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Prediction of multiproject resource conflict risk via an artificial neural network

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Abstract

Purpose – Inadequate balancing of resources often results in resource conflict in the multiproject management process. Past research has focused on how to allocate a small amount of resources optimally but has scarcely explored how to foresee multiproject resource conflict risk in advance. The purpose of this study is to address this knowledge gap by developing a model to predict multiproject resource conflict risk.

Design/methodology/approach – A fuzzy comprehensive evaluation method is used to transform subjective judgments into quantitative information, based on which an evaluation index system for multiproject resource conflict risk that focuses on the interdependence of multiple project resources is proposed. An artificial neural network (ANN) model combined with this system is proposed to predict the comprehensive risk score that can describe the severity of risk.

Findings – Accurately predicting multiproject resource conflict risks in advance can reduce the risk to the organization and increase the probability of achieving the project objectives. The ANN model developed in this paper by the authors can capture the essential components of the underlying nonlinear relevance and is capable of predicting risk appropriately.

Originality/value – The authors explored the prediction of the risks associated with multiproject resource conflicts, which is important for improving the success rate of projects but has received limited attention in the past. The authors established an evaluation index system for these risks considering the interdependence among project resources to describe the underlying factors that contribute to resource conflict risks. The authors proposed an effective model to forecast the risk of multiproject resource conflicts using an ANN. The model can effectively predict complex phenomena with complicated and highly nonlinear performance functions and solve problems with many random variables.

Keywords Multiproject management, Resource conflict, Risk prediction, Artificial neural network

Paper type Research paper

1. Introduction

With the rapid development of projectification, organizations are facing many project-related challenges Because the projects have become more diversified, organizations are engaged in more than one project simultaneously. The parallel operation of multiple projects poses a huge challenge to the allocation and management of corporate funds, materials and human resources (Delisle 2020). However, traditional project management is not able to coordinate multiple projects effectively because it mainly focuses on the performance of individual projects (Chen *et al.*, 2019). As a result, multiproject management methods have been widely

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applied to help project managers systematically manage various projects with different scopes, complexities and timelines; this approach can deliver better benefits than those achieved when projects are managed independently (Yaghootkar and Gil 2012)

The competition for limited resources among projects is the uppermost characteristic of multiproject scenarios and may result in resource conflict risks. The multiproject context mainly refers to the interactions among projects, especially those produced by the sharing of common resources. Nevertheless, because resources are limited, the amount of resources allocated to each project may not meet the resource requirements of the project. Each project competes for resources to ensure the normal operation of the project to maximize its own interests, which often causes multiproject resource conflict problems. In order to avoid the risk of multiproject resource conflict, it is a need that requires the organization to constantly manage their resources and ensure the right balance between resource needs and its availability (Abrantes and Figueiredo 2015).

Accurately predicting multiproject resource conflict risks in advance can effectively reduce the risk to the organization and increase the probability of achieving the project objectives. By predicting unstable factors in advance, the risk monitoring information provided to managers can help them reduce the influence of uncertain factors on multiproject operations and further improve the emergency management capability of the organization. Unfortunately, resource conflict risk prediction is relatively uncommon. Previous studies focused on the rational scheduling of projects under resource constraints to achieve organizational goals (Beşikci *et al.*, 2015; Chen *et al.*, 2018; Zamani 2019). These studies assessed the prioritization of resource scheduling and proposed resource allocation schemes when multiproject resource conflicts occurred but did not monitor resource risk before the conflicts occurred.

Therefore, this study aims to develop a model to predict multiproject resource conflict risk. First, a comprehensive evaluation index system for multiproject resource conflict risk is constructed based on a literature review and interviews with experts. Then, to convert the characteristics of a risk event into quantitative risk values, risk evaluation is performed using the fuzzy comprehensive evaluation method that is suitable for systematically evaluating factors with nonlinear, multivariable and fuzzy correlations. Moreover, an artificial neural network (ANN) model is applied in the risk prediction process based on the converted data because of its excellent self-learning and self-adaptation characteristics, which make the risk prediction process highly scientific and justifiable. To prevent model overfitting, the dropout regularization method is implemented in the model training phase. Finally, the validity of the model is verified with data from actual cases.

The organization of the paper is as follows. The next section reviews the literature on risk assessment and risk management methods. Section 3 introduces the process of model construction, including the methods applied in each step. Section 4 presents the experimental results and assesses the validity of the model. Section 5 discusses the identified theoretical and practical implications.

