**Research and development project risk assessment using a belief rule-based system with random subspaces**

Ying Yang a,b\*, Jun Wang a, Gang Wang a,b, Yu-Wang Chenc

a. School of Management, Hefei University of Technology, Hefei 230009, China

b. Key Laboratory of Process Optimization and Intelligent Decision-making, Ministry of Education, Hefei, China

c. Alliance Manchester Business School, The University of Manchester, Manchester M15 6PB, UK

\*Corresponding author: Ying Yang. Email: hfyyonline@126.com

**Abstract:** Research and development (R&D) project risk assessment mainly focuses on predicting the likelihood of project success and effectively controlling risks. The belief rule-based (BRB) inference method has been applied for risk assessment, due to its strong interpretability and high prediction accuracy. However, lots of risk factors related to R&D projects will lead to an oversized rule base when the standard BRB method is used to evaluate project performance. In this research, a novel predictive evaluation framework is proposed to address this issue, where a RS-BRB model, namely the BRB with random subspaces, is developed to assess R&D project risks in a modular way. Firstly, multiple subspaces with low attribute dimensions are constructed by random sampling. Subsequently, a BRB subsystem is developed as a base learner in each subspace to obtain a prediction result, and the evidential reasoning rule is adopted to combine the prediction results from different BRB subsystems. The proposed model was validated using the data from R&D projects in Chinese industries. Comparative analysis results show that the proposed model has superior prediction accuracy and can overcome the problem of combinational explosions without the information loss of project risks.

**Keywords:** Project risk assessment; Random subspaces; Belief rule-based systems; Evidential reasoning rule

# 1 Introduction

Decision makers in research and development (R&D) project management need to manage various risks for the continuous improvement of performance. R&D projects are imperative for companies to achieve sustainable competitive advantages. Today’s ever-changing and highly uncertain environment makes R&D activities core elements in determining corporate status (Mohagheghi et al., 2017). However, R&D projects tend to be delayed and overrun easily, due to their characteristics of large investment, long lifecycle and high uncertainty (Mishra et al., 2016). R&D project success is threatened by lots of risk events, including external market uncertainty, internal project complexity, and so on (Mohagheghi et al., 2017). Successful projects are always those projects where risks can be estimated and effectively controlled (Fan and Yu, 2004). Therefore, how to assess R&D project risks and predict the likelihood of project success effectively is a very important issue in risk management.

To effectively assess project risks, many prediction methods have been proposed in the past decades. These methods can be divided into two categories including statistical methods and artificial intelligence methods. The statistical methods mainly include multiple regression analysis (MRA), logistic regression (LR) and structural equation modeling (SEM). Thitima et al. (2015) used multiple LR to predict risk factors of software development projects. Du et al. (2009) developed a structural equation model to predict the project success of uncertain international construction projects. Meanwhile, the artificial intelligence methods have been used for predicting project performance, such as artificial neural networks (ANNs), adaptive neuro-fuzzy inference system (ANFIS), Bayesian networks (BNs) and the belief rule-based (BRB) method. The ANN has outperformed the MRA method in modelling bridge risks with a black box, while the ANFIS has demonstrated an even more effective performance (Wang and Elhag 2007; 2008). In order to model the risks transparently, the BN is used to model the complex relationships among risks and predict project performance (Hu et al., 2013; Yet et al., 2016; Sharma and Chanda, 2017). Meanwhile, the BRB method is recently developed for risk assessment because of its strong interpretability and high prediction accuracy (Yang et al., 2017a). Since the BRB method may result in combinatorial explosion issues when there are a large number of attributes. Several strategies of dimensional reduction have also been proposed to overcome the challenge by reducing the number of rules (Zhou et al., 2010; Wang et al., 2016; Yang et al., 2016; Yang et al., 2017b) or attributes (Yang et al., 2012; Chang et al.,2014; Yang et al. 2016). However, the reduction of either attributes or rules may cause much information loss so that some risks might be neglected and the likelihood of project success cannot be effectively predicted.

In this research, we aim to develop an improved BRB method to overcome the combinatorial explosion and enhance the prediction accuracy of R&D project performance. A random subspace (RS) method is integrated with the BRB for reducing attribute dimensionality. It is a kind of ensemble learning method (Ho, 1998) and commonly used in machine learning for combining different models (Wang et al., 2018). We developed a predictive evaluation framework for project risk assessment using the BRB and RS methods. In the framework, multiple subspaces with low dimensions are constructed by random sampling, a BRB subsystem is developed in each subspace, and the prediction results of BRB subsystems are combined by the evidential reasoning (ER) rule. A RS-BRB model, namely the BRB with random subspaces, is developed based on the framework for modelling R&D project risks. A case study revealed that the proposed model has high prediction accuracy and can be used to assess project risks effectively.

This study makes two important contributions: (1) we proposed a novel framework combining the RS and BRB method for R&D project risk assessment. The ER rule is used as a new ensemble strategy in the proposed framework to combine different prediction results of BRB subsystems. When there are many risk factors related to R&D projects, the proposed framework can overcome combinatorial explosions and avoid the loss of information. (2) we developed an R&D project risk assessment model based on the framework and conducted a case study on the data from 169 R&D projects in Chinese industries. Experiment results show that the proposed model has superior prediction performance in R&D project assessment compared with other methods.

The rest of the paper is organized as follows. Related research is reviewed in Section 2. A RS-BRB framework including generating random subspaces, constructing BRB subsystems, and combining results is developed in Section 3. Then the proposed RS-BRB model is validated by a case study in predicting R&D project performance in Section 4. Comparative experiments are presented in Section 5. Finally, conclusions and further research are provided in Section 6.

# 2 Literature review

 Project risk management is a key practice in project management to ensure the achievement of project objectives. It is an iterative process including risk identification, risk assessment, risk response, risk monitoring and controlling (Boehm, 1989). Risk assessment is an important component in risk management. The purpose of risk assessment is to quantify uncertain risk events, and obtain the probability of various risk events and their impact on project objectives (Karimiazari et al., 2011).

