**World Journal of Environmental Biosciences**

Available Online at: **www.environmentaljournals.org**

**Volume 9, Supplementary: 88-93**

**ISSN 2277- 8047**

# Selection of a Combination of Bird and Fuzzy Algorithms to Predict Project Risk

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**ABSTRACT**

*This article proposes a method with the integration of PSO and fuzzy optimization to provide decision support in project risk response. The main steps of the method included: (1) formulation of alternative risk response actions based on PSO, and (2) determination of the optimal set of RRAs using a fuzzy optimization model. In this method, project managers can find alternative RRAs and further determine the optimal set of RRAs. Some managerial suggestion and implication are drawn from the results of the article. First, to perform better risk response in the future, it is suggested that organizations should always capture a long-term perspective, with an awareness of keeping documents of all handled historical projects. Second, because any RRA obtained from alternative historical cases must be adapted to the existing situations, adaptation costs must also be considered when allocating budget for selecting RRAs.*

**Keywords:** *Project Risk Management; PSO; Risk Response Action (RRA); Fuzzy optimization*

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**Received:**19 August2020
**Accepted:** 29 November 2020

## 1. INTRODUCTION

Project performance is constantly exposed to risks, so the performance of effective project risk management (PRM) is important for the success of the whole project (ISO 31000., 2009; Simon et al., 1997). PRM generally contains 3 phases: risk identification, risk assessment, and risk response (Buchan, 1994; Hatefi and Seyedhoseini, 2012). Risk identification is the recognition and documentation of related risks. Risk assessment is the process of assessing project risks according to their characteristics such as probability and impact. Risk response is to develop, select, and implement strategies in order to decrease risk exposure caused by project goals (Wang et al., 2018). Of these three phases, risk response is always considered to have a direct effect on reducing risk exposure, and if not done properly, the effect of risk identification and risk assessment is reduced (Hillson, 1999; Hillson, 2002; Marmier et al., 2013).

In the risk response phase, the selection of risk response actions (RRAs) is an important task that has attracted a lot of attention. In existing studies, the determination of RRA is mostly on the basis of the project managers' (PMs) experience and professionals (Fan et al., 2008; Isaac, 1995; Klein, 1993). In particular, to support the decision-making process when managing risk in a project, experts usually first refer to the documents and historical databases and RRA information stored in previous projects. Just as Hume said, "We expect the same effects from the same causes" (Hume, 1902), if we expect to achieve similar effects when developing an RRA, it would be wise to adopt RRAs derived from historical projects where similar risks have been successfully addressed. However, some other options may not be suitable to reduce the risk in the current project, in which case, the elite must first choose one of the available options. Also, in selecting RRAs, PMs should consider limited resources and other constraint conditions that would be a bit challenging without the aid of auxiliary methods. Therefore, it is imperative to use quantitative methods such as optimization models to evaluate and select RRAs to achieve the objectives of the project (Jaafari, 2001). To date, practitioners and academics have developed some optimization models to determine the optimal set of RRAs (Ben-David and Raz, 2001; Ben-David et al., 2002; Fang et al., 2013; Kayis et al., 2007; Sherali et al., 2008; Zhang and Fan, 2014; Zhang, 2016).

In these models, minimizing the cost of implementation or maximizing the effect of risk response is usually defined as objective performance, while the budget, duration, and other characteristics of a project are often defined as constraints. Usually, the above parameters in the form of integers should be evaluated as model input before making models. However, estimating the effect of performing any RRA with an integer value is difficult because experts usually have vague knowledge about it. This is an example of Professor Lotfi Zadeh's "principle of incompatibility", which states that some qualitative aspects of real-life conditions, especially humanistic contexts, cannot be fully explained in sufficient numbers because of their complexity. Therefore, to avoid such "incompatibility", researchers have found a less but more specific way to evaluate complex phenomena related to human perception, the fuzzy linguistic approach. This approach uses sentences or words in a natural context for evaluation (Herrera and Martinez, 2000; Zadeh, 1975). For example, for a subway project, it may be more appropriate to use the exact value of $15,800,000 to describe the effect of increasing support for a steel structure for using the linguistic term "fair" (representing a scale of values).

In this study, the authors attempt to provide a decision support method that offers both a PSO and an optimization model to help PMMs select appropriate RRAs. PM using the PSO method can obtain RRA options from a historical file database. Then, by building a fuzzy optimization model, the optimal set of RRAs can be selected from other options. Finally, a case study is presented to prove the application of the proposed method, and management reasons and suggestions can be plotted.