2. Literature review

Project risk management (PRM) is an important task highlighted in the Project Management Body of Knowledge. In an ever-changing and high uncertainty project environment, risk management is an important component in achieving project objectives (Zhang and Fan 2014).

Previous research mainly focused on cost and schedule risks, which affect the performance of a project directly (Love *et al.*, 2015). Islam *et al.* (2019), for example, combined a fuzzy group decision-making approach and a fuzzy canonical model to propose a novel model that can overcome the complexity and uncertainty issues of the risk assessment process and used this model to evaluate the cost overrun risk of power plant projects. Gurcanli *et al.* (2015) considered safety management as an important component of cost analysis and presented a safety cost analysis model to estimate the safety costs and their distribution throughout a project. Yildiz *et al.* (2014) developed a knowledge-based cost risk mapping tool that considers the causality among interdependent cost overrun risk factors for the identification of risk paths and assessment of risk levels. For project schedule risk, Lu *et al.* (2019) considered the cooperative relationships between the client and vendors to propose a two-level schedule risk control model consisting of minimizing the schedule risk and maximizing the benefit of vendors. Ballesteros-pérez *et al.* (2019) stressed the importance of activity sensitivity to determine which activities could increase the risk of a project schedule delay and proposed a new method to evaluate the performance of activity sensitivity metrics. Hossen *et al.* (2015) combined an analytical hierarchy process and the relative importance index to develop a hybrid model that is able to qualitatively and quantitatively assess schedule risk. There have been many studies on the project cost and schedule risks. However, project resource, as a significant unstable factor in the project management process, has not been extensively considered.

Project resource are an important part of the project execution process (Fedyanin 2019). The competition and sharing of project resource among multiple projects is the core issue in the management of multiple projects (Jianyu *et al.*, 2018). How to allocate resources and improve project execution efficiency to reduce cost and period of project is an important issue in project management (Vanhoucke and Coelho 2019). Previous works provided significant insights in resource allocation and project scheduling under constrained resource. In resource constrained project scheduling problems, it is usually assumed that the project are static and known with certainty durations. Chen *et al.* (2016) presented a neighborhood search method for project scheduling scheme with fixed processing time and resource demand. However, in many cases in management practice, the project durations and resource requirements are uncertain (Herroelen and Leus 2005). The dynamic relationship between project completion time and resources affects the realization of project goals in the process of project execution (Coelho and Vanhoucke 2020). It is need to establish the resource allocation plan with the variable activity durations. Chakrabortty *et al.* (2017) representing activity durations as random variables, developed a robust optimization model to solve project scheduling problems with renewable resource requirements and uncertain activity durations. Song *et al.* (2021) introduced a novel resource-based sensitivity metric and proposed selection strategy of normal activity and parallel projects, respectively. Subulan (2020) concentrated on the fully uncertain, multi-objective and multimode resource of project scheduling problem, and presented an interval programming and chance constrained optimization-based hybrid solution approach. Although their significant contributions, the research mostly focus on the model construction of project resource allocation and the optimization of solving algorithms under resource-constrained conditions. It is hard to find some work on monitoring multiproject resource conflict risk status based on risk prediction perspective.

The method of study project risk are mainly divided into statistical methods and machine learning methods. Numerous statistical methods have been normally used to analyze the relationships among risk factors and evaluate project risks. For example, Liu *et al.* (2018) identified nine common safety risk factors for a metro construction project from questionnaire responses and used structural equation modeling to examine the causal relationships among the risk factors for metro safety. Fatemeh and Leila (2020) developed a fuzzy event tree model to evaluate the root causes of a project change and estimate the change occurrence probability. Nasirzadeh *et al.* (2019) presented a risk assessment framework that combines fault tree analysis and event tree analysis and used it to quantitatively assess building project risk severity.

Numerous statistical methods provide a unique advantage in the process of risk management (Acebes *et al.*, 2015). However, the application conditions of many methods are strict; notably, some methods require detailed quantitative information, and some methods cannot capture the relevant risk interaction relationships, which is limited to project risk analysis. With the rapid development of artificial intelligence (Wauters and Vanhoucke 2016), a large number of risk assessment methods based on machine learning have emerged. Due to the ability of machine learning tools to model real situations based on data characteristics, they can effectively overcome the above limitations (Wauters and Vanhoucke 2017).