Statistical methods are adopted commonly and traditionally for analyzing the relationships among risk factors and evaluating project risks. Thitima et al. (2015) combined factor analysis with logistic regression to predict the success probability of a software development project. Mir and Pinnington (2014) used bivariate correlation and multiple regression analysis to study the relationships between project management performance and project success. Du et al. (2009) employed a structural equation model to predict the project success of international construction projects.

Meanwhile, artificial intelligence methods have been proposed for intelligent risk analysis. Wang and Elhag (2007) developed an ANN to model bridge risks. Oliveira et al. (2013) developed a novel ANN to model the non-linear relationships between leadership and project performance. However, ANN is a black box and its reasoning process is not easy to interpret, Wang and Elhag (2008) further developed an ANFIS model for bridge risk assessment using if-then rules and found that ANFIS performs better than ANN and MRA in the case study. Meanwhile, the Bayesian network, as a graphical network based on probabilistic reasoning, is also widely used in risk assessment. Hu et al. (2013) proposed a BN model with causality constraints for the risk analysis of software development projects to achieve effective risk control. Yet et al. (2016) designed a Bayesian network framework for project cost, benefit and risk analysis. Sharma and Chanda (2017) developed a risk quantification model based on Bayesian belief networks to capture the interaction between various risk factors effectively and predict the probability of failure risk of R&D projects.

Recently, another transparent model, the BRB method has been applied in the area of risk assessment, due to its capability in dealing with complex reasoning problems under uncertainty. For example, Tang et al. (2011) used the BRB method to model the risks involved in the new product development process. Yang et al. (2017a) developed a disjunctive belief rule-based expert system to model bridge risks and proposed an improved differential evolution algorithm to train the parameters of BRB systems. Qiu et al. (2018) extended belief rule-based expert systems and proposed a valuation-based system for risk assessment.

Using the BRB method for risk assessment may incur an oversized rule base when there are lots of risk factors in the R&D projects. The oversized rule base will lead to the problems of overfitting (Zhou et al., 2010) and combinatorial explosion (Chang et al., 2014). To overcome the challenges, several kinds of approaches have been proposed in previous studies. One kind of approaches is reducing the number of rules. Zhou et al. (2010) proposed a sequential learning algorithm for constructing a compact BRB system online. Wang et al. (2016) applied the density and error analysis to adjust the belief rule base by dynamically pruning or adding rules. Yang et al. (2016) proposed a multi-attribute search framework to reconstruct the relationship among rules. Yang et al. (2017b) introduced the data envelopment analysis (DEA) to evaluate the efficiency of each rule to downsize belief rule bases. Another kind of approaches is reducing the number of attributes. Yang et al. (2012) used two or three principal components instead of all original attributes to forecast customer performance. Chang et al. (2014) also applied principal component analysis to transform antecedent attributes into several principal components in a new space. Yang et al. (2016) incorporated factor analysis into BRB expert systems and created two new factors from all antecedent attributes to construct a belief rule base.

# 3 The RS-BRB model for project risk assessment

The BRB method can be applied for R&D project risk assessment due to its strong interpretability and high prediction accuracy. However, the challenge of combinatorial explosion should be solved (Chang et al., 2016). Therefore, a novel framework for R&D project risk assessment is proposed in this research, called RS-BRB. The RS-BRB framework consists of multiple BRB systems generated independently in random subspaces. Fig.1 shows the three procedures of the RS-BRB framework, which includes generating random subspaces, constructing BRB subsystems, and combining the results using the ER rule. With random subspaces, multiple subspaces can be constructed with low attribute dimensions by random sampling and the traditional BRB system can be regarded as a base learner in each subspace to obtain a set of prediction results. The final result is obtained through the combination results of all relevant subspaces.



Fig.1 The RS-BRB framework for project risk assessment

## 3.1 Generating random subspaces

The random subspace method is applied to downsize the rule base and avoid information loss. Generating multiple subspaces from an original dataset depends on three important parameters, including the number of attributes *r* in a subspace, the number of subspaces *s*, and the attribute weight *w* that affects the extraction probability of features. Fig.1 shows the process of the generation of subspaces.

 The attribute weight *w* can be calculated using the information gain (IG) of features in the sample data. Suppose that a feature variable *F* is related to a result variable *Y*. The IG is a common indicator which can measure how much information the feature *F* can bring to the result *Y*. The IG value of the feature *F* can be calculated as:

 (1)

 (2)

 (3)

 is the entropy of the variable *Y*. is the entropy of the variable *Y* after adding the feature *F*. is the marginal probability density function of the variable *Y*. is the conditional probability function of *Y* given *F*. Therefore, the information gain refers to the amount of entropy decreased when the feature *F* is added and measures the contribution of the feature*.*

After the calculation of the attribute weight *w*, a set of attribute subspaces can be randomly generated according to the parameter *w* and *r*. That is, *r* attributes are randomly extracted while the attribute weight *w* is the extraction probability in the process of forming a subspace. Therefore, the important attributes are most likely to be extracted in the subset generation process.

## 3.2 Constructing BRB subsystems for risk assessment

After the generation of random subspaces, the BRB subsystem can be constructed in each subspace to predict project performance independently. The inference process in BRB subsystems is described in Fig.2.



Fig.2. The inference learning process of BRB subsystems

### 3.2.1 Risk modelling in a BRB subsystem

The causal relationship between risk factors and project performance can be described as a belief rule. Compared with traditional rules, the belief rule extends knowledge representation using a belief structure with belief degrees embedded in all possible consequents in a rule. It is very flexible and conforms to reality so that it can precisely imitate human reasoning processes (Yang et al., 2006). Risk factors are regarded as antecedent attributes and project performance is a consequent. The causal relationships are represented as a belief rule.

: If , then

with the rule weight () and the attribute weights . Here,  is the referential value of the *i*th antecedent attribute in the *k*th rule,*Tk* is the number of antecedent attributes used in the *k*th rule and *N* is the number of all possible consequences in the brief rule base. The rule represents that if the *i*th attribute matches the referential values , the result will be given to  with the belief degree .