## 2. LITERATURE REVIEW

In the existing literature, the matrix-based method, trade-off method, decision tree method, optimization method, and case-based method and PSO are considered as the main methods in determining RRAs.

In the matrix-based method, 2 selected criteria concerning risks are mapped to the vertical axis and horizontal axis. According to different values of the 2 criteria, a 2-axis graph or matrix composed of multiple zones is designed. There are different strategies in their corresponding zones, in which the coordinates represent two criteria values in that zone (Datta and Mukherjee, 2001; Elkjaer and Felding, 1999; Flanagan and Norman, 1993; Miller and Lessard, 2001; Piney, 2002). Similarly, in the trade-off method, some concepts or approaches such as efficient frontier are utilized to create a trade-off between risk-related criteria for obtaining RRA (Klein, 1993; Chapman and Ward, 2003; Haimes, 2015; Kujawski, 2002; Pipattanapiwong and Watanabe, 2000). Although the above two methods are useful for identifying RRA locations, they are not applicable to selecting RRA from RRA options. Also, most approaches consider only two criteria and do not consider the characteristics of RRAs. To overview the trade-off and matrix-based methods and their advantages and disadvantages, the reader can refer to Zhang and Fan (2014).

The decision tree method is used as a tool for RRA selection. In the investigations, using this method, risk responses (Dey, 2002; Dey, 2012) or risk scenarios (Marmier et al., 2013; Marmier et al., 2014; Kujawski and Angelis, 2010) are modeled as decision tree branches and by comparing the values of branches, the optimal RRA can be selected. However, in the situation of multiple risks or complex projects, creating the decision tree may be a time-consuming and difficult task. Also, although the chosen strategy is optimal for each project risk, it is not certain that the set of all selected strategies is optimal for the overall project risk response from a global optimal perspective.

The optimization method can obtain the optimal set of RRA and avoid the above-mentioned limitations. Ben-David and Raz (Ben-David and Raz, 2001) first proposed the optimization method for RRA selection, in which an integer optimization model was developed to select an optimal set of RRAs with the objective performance of minimizing the estimated total cost. Ben David et al., developed this model by considering the relationship between the two RRAs. (Ben-David et al., 2002) Since then, the optimization method has widely been used in RRA selection for various projects. For example, Kayis et al. (2007) in a new product design project offered an optimization model, through which they determined cost-effective RRAs and compared the calculation results of five different model algorithms. Zhang and Fan (2014) pointed out that project risks are not only direct causes of economic damage, but also lead to quality and project delays. Therefore, they offered an optimization model for maximizing the effect of risk response with a limited budget, program, and quality. Zhang (2016) presented an optimization model that used the maximum expected utility of the elite first to determine the optimal set of RRAs according to the risk dependence. In addition, some researchers also combined the optimal determination method with the existing risk analysis methods when determining RRAs. For example, Sherali et al. (2008) analyzed the project risks and selected the relevant RRAs with the optimization method using the event tree analysis method. During the process, an integer complex number model was constructed that minimized the risk as an objective function. Fang et al. (2013) used a design structure matrix for risk analysis to determine the dependent relationships between risks. After risk analysis, it had a performance of proportionality of budget constraint and target performance and it was used in the design. However, as the RRA options in the optimization method are generally determined on the basis of the knowledge and experience of the PMs, some of the RRAs that have better effects may be left out, which may reduce the risk response effect more. Therefore, determining the correct RRA options is very important in choosing an RRA.

To this end, some researchers used the case-based method to select from a set of alternative RRAs that allow the PM to use their prior knowledge objectively. For example, Lam and his colleagues (Lam et al., 2013) designed a decision support system to reduce potential risks in beverage storage that performs real-time monitoring in the warehouse based on RFID technology. Also, this case-based system can retrieve similar historical risks and provide corresponding RRAs. In the research of Oztekin and Luxhej (2010), a case-based method was used to deal with aviation risks. They built a probabilistic model to demonstrate aviation risks and then used a case-based approach to introduce NASA interventions as RRAs to reduce the negative effects of aviation risks. Fan et al. (2015) used the case-based reasoning method in the construction of the subway, through which a set of RRAs was determined. These case-based methods are possible to achieve appropriate historical RRAs. But, in fact, due to some resource constraints, such as budget constraints, the effect of implementing selected RRAs through this type of approach is generally not desirable.