ANNs have self-learning and self-adaptation characteristics and have the processing power to deal with multifeature samples and nonlinear fitting (Leshno *et al.*, 1993). ANNs have been applied in areas such as risk assessment (Jiang *et al.* 2013; Khashman 2010; Paltrinieri *et al.* 2019), cost prediction (Wang *et al.*, 2012) and project evaluation (Azadeh *et al.*, 2011). Jin (2010) adopted an ANN technique to construct a risk allocation decision-making model and trained the model by collecting data from industry-wide questionnaires. The results showed that the ANN model was satisfactory for risk allocation decision-making. Han (2015) presented an ANN model to predict the risk level of software projects. The advantages of the ANN were demonstrated by a comparison with the logistic regression method. ANNs can model the nonlinear interactions between input and output variables through various training algorithms without detailed information on the relationships between the input and output variables. The strong learning ability of ANNs makes them ideal for predicting complicated phenomena. As a consequence, multifeature analysis and the prediction of multiproject resource conflict risk using ANN techniques can add significant value to risk studies.

3. Methodology

This paper proposes a multiproject resource conflict risk prediction model. This section consists of three parts. First, an evaluation index system for multiproject resource conflict risk is established through a review of the previous literature. Second, by means of determining the comment sets and the weight of index, the overall risk value is calculated by fuzzy comprehensive evaluation. Third, by treating the evaluation indicators as risk characteristics, an ANN model is applied to predict risk. The entire framework is introduced in Figure 1.

3.1 Construction of the risk evaluation system

In the process of PRM, an essential prerequisite is to identify the risk factors and establish the risk evaluation system. For multiproject resource conflict risk, a general risk evaluation

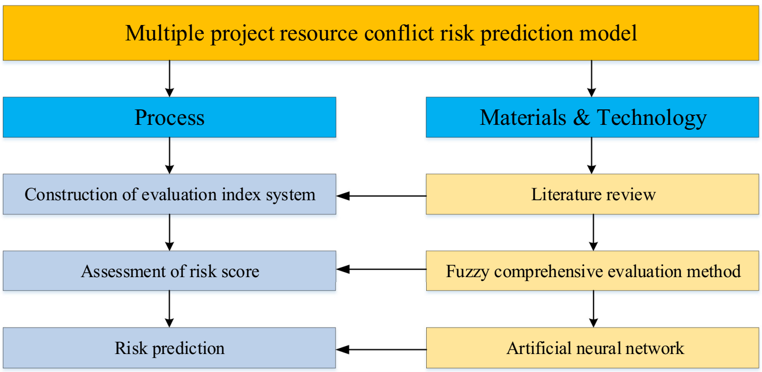

Figure 1.
Stepwise framework for the multiproject resource conflict risk prediction approach

system is not available. Thus, to systematically describe the risk of multiproject resource conflicts, a comprehensive risk evaluation system is constructed in this study considering the interdependence among the resources of the project. Based on the features of multiproject resource sharing, this risk evaluation system includes the risk factors that may result in resource conflicts from six perspectives: material, equipment, human, capital, time and organization resource perspectives. A total of 19 risk factors related to multiproject resource conflict were identified in a review literature and expert interviews, as shown in Table 1.

This indicator system collects the risk of resource conflicts that may occur during the implementation of multiple projects. Project managers can choose which risk indicators might affect the operation of their project. Not each risk must occur in the those project. For example, in a fully funded project, the probability of insufficient project funding U_{41} is extremely low or does not occur. Then project manager should ignore this indicator. The criterion layer and index layer constructed in this study are the basis of the whole evaluation system and could provide reference for the project managers. After the construction, the ANN will learn the risk characteristics of the project portfolio resource by inputting the risk data, and eventually accomplish the risk prediction.

3.2 Risk evaluation by fuzzy comprehensive evaluation

Fuzzy comprehensive evaluation (FCE), combined with fuzzy mathematical theory, is an evaluation model that comprehensively considers the influence of various constituent factors on complex variables (Zhang *et al.*, 2020). The primary function of this approach is to transform qualitative evaluations into quantitative evaluations according to the membership degree theory of fuzzy mathematics (Liu *et al.*, 2020). The advantage of FCE is that it can overcome the ambiguity of object evaluation and quantify some factors with unclear boundaries that are difficult to quantify (Wu and Hu 2020). FCE can be summarized in a series of steps, and the detailed explanation is given below.

Step 1: Develop the multilevel evaluation index system.