### 3.2.2 Causal inference

After the establishment of the initial belief rule base, the following inference procedures are activated based on the rules. The rule activation weight (*k*=1, …, *L*) is the degree to which the packet antecedent *Ak* in the *k*th rule is activated by the inputs. It can be calculated as:

 (11)

Here is the relative weight of the *k*th rule. is the total degree of the input matching the packet attribute referential values in the *k*th rule. It can be described as:

 (12)

Here

 (13)

Here is the attribute weight representing the relative importance of the *i*th attribute in the *k*th rule. *Tk* is the number of attributes in the *k*th rule and *L* is the number of belief rules in a BRB subsystem.

 Then the analytical ER algorithm is used to aggregate the activated rules with uncertain consequents (Wang et al., 2006). The final aggregation result is represented by , (*j* = 1, …, *N*).It represents the final combined belief degree associated with the corresponding consequent (*j* =1, …, *N*). The analytic ER algorithm is given as follows:

 (14)

Here

 (15)

Here, is the original belief degree to which is believed to be the consequent in the *k*th rule, and is the activation weight of the *k*th rule.

### 3.2.3 Parameter initialization

Generally speaking, the initial values of parameters, including the belief degree and the rule weight in a belief rule base, are often set by domain experts. Since the subsets are randomly generated, it is lack of operability for domain experts to set rule bases and parameters for each random subset. Therefore, a statistical method based on historical data is proposed in this study. The initial belief degrees and rule weights are obtained through the statistical method.

(1) The initial belief degrees

The referential values for both attributes and consequents are initialized before the determination of initial belief degrees. Then the relationship between attributes and consequents can be transformed into the relationships between the referential values of risk factors and project performance . Suppose a specific value of the *i*th antecedent attribute can be transformed into a similarity distribution about the referential value .

 (4)

Here

 (5)

Here,represents the similarity degree to which the *i*th antecedent attribute matches the referential value . is the number of the referential points used for describing the *i*th antecedent attribute.

Table 1

The rule matching degrees

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | … |  | … |  |
|  |  | … |  | … |  |
| … | … | … | … | … | … |
|  |  | … |  | … |  |
| … | … | … | … | … | … |
|  |  | … |  | … |  |

Table 2

The initial belief degrees in rule bases

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | … |  | … |  |
|  |  | … |  | … |  |
| … | … | … | … | … | … |
|  |  | … |  | … |  |
| … | … | … | … | … | … |
|  |  | … |  | … |  |

For each sample, if the input match the referential values of packet antecedent attributes,,… in the *k*th rule with the similarity degree ,,…,the rule matching degree between input and the *k*th rule can be calculated as:

 (6)

Here

 (7)

Here, when the *j*th referential value of the *i*th attribute contained in the *k*th rule, takes 1, otherwise it is zero. Table 1 shows the statistical result of rule matching degrees using all samples. Here, is the sum of the rule matching degrees of samples *S* whose inputs match the *k*th rule and belong to . can be calculated as:

 (8)

 Table 2 shows a belief matrix for characterizing the relationship between the rule and result. is the belief degree to which is believed to be the consequence in the *k*th rule. It can be calculated as:

 (9)

(2) The initial rule weights

The rule weights can be obtained according to the information entropy (IE), which is commonly used for measuring uncertain information. It measures the amount of information that an unknown event may contain (Zadeh, 2005; Wu et al., 2007). For each rule, the distribution of belief degrees can reflect the amount of information that a rule provided for predicting project performance. If the belief degrees of a rule are very even or equally balanced, it means that the prediction result obtained through this rule is indeterminate and fuzzy. It means that the *IE* value of the rule is high. Therefore, the higher the *IE* value of the result distribution in a rule is, the smaller the weight of the rule is. The rule weight can be calculated as:

 (10)

### 3.2.4 Parameter learning

The knowledge representation parameters in this prediction model, such as the rule weight , the attribute weight and the belief degree, are initially obtained through simple statistics of historical data. They can be improved by data learning from a training process.

For each input-output pair ()() in the training set, the BRB subsystem reference output is .The project performance from the BRB subsystem can be calculated as:

 (16)

Here, is the utility of consequents. An optimal learning model is developed to find the best parameters of attribute weight , the rule weight and the belief degree with a nonlinear minimization method for minimizing the difference between the observed project performance and the predicted one .The optional learning model is represented as follows:

 (17)

When the is minimized, the set of parameters, and are believed to be the best values in their own subsets.

## 3.3 Combining the results of BRB subsystems

Different BRB subsystems can provide some complementary knowledge. An ensemble system can take advantage of such complementarity to improve the prediction accuracy. While the classification result of each BRB subsystem may be uncertain due to the limitation of attributes, the evidential reasoning rule proposed by Yang et al. (2013) is adopted to combine the results from different subspaces.

The evidential reasoning rule can combine multiple pieces of independent evidence conjunctively with weights and reliabilities. Since multiple BRB subsystems are independently reasoned and optimized in their own subsets, their outputs are independent of each other. The prediction result of each BRB subsystem can be regarded as a piece of evidence. The reliability of evidence represents the inherent property of information sources and its weight describes the relative importance in comparison with other evidence (Yang et al., 2013). The BRB subsystems in the RS-BRB model may have different reliabilities since they usually have different prediction abilities. The weight of each subsystem can also be determined by the prediction accuracy of each subsystem (Liu et al., 2018). In this research, it can be assumed that the evidence with high reliability should be of relatively high importance in comparison to other evidence. Thus the weight and reliability of the evidence can be set to the same value, that is, the prediction accuracy of the subsystem. Then the ER rule can be used as an efficient tool to combine the different classification results generated from multiple BRB subsystems.

Suppose that there are *S* results which are from *S* independent BRB subsystems and each result has *N* consequents { which are a set of mutually exclusive and collectively exhaustive hypotheses donated as Θ. The power set of Θ consists of all its subsets, denoted by P(Θ). A piece of evidence from a BRB subsystem is profiled by a belief distribution as:

 (18)

Here is an element of evidence , representing that the evidence points to proposition with the probability degree . With the reliability and weight of evidence into consideration, a so-called weighted belief distribution with reliability can be defined as:

 (19)

Here represents the degree of support for from considering both the weight and reliability of , defined as:

 (20)

Here ,is a normalization factor. The combined belief degree to which jointly support can be obtained by the ER rule as:

 (21)

 (22)

Here, represents the first *s* pieces of evidence. For each input , the final output, that is project performance, can be calculated as:

 (23)

# 4 Case study

To validate the proposed RS-BRB model, we collected data on 169 R&D projects in a survey. The questionnaires were filled out bytop managers, departmental managers and project managers in Chinese industry. Comparative analysis is conducted among the existing BRB models and conventional approaches used to predict project performance. We use the mean absolute percentage error (MAPE) and root mean square error (RMSE) to describe the difference between the prediction output and the real output for the same input to test the validity of the proposed RS-BRB method.