Overall, all the above-mentioned methods have played an important role in RRA selection from different perspectives. Based on the above analysis, our idea is to obtain RRA options by the PSO method. Therefore, in choosing RRA, the authors use the cost and efficiency by PSO in the possible space of the problem. In addition, in selecting RRAs, the initial states of particle placement can be obtained from a group of experts, which can help the algorithm to speed up.

## 3. ALTERNATIVE FORMULA TO RRA

In this section, a method for formulating alternative RRAs is presented that includes risk description, fuzzy similarity measure, case representation, RRA screening, and RRA compatibility.

### 3.1. Risk Description

In PRM, project risk is, in general, defined as an uncertain condition or event that disturbs project aims and can be the product of its impact and probability. In our research, linguistic terms have been used to describe risk probability and impact on the risk assessment process. Terms such as "very unlikely", "unlikely", "moderate", "likely" and "very likely" are used to define the probability of risk, while "minimum", "low", "moderate", "high" and "important" are used to describe the effect of risk. Each linguistic term has a corresponding membership function. In this study, membership functions are represented by triangular fuzzy numbers that are commonly used in managerial decisions (Herrera and Martinez, 2000). Table 1 shows the fuzzy set index for each linguistic term. The triangular mean formula shown by an equation is used to gather the opinions of various experts about probabilities and effects (Bcjadziev and Bojadziev, 1997).

**Table 1.** Fuzzy set index for each linguistic term.

| Linguistic term | Range | Equivalent fuzzy number |
|---|---|---|
| Very unlikely / minimal / weak | 0≤x≤0.25 | [0, 0, 0.25] |
| Unlikely / low / fair | 0≤x≤0.25; 0.25≤x≤0.5 | [0, 0.25, 0.5] |
| Moderate / moderate / good | 0.25≤x≤0.5; 0.5≤x≤0.75 | [0.25, 0.5, 0.75] |
| Likely / high / very good | 0.5≤x≤0.75; 0.75≤x≤1 | [0.5, 0.75, 1] |
| Very unlikely / critical / excellent | 0.75≤x≤1 | [0.75, 1, 1] |

### 3.2. Case representation

To build a historical case database, the structure of the database provided by Evans et al. (2012) is approved, in which each item contains three types of information: risk information, project information, and RRA information.

**Table 2.** Case model

| Historical type | Example | Values |
|---|---|---|
| Risk | ID: | The first historical risk |
| | Name: | Evacuation with instability |
| | category: | Tunnel structure risk |
| | Probability: | Unlikely |
| | Impact: | Low |
| | Date: | May 22, 2019 |

Consider, for example, a historical case. The probability and impact of risk are assessed as "unlikely" and "low" by experts, respectively. All information about case 1 is shown in Table 2. Similarly, the effect of performing each RRA is also shown linguistically. A 5-point scale including the terms "poor", "fair", "good", "very good" and "excellent" is used to indicate the effect of performance of RRAs (Vagias, 2006). Table 1 shows the fuzzy set representations for these linguistic terms.

### 3.3. Fuzzy similarity measure

To obtain historical RRAs, historical risks similar to the target risks must be recovered. To determine the similarity between target risks and historical risks, one must first determine the fuzzy similarity between target risks and historical risks.

### 3.4. PRA screening

After measuring fuzzy similarities, we can examine historical risks whose similarities are above a predefined threshold. For example, if an elite sets a higher threshold when choosing historical risks, there will be fewer but more relevant alternative RRAs for greater selection, thus improving selection efficiency. On the other hand, if the PM sets a lower threshold, there are more options to consider.

The threshold can generally be set with a clear number between 0 and 1. Therefore, to compare the fuzzy similarity with the threshold, the fuzzy similarity must be converted to an integer value using Chu and Tsao's method (Chu and Tsao, 2002).

The center point of fuzzy number A can be described as (x (A), y (A)). The values x (A) and y (A) indicate the distances from the center point to the principal point on the horizontal and vertical axes.

Based on the center point, the area of fuzzy number A denoted by S(A) can be calculated by Equation (1), and its properties are given below.

$$S(A)= x(A).y(A) \qquad \text{Equation (1)}$$

Property 1. If S (A)> S (B), then A> B

Property 2. If (S (A) <S (B), then A <B.

