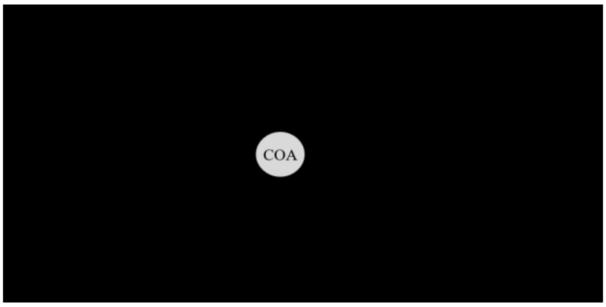

Figure 6. COA, SOM, and LOM defuzzification methods.

When ranking risk responses based on the defuzzified value of their effectiveness, the use of different defuzzification methods can mimic different human attitudes towards risk. Ranking risk responses based on the results of the SOM method means that the decision maker considers the smallest maximum value of effectiveness for each risk response and ignores all other possible values for the effectiveness of the risk response (see Figure 6). Thus, ranking risk responses based on the results of the SOM method mimics a risk-averse attitude. In contrast, ranking the risk responses based on the results of the LOM method means that the decision maker considers the largest maximum value of effectiveness for each risk response and ignores all other possible values for the effectiveness of the risk response (see Figure 6). Thus, ranking the risk responses based on the results of the LOM method mimics a risk-taking attitude. The COA, on the other hand, determines the defuzzified value of effectiveness by taking into consideration all possible values of effectiveness for each risk response. Accordingly, ranking risk responses based on the results of the COA method mimics a neutral human attitude towards risk. In this paper, the three aforementioned defuzzification methods (i.e., SOM, LOM, and COA) are used to rank risk responses based on their effectiveness so that all three human attitudes towards risk can be mimicked in the selection of the most effective risk responses.

4 Hypothetical Example

In this section, a hypothetical example is presented to demonstrate how to use the proposed approach to evaluate the effectiveness of risk responses and select the most effective. Assume two risk events: (1) incomplete design and (2) operation interruption due to adverse weather conditions. The first risk event can be addressed by two possible risk responses: (1-1) outsourcing design to subcontractors or (1-2) employing professional design teams. To mitigate the second risk event, two risk responses are possible: (2-1) schedule compression using extra resources or (2-2) considering alternative construction methods, such as using precast materials. A number between 0 and 10 represents achievability (where 10 is high) and another number between 0 and 10 represents controllability (again, 10 is high); these numbers are determined for each risk response by expert judgment. The values for each criterion can be found in Table 2.

Table 2. The input values of each risk response and its related risk event.

Risk Event	Risk Response	Affordability (RRL)	Achievability	Controllability
1	1-1	7.00	9.00	6.00
	1-2	12.00	5.00	6.00
2	2-1	7.00	6.00	2.00
	2-2	5.00	3.00	2.00

Since this hypothetical example is presented simply for illustrating the proposed approach, a limited number of risk factors are identified for risk response evaluation. In a real construction case study, a comprehensive list of risk factors such as environmental and safety risk factors may be considered for risk response evaluation. Table 3 shows the effectiveness values, which are based on the information in Table 2. The inputs are imported to the FRBS to evaluate the effectiveness of the risk responses. Crisp numbers representing the effectiveness of the risk responses are then predicted by the FRBS using three defuzzification methods (i.e., SOM, LOM, and COA) as discussed in Section 3.3 and the risk responses are ranked accordingly. Table 3 presents the effectiveness of the risk responses and their rankings for the two risk events.

Table 3. The effectiveness values of each risk response and its related risk event.

Risk Response	Effectiveness					
	(SOM)	Rank	(LOM)	Rank	(COA)	Rank
1-1	8.50	1	10.00	1	6.95	1
1-2	4.10	2	6.00	2	5.00	2
2-1	0.00	-	2.00	2	3.74	2
2-2	0.00	-	2.50	1	3.92	1

Table 3 presents the most effective risk response for each of the two risk events as determined by three different defuzzification methods. The effectiveness value determined using the SOM defuzzification method mimics a risk-averse attitude; the LOM defuzzification method mimics a risk-taking attitude; and the COA defuzzification method mimics a neutral attitude towards risk. Although in this case study the rankings of the risk responses are similar for each of the three defuzzification methods, on real construction projects with numerous risk responses, rankings can be different for different defuzzification methods. Since higher effectiveness of risk responses is favorable, in the hypothetical example, risk responses 1-1 and 2-2 should be selected for risk events 1 and 2, respectively. As shown in Table 3, the values of effectiveness for risk responses 2-1 and 2-2 are equal to zero, which indicates neither of these two risk responses should be applied to risk event 2 if the risk response strategy is based on a risk-averse attitude. Moreover, as discussed in Section 3.1, risk responses can be rejected if their effectiveness is less than a threshold value that is determined by the decision maker. For instance, assuming an effectiveness value of 5 as the threshold for the risk responses' effectiveness, both risk responses for the second risk event (i.e., 2-1 and 2-2) are not acceptable in this case study (refer to Table 3). In this situation, new risk responses should be identified for the second risk event or its adverse effects on the project should be accepted.

5 Conclusions and Future Research

This paper presents a methodology for evaluating the effectiveness of identified risk responses by applying an FRBS that has three inputs as evaluation criteria and that produces the effectiveness of risk responses as an output.