## 4.1 Data description and evaluation criteria

There are many risks that may affect the success of R&D projects. It is very challenging to predict the likelihood of R&D project success. In this study, thirteen risk factors including project manager competency(*PMC*), project termination quality (*PTQ*), formalization of portfolio management(*FPM*), top management involvement(*TMI*), strategic consistency(*SC*), business cooperation(*BC*), market uncertainty(*MU*), technology uncertainty(*TU*), company sales growth(*CSG*), average net profit(*ANP*), project success rate (*PS*), company scales (*CS*) and the number of ongoing projects (*NOP*) are used to predict the likelihood of R&D project success. The specific meanings of these attributes are defined in Table 3.

Table 3 The definition of variables

|  |  |
| --- | --- |
| Risks | Explanation |
| PMC | The competency of project managers in R&D project management |
| PTQ | The quality of a process for terminating a project that do not meet company expectations |
| FPM | The formalization of the process of project portfolio management |
| TMI | Top managers’ participation and contribution in R&D projects |
| SC | The conformity between company strategy goals and project objectives |
| BC | The effectiveness of information transfer and exchange among project-related organizations  |
| MU | The uncertainty in the market environment |
| TU | The uncertainty in the technological environment outside an organization |
| CSG | The average sales growth rate in the past three years  |
| ANP | The condition of average net profit in the past three years  |
| PS | The success rate of R&D projects in the past three years |
| CS | Company scales |
| NOP | The number of ongoing projects in a company  |

 The project performance (*PP*) is regarded as the consequent that can be measured by the project development time, quality, cost and achievement of expected objectives.

These research attributes and consequent are qualitative and cannot be observed directly. According to prior literature research, their measurement indicators are designed and a survey was conducted to collect sample data. Each measurement indicator is measured by Likert-5 scales (1= extremely inconformity, 5= extremely conformity). The final value of each variable is obtained by averaging the answers of its corresponding indicators.

Some criteria have been widely used in previous literature to evaluate the performance of a prediction model (Wang and Elhag, 2007). MAPE is used to measure the prediction performance and the RMSE is used to measure the deviation between an observed value and a true value. The smallest MAPE and RMSE are considered to be the best level for the prediction of project performance. These criteria are defined as:

 (24)

 (25)

## 4.2 Model development

### 4.2.1 Referential points

The values of antecedent attributes and consequents used for modelling R&D project risks in this study are continuous. An unsupervised equal frequency discretization method is used for data preparation here. All data is categorized into three classes with equal frequency of 33.3%. The referential values of thirteen attributes and consequents are discretized into three levels, such as low(L), medium (M) and high(H), as shown in Table 4.

Table 4 Referential points of the antecedent attributes and consequent

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Level | PMC | PTP | FPM | TMI | SC | BC | MU | TU | CSG | ANP | PS | CS | NOP | PP |
| Low | 3.6 | 3.2 | 3.75 | 3.57 | 3.4 | 3.33 | 3.2 | 3.5 | 3 | 3 | 3 | 3 | 3 | 3.5 |
| Medium | 4.2 | 3.8 | 4.25 | 4.14 | 4 | 4 | 3.8 | 4.25 | 4 | 4 | 4 | 4 | 4 | 4 |
| High | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 | 5 |

For each antecedent attribute, three referential values, as shown in Table 4, are used to establish the belief rule base, that is

  For the consequent *PP*, three referential values are also set to calculate initial belief degrees together with referential values and project performance. The referential values of the consequent are set as

And the utilities of the three referential value of consequence are set as:

### 4.2.2 Subspace parameters

When generating random subspaces, the number of subspaces and the number of attributes in each subspace are two important parameters for ensemble learning. Previous studies have showed that around ten classifiers in ensemble learning can achieve a balance between classification accuracy and calculation efficiency. Therefore, we also generated ten subspaces for experiments and compared the fusion results of ten BRB systems with those of five and fifteen BRB systems.

The number of attributes used in each subspace determines the size of BRB subsystems in the subspace. According to previous studies, when the number of attributes in a subspace is 3 or 4, the calculation efficiency and the prediction accuracy of the BRB model can be effectively balanced. Therefore, we use three and four attributes to establish two comparative models respectively which are called RS-BRB-r3 and RS-BRB-r4.

The attribute weights are obtained by calculating the information gain of attributes. The IG values of the thirteen attributes can be calculated from the formula (1) ~ (3). Take calculating the IG value of the attribute PMC, IG (PP, PMC) as an example. The variable *PP* and *PMC* have been discretized into three categories: low (L), medium (M) and high (H). The marginal probability density function of the variable *PP* is represented by and the conditional probability of *PP* given *PMC* are The attribute weight can be obtained by normalizing the IG values of all attributes, as shown in Table 5.

Table 5 Weights and IG values of thirteen attributes

|  |  |  |
| --- | --- | --- |
| Attributes | IG values  | Weights |
| PMC | 0.8411 | 0.1019 |
| PTQ | 1.0468 | 0.1268 |
| FPM | 0.7603 | 0.0921 |
| TMI | 1.0648 | 0.1290 |
| SC | 0.8921 | 0.1081 |
| BC | 0.7853 | 0.0951 |
| MU | 0.9464 | 0.1147 |
| TU | 0.6393 | 0.0775 |
| CSG | 0.3316 | 0.0402 |
| ANP | 0.3295 | 0.0399 |
| PS | 0.2774 | 0.0336 |
| CS | 0.2048 | 0.0248 |
| NOP | 0.1339 | 0.0162 |

### 4.2.3 Experiment procedures and results

The ten-fold cross-validation is used in this study to reduce contingency. The experiment process is outlined by the following steps and implemented in the software package of MATLAB 2016a.