The first step in this method is to identify the factors that influence multiproject resource conflict risk and construct a risk factor set. A reasonable evaluation index system is the foundation of multiproject resource conflict risk evaluation. An evaluation index system usually consists of a target layer, a criteria layer and an index layer. Assuming the multiproject resource conflict risk evaluation index system is U, each element of U is a factor that affects the multiproject resource conflict risk.

$$U = \{U_1, U_2, \ldots, U_n\} \tag{1}$$

$$U_n = \{u_{n1}, u_{n2}, \ldots, u_{nm}\} \tag{2}$$

where U is the multiproject resource conflict risk index system; $U_1, U_2, \ldots, U_n$ are factors that affect the factor set U in the criteria layer; and $u_{n1}, u_{n2}, \ldots, u_{nm}$ are factors that affect the criteria U_n in the index layer. The index system is established in the first part of this section.

Step 2: Determine the evaluation criteria and ranks.

The second step in this approach is to establish a comment set. The comment set is a collection of all possible evaluation results for the evaluation object. It is assumed that k factors can influence the evaluation results.

$$V = \{v_1, v_2, \ldots, v_k\} \tag{3}$$

where v_i $(i = 1, 2, \ldots, k)$ is a possible evaluation result.

Criterion layer		Index layer	Reference
Multiproject resource conflict risk (R)	Material resources (U_1)	Inadequate material sharing among projects (U_{11})	Browning and Yassine (2010)
		Inferior quality of the materials shared among projects (U_{12})	Zhang (2016), Liu *et al.* (2017), Zhao *et al.* (2016)
		Unresponsive supply of shared materials among projects (U_{13})	Keshk *et al.* (2018), Nieto-Morote and Ruz-Vila (2011)
	Equipment resources (U_2)	Unreasonable equipment configuration among projects (U_{21})	Browning and Yassine (2010), Taylan *et al.* (2014)
		Inferior quality of the shared equipment among projects (U_{22})	Zhang (2016), Liu *et al.* (2017), Zhao *et al.* (2016)
		Insufficient supply of shared equipment among projects (U_{23})	Keshk *et al.* (2018), Nieto-Morote and Ruz-Vila (2011)
	Human resources (U_3)	Insufficient technical staff members (U_{31})	Hu *et al.* (2013), Qazi *et al.* (2016)
		Poor mobility of technicians among projects (U_{32})	Browning and Yassine (2010), Hofman and Grela (2015)
		Unreasonable staff configuration among projects (U_{33})	Elonen and Artto (2003), Romano *et al.* (2002)
	Capital recourses (U_4)	Insufficient project funding (U_{41})	Zhang (2016), Hofman and Grela (2015), Hofman *et al.* (2017)
		Unbalanced funding allocation for parallel projects (U_{42})	Zhang (2016), Hofman and Grela (2015)
		Cost increase during project implementation (U_{43})	Khodeir and Nabawy (2019), Qazi *et al.* (2016), Hofman *et al.* (2017)
		Poor funding liquidity among projects (U_{44})	Zhao *et al.* (2016)
	Time resources (U_5)	Project task time conflicts with the resource calendar (U_{51})	Zhao *et al.* (2016)
		The functions of key projects have not been achieved, resulting in the extension of the subsequent projects (U_{52})	Khodeir and Nabawy (2019), Zhang (2016), Liu *et al.* (2017), Taylan *et al.* (2014)
	Organization resources (U_6)	Inadequate technology sharing among projects (U_{61})	Romano *et al.* (2002), Keers and van Fenema (2018), Zhao *et al.* (2016)
		Inadequate information sharing among projects (U_{62})	Keers and van Fenema (2018), Qazi *et al.* (2016), Taylan *et al.* (2014)
		Defective internal resource management plan (U_{63})	Nieto-Morote and Ruz-Vila (2011), Qazi *et al.* (2016), Hu *et al.* (2013)
		Project managers are dissatisfied with project priorities (U_{64})	Keshk *et al.* (2018), Hofman and Grela (2015)

Table 1.
The multiproject resource conflict risk assessment system

Step 3: Calculate the index weights.