Property 3. If S (A) = S (B), then A = B

Based on the area of the fuzzy number and its characteristics, for each targeted risk, it is possible to examine historical risks whose similarity is above the threshold. Accordingly, historical RRAs related to similar risks are obtained for greater compatibility.

### 3.5. PRA compatibility

After screening historical RRAs, a compatibility process is necessary because historical RRAs are designed for historical risks rather than target risks. Compatibility can be achieved in three ways: the RRA itself, the cost of implementation, and the estimated impact of RRA implementation. For example, when elites try to reduce the main risk of "worker safety accidents" in the current project, there are three similar risks: "workplace injury", "worker accident" and "worker accidents involving large engineering vehicles and heavy equipment" of historical projects are displayed and their related RRAs "purchase of workers' insurance", "removal or replacement of unsafe operations" and "use of warnings and administrative controls such as training and inspection" are taken and RRA may be considered for the purpose. But the type of insurance, special operations, and warning signals and training programs used at the time may not be available at this time. Therefore, professionals should at least revise the RRA to make them applicable to cope with the current risk. Accordingly, the costs and effects of implementing RRA revisions need to be re-evaluated.

Adapted historical RRAs can then be considered as RRA options for the next stage of optimal selection.

## 4. PRA SELECTION OPTIMIZATION MODEL

### 4.1. PSO Algorithm (Fan et al., 2015)

Particle swarm optimization algorithm is one of the optimization algorithms based on random generation of the initial population. In this algorithm, it is built by modeling and simulating the group flight behavior of birds or the group movement of fish. Each member in this group is defined by the velocity vector and the position vector in the search space. At each repetition, the new position of particles is defined according to the velocity vector and the position vector in the search space. At each iteration, the new position of particles is updated according to the current velocity vector, the best position found by that particle, and the best position found by the best particle in the group. In this project, instead of randomly generating the population, we use the RRAs of the previous stage.

### 4.2. Stages of PSO algorithm

The stages to reach the best position, in other words, how the algorithm converges to the near-optimal solution are presented in this section. The position of the i-th particle is shown using Equation (2):

$$X_i = (x_{i1}, \ldots, x_{id}, \ldots x_{iD})$$

Equation (2)

The best previous position of i particle is also stored and displayed using Equation (3):

$$P_i = (p_{i1}, \ldots, p_{id}, \ldots p_{iD})$$

Equation (3)

Which is called pbest. The best pbest of all particles is also called gbest. The velocity of the i-th particle is also represented by the vector Vi shown in Equation (4):

$$V_i = (v_{i1}, \ldots, v_{id}, \ldots v_{iD})$$

Equation (4)

The concept of particle swarm optimization is in fact to change the position and velocity of each particle to its pbest and gbest at each stage of the algorithm using Equations (5) and (6):

$$v_{id} = w * v_{id-1} + c_1 * rand_1 * (p_{id} - x_{id-1}) + c_2 * rand_2 * (p_{gd} - x_{id-1})$$

Equation (5)

$$x_{id} = x_{id-1} + v_{id}$$

Equation (6)

Where w is the weight of inertia and $c_1$ and $c_2$ are the constants of acceleration and rand is a random number with uniform distribution in the range [0,1].

PSO population: The position and velocity of particles are updated using the base particle optimization algorithm.

The particle size of the PSO population also changes dynamically and is determined using Equation (7).

$$New\ PSO\ population = \frac{finess\ of\ current\ global\ best}{finess\ of\ previous\ global\ best} \times population\ size$$

Equation (7)

## 5. CASE STUDY

### 5.1. Introduction to case study

To illustrate the possibility of using the proposed model in real projects, a subway construction project S in City D is presented. The project involves the construction of two stations (Station A and Station B) with side platforms and a single-line tunnel between two stations in a city located in the Iranian capital and it appears to be unfavorable. Geological conditions for subway construction, which increases the difficulty of construction. Therefore, the project team should learn from past experiences and historical construction projects with similar geological conditions to deal with the construction risks of Project S.

Following the proposed method, a list of risk information is first provided in Table 3, and a historical case database containing information on six historical projects is constructed as shown in Table 4. Historical risks are then displayed and the corresponding RRAs are adapted. Next, a fuzzy optimization model is built. Since the screening process includes parameters of thresholds and time coefficient values, the calculation results are presented and discussed under different values of the parameters mentioned in the following sections.