**Step 1:** Splitting data into a training set and a test set

All samples were randomly divided into ten parts with the same sizes. The collection of nine parts was used as training data and the rest one was used as testing data. By repeating this step, each part was used as testing data once.

**Step 2:** Generating random subspaces

According to the weights of antecedent attributes which are calculated with the *IG* value and the number of attributes in each subspace, 5/10/15 subsets were randomly generated with three or four attributes, respectively.

**Step 3:** Obtaining results from different BRB subsystems

A BRB subsystem is automatically created according to the attributes selected for each subspace. The initial brief degrees and rule weights were independently calculated through the way in the proposed method in their own subsets. The initial attribute weights are calculated with IG from all datasets. For example, if there is a subset with the attributes of *PMC*, *PTP* and *FPM*, the initial BRB subsystem can be developed based on the three attributes, as shown in Table 6.

Table 6 The initial BRB subsystem with the features of PMC, PTQ and FPM

|  |  |  |  |
| --- | --- | --- | --- |
| Rule | Ruleweight | Antecedent attributes (attribute weights) | Consequent (utility values) |
|  | PMC(0.1019) | PTP(0.1268) | FPM(0.0921) | Low(3.5) | Medium(4) | High(5) |
| 1 | 0.5987  | Low(3.6) | Low(3.2) | Low(3.75) | 0.5562  | 0.3925  | 0.0513  |
| 2 | 0.5536  | Low(3.6) | Low(3.2) | Med(4.25) | 0.3638  | 0.5464  | 0.0899  |
| 3 | 0.5487  | Low(3.6) | Low(3.2) | High(5) | 0.2838  | 0.5946  | 0.1216  |
| 4 | 0.5576  | Low(3.6) | Med(3.8) | Low(3.75) | 0.3132  | 0.5860  | 0.1008  |
| 5 | 0.5249  | Low(3.6) | Med(3.8) | Med(4.25) | 0.2356  | 0.5832  | 0.1811  |
| 6 | 0.7954  | Low(3.6) | Med(3.8) | High(5) | 0.0000  | 0.6667  | 0.3333  |
| 7 | 1.0000  | Low(3.6) | High(5) | Low(3.75) | 0.0000  | 0.7957  | 0.2043  |
| 8 | 0.8145  | Low(3.6) | High(5) | Med(4.25) | 0.0000  | 0.6869  | 0.3131  |
| 9 | 0.9869  | Low(3.6) | High(5) | High(5) | 0.0000  | 0.7907  | 0.2093  |
| 10 | 0.4942  | Med(4.2) | Low(3.2) | Low(3.75) | 0.2701  | 0.5165  | 0.2134  |
| 11 | 0.5192  | Med(4.2) | Low(3.2) | Med(4.25) | 0.2205  | 0.5760  | 0.2036  |
| 12 | 0.4710  | Med(4.2) | Low(3.2) | High(5) | 0.2351  | 0.3684  | 0.3965  |
| 13 | 0.5169  | Med(4.2) | Med(3.8) | Low(3.75) | 0.1714  | 0.5607  | 0.2679  |
| 14 | 0.5679  | Med(4.2) | Med(3.8) | Med(4.25) | 0.0836  | 0.5769  | 0.3396  |
| 15 | 0.7330  | Med(4.2) | Med(3.8) | High(5) | 0.0000  | 0.4653  | 0.5347  |
| 16 | 0.6512  | Med(4.2) | High(5) | Low(3.75) | 0.0773  | 0.7039  | 0.2189  |
| 17 | 0.6188  | Med(4.2) | High(5) | Med(4.25) | 0.0392  | 0.4009  | 0.5599  |
| 18 | 0.7929  | Med(4.2) | High(5) | High(5) | 0.0000  | 0.3363  | 0.6637  |
| 19 | 0.4839  | High(5) | Low(3.2) | Low(3.75) | 0.2550  | 0.4901  | 0.2550  |
| 20 | 0.5357  | High(5) | Low(3.2) | Med(4.25) | 0.2321  | 0.6000  | 0.1679  |
| 21 | 0.5499  | High(5) | Low(3.2) | High(5) | 0.1534  | 0.6196  | 0.2270  |
| 22 | 0.5563  | High(5) | Med(3.8) | Low(3.75) | 0.0851  | 0.5402  | 0.3747  |
| 23 | 0.6225  | High(5) | Med(3.8) | Med(4.25) | 0.0371  | 0.5595  | 0.4033  |
| 24 | 0.5960  | High(5) | Med(3.8) | High(5) | 0.0477  | 0.5087  | 0.4436  |
| 25 | 0.5543  | High(5) | High(5) | Low(3.75) | 0.0845  | 0.3873  | 0.5282  |
| 26 | 0.6199  | High(5) | High(5) | Med(4.25) | 0.0346  | 0.5187  | 0.4467  |
| 27 | 0.5690  | High(5) | High(5) | High(5) | 0.0656  | 0.4595  | 0.4748  |

Then, the activation weight of each rule can be calculated for each sample. The ER approach was used to combine the activated rules to generate the inference result. A training process is designed to minimize the difference between the real output and the BRB subsystem output to find a set of optimal parameters including rule weights, attribute weights and belief degrees for BRB subsystems. After training, we input the test set into the trained BRB subsystem to get the predict result of project performance. And the MAPE is used to measure the prediction performance and to calculate the reliability and weight of the evidence from each BRB subsystem. For example, subspaces are generated randomly on the condition that the number of random subspaces is ten and the number of attributes is three. The ten random subspaces with different risk factors and the prediction performance of the ten BRB subsystems are obtained from the ten-fold cross-validation, as shown in Table 7.