The three inputs are the affordability of each risk response, the achievability of each risk response, and the controllability of related risk events. The FRBS uses the estimated crisp values of affordability, achievability, and controllability to evaluate the effectiveness of risk responses according to the rules developed based on experts' opinions. The output, which is a fuzzy set, is used as an input for three different fuzzy ranking methods, one based on SOM, one based on LOM, and one based on COG (COA), to determine the most effective risk response in terms of affordability, achievability, and controllability. Applying an expert-driven FRBS and fuzzy ranking methods can help automate the evaluation of risk response strategies, and this technique delivers an expert-level risk management tool to a non-expert in the field. The contributions of this paper are threefold: first, the appropriate criteria for evaluating risk responses are identified from the literature; second, an FRBS is developed to automate the evaluation of risk responses; and third, the application of different fuzzy ranking methods is proposed to mimic the risk-taking attitude of experts for risk response evaluation.

On construction projects, risk events are often dependent on one another; for example, the risk of precipitation is linked to the risk of excessive soil moisture in earthmoving operations. In order to develop a comprehensive risk response planning tool, interdependencies between different risk events need to be taken into consideration. In future research, the FRBS developed in this paper will be extended to capture these interdependencies and determine the most effective risk responses for each risk event, accounting for all risk events that affect a project throughout its life cycle.

6 Acknowledgments

This research is funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) Industrial Research Chair in Strategic Construction Modeling and Delivery (NSERC IRCPJ 428226–15), which is held by Dr. Aminah Robinson Fayek. The authors gratefully acknowledge the financial support provided by industry partners and NSERC through the Chair.

7 References

[1] Abdelgawad M. and Fayek A.R. Risk management in the construction industry using combined fuzzy FMEA and fuzzy AHP. Journal of Construction Engineering Management, 136(9):1028–1036, 2010.

[2] Project Management Institute. Construction extension to the PMBOK guide. Newtown Square, Pennsylvania, 2016.

[3] Ben-David I. and Raz T. An integrated approach for risk response development in project planning. Journal of Operation Research Society, 52(1):14–25, 2001.

[4] Hillson D. Effective opportunity management for projects: Exploiting positive risk. Marcel Dekker, New York, 2004.

[5] Fan M., Lin N. and Sheu C. Choosing a project risk-handling strategy: An analytical model. International Journal of Production Economics, 112(2):700–713, 2008.

[6] Kujawski E. Selection of technical risk responses for efficient contingencies. Systems engineering, 5(3):194–212, 2002.

[7] Qazi A., Quigley J., Dickson A. and Kirytopoulos K. Project complexity and risk management (ProCRiM): Towards modelling project complexity driven risk paths in construction projects. International Journal of Project Management, 34(7):1183–1198, 2016.

[8] Datta S. and Mukherjee SK. Developing a risk management matrix for effective project planning—An empirical study. Project Management Journal, 32(2):45–57, 2001.

[9] Piney C. Risk response planning: Selecting the right strategy. In Proceedings of the fifth European project management conference, 2002.

[10] Kayis B., Arndt G., Zhou M. and Amornsawadwatana S. A risk mitigation methodology for new product and process design in concurrent engineering projects. CIRP Annals, 56(1):167–170, 2007.

[11] Zhang Y. and Fan Z. An optimization method for selecting project risk response strategies. International Journal of Project Management, 32(3):412–422, 2014.

[12] Zhang Y. Selecting risk response strategies considering project risk interdependence. International Journal of Project Management, 34(5):819–830, 2016.

[13] Wu D., Li J., Xia T., Bao C., Zhao Y. and Dai Q. A multiobjective optimization method considering process risk correlation for project risk response planning. Information Sciences, 467:282–295, 2018.

[14] Nik E.R., Zegordi S.H. and Nazari A. A multi-objective optimization and fuzzy prioritization approach for project risk responses selection. In Proceedings of the 2011 IEEE International Conference on Industrial Engineering and Engineering Management, pages 889–892, Singapore.

[15] Miller R. and Lessard D. Understanding and managing risks in large engineering projects. International Journal of Project Management, 19(8):437–43, 2001.

[16] Fayek A.R. and Lourenzutti R. Introduction to fuzzy logic in construction engineering and management. In Fuzzy hybrid computing in construction engineering and management. Ed. Fayek A.R. Emerald Publishing Limited, Bingley, United Kingdom, 2018.

[17] Bezdek JC. Pattern recognition with fuzzy objective function algorithms. Plenum Press, New York, 1981.

[18] Khanzadi M., Nasirzadeh F. and Alipour M. Integrating system dynamics and fuzzy logic modeling to determine concession period in BOT projects. Automation in Construction, 22:368–376, 2012.

[19] Gerami Seresht N. and Fayek A.R. Dynamic modeling of multifactor construction productivity for equipment-intensive activities. Journal of Construction Engineering Management, 144(9):04018091, 2018.

[20] Sadeghi N., Fayek A.R. and Gerami Seresht N. A fuzzy discrete event simulation framework for construction applications: Improving the simulation time advancement. Journal of Construction Engineering and Management, 142(12):04016071, 2016.

[21] Chen S. J. and Chen S.M. Fuzzy risk analysis based on the ranking of generalized trapezoidal fuzzy numbers. Applied Intelligence, 26(1):1–11, 2007.

[22] Chen S.M. and Wang C.H. Fuzzy risk analysis based on ranking fuzzy numbers using α-cuts, belief features and signal/noise ratios. Expert Systems with Applications, 36(3):5576–5581, 2009.

[23] Cheng C.H. A new approach for ranking fuzzy numbers by distance method. Fuzzy Sets and Systems, 95(3):307–317, 1998.