**Table 3.** Collection of risk information

| Risk ID | Name | Category | Total probability | Effect probability |
|---|---|---|---|---|
| R1 | Instability of the retaining wall | Retaining wall structure | [0.500, 0.667, 0.917] | [0.417, 0.500, 0.750] |
| R2 | Leakage from the bottom of the base pit | Leakage | [0.333, 0.583, 0.833] | [0.250, 0.500, 0.750] |
| R3 | Internal slope of the base pit | Base pit structure | [0.167, 0.417, 0.667] | [0.250, 0.417, 0.667] |
| R4 | Frozen metal strap | Construction materials | [0.500, 0.667, 0.917] | [0.500, 0.667, 0.917] |
| R5 | Deviation of the arc axis when drilling | Parameter adjustment | [0.583, 0.750, 1.000] | [0.500, 0.667, 0.917] |
| R6 | Tunnel subsidence | Tunnel structure | [0.250, 0.500, 0.750] | [0.333, 0.583, 0.833] |

**Table 4.** Historical structure of the database case

| Case ID | Project ID | Project ID | Risk name | Category | Probability | Impact | Effect |
|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Case 1 | P1 | R11 | Sufficient strength of the retaining wall | Maintaining wall construction | Has | Moderate | Relatively good |
| Case 2 | P1 | R21 | Leakage from the base pit sidewalk | Leakage | Unlikely | Moderate | Good |

### 5.2. Case study results

To compare the results of calculations under different parameters, a total of 36 scenarios are selected in which the threshold a is set as 0, 0.35, and 0.45, the time coefficient value d is set as 0, 0.15, and 0.3 and the budget is set to be between 1 and 4 billion, respectively. In particular, selected sets of historical RRAs and risk response effects are calculated in different parameters, respectively.

It can be seen that the selected sets of historical RRAs are affected by the values of d and a. In particular, the number of selected historical RRAs is reduced by the values a and d. A high threshold value means that elites focus only on historical cases that are very similar to the target risks, and a high value of the time coefficient d means that PMs focus only on recent historical cases. Therefore, the number of historical items as a reference for the target project is reduced so that the final effect of the risk response is reduced. It can also be seen that the effects of project risk response can be greater when more budget is allocated to it.

## 6. DISCUSSION

From the above analysis, it can be deduced that lower threshold values are effective to achieve better effects of project risk response. Under these conditions, the number of historically selected RRAs increases. Here, the cost incurred in the compatibility process is defined as the cost of compatibility. In practice, some additional work such as obtaining additional information and expert advice may be required when matching recovered historical RRAs. Therefore, the cost of human resources and other financial resources must be considered in the compatibility process. Since the total budget for project risk response is fixed, the budget allocated to the implementation of RRAs is reduced due to increased compatibility costs, and then the effect of the total project risk response may be reduced. In addition, the PSO algorithm has the ability to use random values in addition to selected RRAs.

## 7. CONCLUSION

Choosing the right RRA is critical to the success of PRM. The proposed method provides decision support for PMs during the RRA selection process in PRM. Compared to the existing RRA selection methods, the proposed method has two contributions to this study. First, the case-based method and the optimization method are integrated to support the decision in the project risk response. Alternative RRAs can be obtained using the case-based method. While the optimal set of RRAs with the optimization model is selected more than other options. Second, the fuzzy set theory is used to assess risk probability, risk impact, and similarity between risks in the RRA selection process. This allows elites and professionals to make assessments with linguistic terms, which is more appropriate for human understanding in real-world situations. Third, in addition to selected samples, random samples can be used in optimization to reduce costs.

Some managerial suggestions and implications can also be drawn. First, to perform better risk response in the future, organizations should always capture a long-term perspective, with an awareness of keeping documents of all handled historical projects. Integrating knowledge management and the PRM process will help elites to some extent. A knowledge management system can be set up to monitor project risk and profile, and this ultimately provides decision support by providing risks and RRAs that may affect project risk based on previous reports. Second, relatively low thresholds may incur significant compatibility costs regarding recovery RRAs. Therefore, the RRA implementation budget may not be sufficient and the effect of the project risk response may be reduced. But if the thresholds are set to large values, few or no RRA options are displayed. Therefore, in order to achieve the maximum effect of risk response in a limited budget, the elites must voluntarily set reasonable thresholds and consider the exchanges between the budget for RRA implementation and the historical adaptation of RRA. Also, choosing random options in these situations can help reduce costs significantly.

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