Table 7 Random subspaces and the prediction performance of subsystems

|  |  |  |
| --- | --- | --- |
| Subspaces | Attributes | MAPEs |
| RS 1 | PMC, PTQ, TMI | 0.1180 |
| RS 2 | PMC, PTQ, FPM | 0.1283 |
| RS 3 | PMC, SC, CSG | 0.1277 |
| RS 4 | SC, BC, CS | 0.1415 |
| RS 5 | TMI, SC, NOP | 0.1468 |
| RS 6 | PMC, PTQ, TU | 0.1386 |
| RS 7 | PTQ, TMI, ANP | 0.1248 |
| RS 8 | TMI, SC, MU | 0.1295 |
| RS 9 | FPM, TMI, BC | 0.1301 |
| RS 10 | TMI, SC, PS | 0.1198 |

**Step 4**: Combining results from different BRB subsystems.

Since the number of subspaces is set to be 5, 10 and 15, respectively, there are 5/10/15 prediction results from different BRB subsystems which can be considered as multiple pieces of evidence to be combined. The BRB subsystem output is achieved as:

Since the 1-MAPE value reflects the accuracy of the subsystem prediction, the reliability and weight of the evidence are set to be 1-MAPE equally as discussed in Section 3.3. The ER rule is used to combine the different results to get a final prediction result. Then the distribution is transformed to a value to get the system output.

 Moreover, the five-fold cross-validation is conducted for comparison. The experimental results of both five-fold and ten-fold cross-validation are shown in Table 8.

Table 8 Prediction performance of different RS-BRB systems

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | 5-fold | 10-fold |
| MAPE (%) | RMSE | MAPE (%) | RMSE |
| s5 | r3r4 | 14.2914.16 | 0.5928**0.5805** | 14.0315.08 | 0.57990.5240 |
| s10 | r3r4 | **14.10**14.42 | 0.58210.5977 | **13.73**14.44 | 0.5637**0.5092** |
| s15 | r3r4 | 14.6814.73 | 0.60950.6123 | **13.70**14.66 | 0.56770.5231 |

It is evident that the proposed method performs well in predicting project performance from the comprehensive view of both MAPE and RMSE indicators. The proposed models with different parameters produce different results. For example, the RS-BRB system with parameters *s10-r3* achieved the minimized MAPE value in ten-fold cross-validation, similar to the RS-BRB system with parameters *s15-r3*. And the minimized RMSE is obtained in the RS-BRB system with parameters *s10-r4* in the 10-fold cross validation.

Since the RS-BRB system with the parameters *s10-r3* achieved more accurate performance in both five-fold and ten-fold cross-validations from the overall trend. Therefore, we use the RS-BRB system with the parameters *s10-r3* for the comparative experiment below.

# 5 Comparative experiment

In order to further verify the effectiveness of the proposed model, the results derived from five-fold and ten-fold cross-validations are further compared with other models which are constructed using the same dataset for training and testing. The MAPE and RMSE under the five-fold and ten-fold cross-validations are used to compared the performance of different models.

## 5.1 Comparative models

First, the proposed RS-BRB model is compared with two existing BRB models which overcome combinatorial explosions from the aspect of attribute dimensions. One is the PCA-BRB model and the other is the FA-BRB model. The PCA-BRB model proposed by Chang et al. (2014) combines the traditional BRB method with principal component analysis (PCA). It transforms antecedent attributes into several principal components in a new space, and then selects the key antecedent attributes that contribute most to each principal component for constructing a belief rule base. In this study, three principal components are extracted from the experimental data in PCA. The loading matrix, denoted as matrix *M* , as shown in Table 9. Then the attributes PMC, CSG, ANP and NOP are selected as the key antecedent attributes to construct the BRB model to predict the project performance. Also, we developed the FA-BRB model which combines the traditional BRB method with factor analysis. Through factor analysis, new factors which are extracted from original attribute spaces are used to construct a belief rule base. The values of three new factors are calculated with the loading matrix as:

Table 9 Component loading matrix

|  |  |  |  |
| --- | --- | --- | --- |
|  | principal component 1 | principal component 2 | principal component 3 |
| PMC | **0.8052**  | 0.2469  | 0.0215  |
| PTQ | 0.6988  | 0.1571  | -0.1291  |
| FPM | 0.7430  | 0.1479  | -0.1328  |
| TMI | 0.7874  | 0.1915  | -0.0293  |
| SC | 0.6358  | 0.2836  | 0.1905  |
| BC | 0.6941  | 0.3326  | -0.1389  |
| MU | 0.5865  | -0.1185  | 0.3367  |
| TU | 0.6325  | -0.1421  | 0.4364  |
| CSG | 0.2186  | **0.8630**  | 0.0967  |
| ANP | 0.1697  | **0.8800**  | 0.0468  |
| PS | 0.4047  | 0.4226  | 0.4151  |
| PS | -0.0482  | 0.2066  | 0.5434  |
| NOP | -0.0853  | -0.0492  | 0.8476  |

Second, the proposed RS-BRB model is compared with four popular methods for risk assessment, including ANNs, ANFIS, BNs, and MRA. (1) The ANN is a computing system inspired by the biological neural networks (Gerven and Bohte, 2017). The relationships between 13 attributes and project performance are modelled as a three-layer back propagation neural network. The Hecht–Nelson method is used to determine the number of neurons in hidden layers to improve model performance (Ren et al., 2014). Thirteen input neurons, 27 hidden neurons and one output neuron constitute a network to predict project performance. (2) An ANFIS model is further developed for project risk analysis in comparative experiments. In order to avoid too many rules generated from these thirteen attributes, the PCA method is used for dimensionality reduction. Four attributes including PMC, CSG, ANP and NOP are selected as input nodes to build the ANFIS model. The model structure is developed using the fuzzy logic toolbox of MATLAB software, where the parameters are set in a similar way as in Wang and Elhag (2007). (3) The BN is a prevalent method to model risks and has been applied in lots of specific domains. We adopted the K2 algorithm to obtain the network structure in this experiment and then predicted project performance by parameter learning. (4) The MRA is a statistical method to model the relationship between a scalar response and one or more explanatory variables. It has been adopted in previous studies to predict risks (Wang and Elhag, 2007; Du et al. 2009; Mir and Pinnington, 2014).

Third, a random initialization method is compared with the proposed initialization method in the RS-BRB framework. Since a BRB system with different initialization methods can provide different results (Yang et al., 2016), a R-RS-BRB system is developed for comparison. It is a RS-BRB model with the random initialization method. The attributes weights, rule weights and belief degrees are randomly generated to construct an initial belief rule base in a subspace.

Last, different combination strategies are compared with the ER rule for combining the prediction results of multiple BRB subsystems. The combination of the different prediction results from base learners is an important part in ensemble learning, which can affect prediction accuracy (Liu et al., 2018). Two different combination methods, including average fusion (AF) and weighted average fusion (WAF), were compared with the ER rule in the proposed method. The AF-RS-BRB is a RS-BRB model with the average fusion method to combine different results from BRB subsystems. In the simple average fusion, the results obtained from different base learners are averaged to get the final result. The AF method can calculate as:. is the combination result with AF method and is the result of the *s*th BRB subsystem. The WAF-BRB is a RS-BRB model with the weighted average fusion to combine different results from BRB subsystems. The 1-MAPE values of BRB subsystems are taken as the weights and then normalized. The WAF method can calculate as is the combination result with the WAF method, is the result of the *s*th BRB subsystem and is the normalized weight of the *s*th BRB subsystem.

## 5.2 Result analysis

All the compared models are trained and tested using the same dataset. And the MAPE and RMSE are used to compare the performance of different models in both the five-fold and ten-fold cross-validations, respectively.

Table 9 Comparative results

|  |  |  |
| --- | --- | --- |
|  | 5-fold | 10-fold |
| MAPE (%) | RMSE | MAPE (%) | RMSE |
| RS-BRB | **14.18** | **0.5821** | **13.73** | **0.5737** |
| PCA-BRB | 16.47 | 0.6557 | 15.80 | 0.5968 |
| FA-BRB | 15.50 | 0.6173 | 15.60 | 0.6209 |
| ANNs | 15.77 | 0.6176 | 16.82 | 0.7423 |
| ANFIS | 15.33 | 0.7423 | 16.14 | 0.7401 |
| BNs | 16.02 | 0.6843 | 17.45 | 0.6965 |
| MRA | 17.91 | 0.7070 | 17.16 | 0.6107 |
| R-RS-BRB | 16.14 | 0.6841 | 15.85 | 0.6958 |
| AF-RS-BRB | 15.98 | 0.6352 | 15.01 | 0.6257 |
| WAF-RS-BRB | 15.46 | 0.6310 | 15.05 | 0.6143 |

It indicates that the proposed RS-BRB model produced satisfactory results compared with other methods. The size of a rule base depends on the number of antecedent attributes and the number of their referential values. Without random sampling, the thirteen factors and their reference values in this experiment would establish a large-scale rule base with 313=1,594,323 rules. In the proposed RS-BRB model, the number of attributes in a subspace is reduced to 3 or 4, that is, the number of rules is 33=27 or 34=81. The calculation efficiency is greatly improved while the prediction accuracy of the RS-BRB model is even slightly higher than other methods.

First, compared to other dimensionality reduction methods, such as PCA and FA, the proposed RS-BRB method integrated random subspaces into BRB to overcome combinatorial explosions and achieved better predictive performance. When using the PCA and FA method to reduce the dimension of attributes, a lot of information may be lost. When using the RS method to reduce the attribute dimensions and combine the results of subspaces, all of the attributes will be randomly selected to develop a BRB system. Therefore, the proposed RS-BRB method can avoid information loss and improve prediction accuracy. The prediction accuracy of the RS-BRB model is more than both the PCA-BRB and the FA-BRB model, which further proves the validity of combining the RS with BRB.

Second, compared to popular methods for project risk assessment, such as ANN, ANFIS, BN and MRA, the RS-BRB model achieves the best MAPE an RMSE whether in the five-fold cross-validation or ten-fold cross-validation. It further proves the effectiveness of the proposed model in risk assessment.

Next, we compared different initialization methods for BRB systems. Compared to a random initialization, the statistical initialization method proposed in this study is suitable for constructing an initial belief rule base for risk assessment. The proposed RS-BRB model has achieved great prediction performance than the R-RS-BRB model.

Last, we compared different combination strategies including AF and WAF with the ER rule adopted in this study. Experimental results show that the ER rule can achieve good results from the perspective of either MAPE or RMSE. It indicates that the ER rule can be a new and effective paradigm to combine different base learners. In summary, the proposed RS-BRB method is effective in project risk assessment and has great application potential.

# 6 Conclusions

Nowadays R&D projects are important for companies to enhance their competitiveness. Since the projects usually have long lifecycle, large investment and high uncertainty, risk assessment is very important in project management. To improve the prediction accuracy of the likelihood of project success, a novel predictive evaluation framework for R&D project risk assessment is proposed in this paper. A RS-BRB model is developed based on the framework to combines the random subspaces method in ensemble learning with the BRB. The proposed model can overcome the problem of oversized rule bases and effectively control R&D project risks to improve project performance.

A case study conducted in Chinese industries verified the effectiveness of the proposed model. Compared with other methods, including four popular risk assessment models, two traditional BRB models for attribute reduction, a random initialization method, and two fusion methods, the proposed RS-BRB model provides a better prediction performance while presenting the relationships between risk factors and project performance transparently.

Future work can be done in the following directions. Due to dynamic changes in the environment, it is necessary to take more project risk factors into consideration for modelling R&D project risks. The relationships between risk factors and project performance will become more complex, new causal modelling methods may be taken into consideration in each subspace. When combining different results from subspaces, the weight of each subsystems is set to be equal to its reliability in this study. Future research may focus on the determination of parameters in result fusion or the construction of random subspaces for subsystems.

# Acknowledgements

This research was supported by the National Nature Science Foundation of China (Nos. 71573071, 71571060, 71671057, 71771077, 71801108).

# References

Boehm B W. Software Risk Management[J]. IEEE Computer Society Press, Les Alamitos, CA, 1989, 14(3):17-19.

Chang L L, Li M J, Lu Y J, et al. Structure learning for belief rule base using principal component analysis[J]. Systems Engineering-Theory & Practice, 2014, 34(5):1297-1304.

Chang L, Zhou Z J, You Y, et al. Belief rule based expert system for classification problems with new rule activation and weight calculation procedures[J]. Information Sciences, 2016, 336(C):75-91.

Du Y K, Han S H, Kim H, et al. Structuring the prediction model of project performance for international construction projects: A comparative analysis[J]. Expert Systems with Applications, 2009, 36(2):1961-1971.

Fan C F, Yu Y C. BBN-based software project risk management[J]. Journal of Systems & Software, 2004, 73(2):193-203.

Gerven M V, Bohte S. Editorial: Artificial Neural Networks as Models of Neural Information Processing[J]. Frontiers in Computational Neuroscience, 2017, 11:1-2.

Ho T K. The random subspace method for constructing decision forests[J]. IEEE Transactions on Pattern Analysis & Machine Intelligence, 1998, 20(8):832-844.

Hu Y, Zhang X, Ngai E W T, et al. Software project risk analysis using Bayesian networks with causality constraints[J]. Decision Support Systems, 2013, 56(1):439-449.

Karimiazari A R, Mousavi N, Mousavi S F, et al. Risk assessment model selection in construction industry[J]. Expert Systems with Applications, 2011, 38(8):9105-9111.

Liu Z, Pan Q, Dezert J, et al. Combination of classifiers with optimal weight based on evidential reasoning[J]. IEEE Transactions on Fuzzy Systems, 2018, 26(3):1217-1230.

Mir F A, Pinnington A H. Exploring the value of project management: Linking Project Management Performance and Project Success[J]. International Journal of Project Management, 2014, 32(2):202-217.

Mishra A, Das S R, Murray J J. Risk, process maturity, and project performance: an empirical analysis of us federal government technology projects[J]. Production & Operations Management, 2016, 25(2):210-232.

Mohagheghi V, Mousavi S M, Vahdani B, et al. R&D project evaluation and project portfolio selection by a new interval type-2 fuzzy optimization approach[J]. Neural Computing & Applications, 2017, 28(12):3869-3888.

Oliveira M A D, Possamai O, Valentina L V O D, et al. Modeling the leadership – project performance relation: radial basis function, Gaussian and Kriging methods as alternatives to linear regression[J]. Expert Systems with Applications, 2013, 40(1):272-280.

Qiu S, Sallak M, Schön W, et al. A Valuation-Based System approach for risk assessment of belief rule-based expert systems[J]. Information Sciences, 2018,177:323-336.

Ren C, An N, Wang J, et al. Optimal parameters selection for BP neural network based on particle swarm optimization: A case study of wind speed forecasting[J]. Knowledge-Based Systems, 2014, 56:226-239.

Sharma S K, Chanda U. Developing a Bayesian belief network model for prediction of R&D project success[J]. Journal of Management Analytics, 2017, 4:321-344.

Tang D, Yang J B, Chin K S, et al. A methodology to generate a belief rule base for customer perception risk analysis in new product development[J]. Expert Systems with Applications, 2011, 38(5):5373-5383.

Thitima C, Pongpisit W, Somchai P, et al. Prediction of risk factors of software development project by using multiple logistic regression[J]. ARPN Journal of Engineering and Applied Sciences,2015, 10(3):1324-1331.

Wang G, Chen G, Chu Y. A new random subspace method incorporating sentiment and textual information for financial distress prediction[J]. Electronic Commerce Research & Applications, 2018, 29:30-49.

Wang Y M , Elhag T M S . An adaptive neuro-fuzzy inference system for bridge risk assessment[J]. Expert Systems with Applications, 2008, 34(4):3099-3106.

Wang Y M, Elhag T M S. A comparison of neural network, evidential reasoning and multiple regression analysis in modelling bridge risks [J]. Expert Systems with Applications, 2007, 32(2):336-348.

Wang Y M , Yang J B , Xu D L . Environmental impact assessment using the evidential reasoning approach[J]. European Journal of Operational Research, 2006, 174(3):1885-1913.

Wang Y M, Yang L H, Fu Y G, et al. Dynamic rule adjustment approach for optimizing belief rule-base expert system[J]. Knowledge-Based Systems, 2016, 96(C):40-60.

Wu D, Mendel J M. Uncertainty measures for interval type-2 fuzzy sets[J]. Information Sciences, 2007, 177(23):5378-5393.

Yang J B, Liu J, Wang J, et al. Belief rule-base inference methodology using the evidential reasoning Approach-RIMER[J]. IEEE Transactions on Systems Man & Cybernetics Part A Systems & Humans, 2006, 36(2):266-285.

Yang J B, Wang Y M, Xu D L, et al. Belief rule-based methodology for mapping consumer preferences and setting product targets[J]. Expert Systems with Applications, 2012, 39(5):4749-4759.

Yang J B, Xu D L. Evidential reasoning rule for evidence combination[J]. Artificial Intelligence, 2013, 205(205):1-29.

Yang L H, Wang Y M, Chang L L, et al. A Disjunctive Belief Rule-Based Expert System for Bridge Risk Assessment with Dynamic Parameter Optimization Model[J]. Computers & Industrial Engineering, 2017, 113:459-474.

Yang L H, Wang Y M, Lan Y X, et al. A data envelopment analysis (DEA)-based method for rule reduction in extended belief-rule-based systems[J]. Knowledge-Based Systems, 2017, 123(C):174-187.

Yang L H, Wang Y M, Su Q, et al. Multi-attribute Search Framework for Optimizing Extended Belief Rule-Based Systems[J]. Information Sciences, 2016, 370-371:159-183.

Yang Y, Fu C, Chen Y W, et al. A belief rule based expert system for predicting consumer preference in new product development[J]. Knowledge-Based Systems, 2016, 94(C):105-113.

Yet B, Constantinou A, Fenton N, et al. A Bayesian network framework for project cost, benefit and risk analysis with an agricultural development case study[J]. Expert Systems with Applications, 2016, 60(C):141-155.

Zadeh L A. Toward a generalized theory of uncertainty (GTU)––an outline[J]. Information Sciences, 2005, 172(1):1-40.

Zhou Z J, Hu C H, Yang J B, et al. A sequential learning algorithm for online constructing belief-rule-based systems[J]. Expert Systems with Applications, 2010, 37(2):1790-1799.