Determining the weight of an index is an important step in assessing the risk of multiproject resource conflicts. The essence of weighting is to fundamentally reflect the relative importance of various indexes. The scientific and reasonable determination of weights directly affects the evaluation results. In this paper, the analytic hierarchy process (AHP) is used to determine the weight of each index in the index system because it can breakdown complex problems into several simple problems and be widely applied in a variety of decision situations.

$$M = [M_1, M_2, \ldots M_n]^T = \left[\prod_{j=1}^{n} u_{i1}, \prod_{j=1}^{n} u_{i2}, \ldots, \prod_{j=1}^{n} u_{ij}\right]^T \tag{4}$$

$$w_i = \frac{\sqrt[n]{M_i}}{\sum_{i=1}^{n} \sqrt[n]{M_i}} \tag{5}$$

$$W = (w_1, w_2, \ldots, w_n) \tag{6}$$

where M_i is the product of the elements in the ith row. M is the set of M_i.

First, the questionnaires, which include pairwise comparison judgment matrices, should be formulated. Experts in related fields are invited to assign relative importance values to factors. The final judgment matrix (C) should have the following characteristics:

$$c_{ij} > 0(i, j = 1, 2, \ldots, n); \; c_{ij} = \frac{1}{c_{ji}}(i \neq j); \; c_{ii} = 1$$

where c_{ij} is the quantified judgment for a pair of factors C_i and C_j.

Second, the relative importance of each factor (w) is estimated according to Eqn (7). Then, the relative importance can be obtained by normalizing the associated eigenvector using Eqn (8).

$$U \cdot w = \lambda_{\max} \cdot w \tag{7}$$

$$\sum_{i=1}^{n} w_i = 1 \tag{8}$$

where w is the relative importance of the factor; $\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix U, and $w = [w_1, w_2, \ldots, w_n]^T$ is the corresponding feature vector of $\lambda_{\max}$.

Finally, a consistency test is conducted. The consistency index and the consistency ratio are popular parameters used in consistency tests, and they can be obtained by Eqs (9) and (10), respectively. When $CR < 0.10$, the matrix has acceptable consistency, and the result is valid.

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{9}$$

$$CR = \frac{CI}{RI} \tag{10}$$

where CI is the consistency index of the evaluation matrix, CR is the consistency ratio of the evaluation matrix and RI is the average random consistency.

Step 4: Determine the fuzzy assessment matrix.

The relationship between the evaluation indexes and the evaluation set is represented by the degree of membership. The degree of membership can be determined as the proportion of the number of experts who rank risk at a certain level to the number of all scoring experts. Assuming that the subordinate level of u_i as related to v_j is r_{ij}, the assessment result of u_i is:

$$R_i = \{r_{i1}, r_{i2}, \ldots, r_{ij}\} \tag{11}$$

where R_i is the evaluation result for factor u_i. Based on the evaluation index system and assessment criteria, the evaluation results of each index can be calculated to obtain a fuzzy evaluation matrix:

$$R = \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_n \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1k} \\ r_{21} & r_{22} & \cdots & r_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nk} \end{bmatrix} \tag{12}$$

Step 5: Calculate a comprehensive evaluation score.

As shown in Eqn 13, the evaluation result can be calculated by combining the weight vector and the fuzzy evaluation matrix. When the evaluation results of the index layer and the criterion layer are successively obtained, an overall evaluation vector of risk can be produced. To obtain the final evaluation values of risk, the fuzzy vector must be singularized by applying the weighted average based on membership.

$$E = W \cdot R = (w_1, w_2, \ldots, w_n) \cdot \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1k} \\ r_{21} & r_{22} & \cdots & r_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nk} \end{bmatrix} = (e_1, e_2, \ldots, e_k) \tag{13}$$

$$B = E \cdot V^T \tag{14}$$

where B is the final risk assessment score.

3.3 Risk prediction with an artificial neural network

3.3.1 Artificial neural network. An ANN is a numerical and mathematical model that mimics the neural structure of the human brain and has some advantages over other statistical regression methods. First, the main characteristics of ANNs are that they do not require predetermined mathematical relationships of the mapping between inputs and outputs, and they can reproduce complex nonlinear input–output relationships and be applied in sequential training procedures. Moreover, due to the high self-organization, adaptability and self-learning capabilities of ANNs, they can successfully achieve distributed storage and parallel information processing.

The network combines a hierarchical frame of synapses consisting of an input layer, one or more hidden layers, and an output layer. The general topology of the three-layered neural network is shown in Figure 2. Each layer is composed of multiple artificial neuron elements, usually called neurons. A combination of signals coming from the neurons of the previous layer is received by the neurons of the next layer, and the signals are transformed through an activation function. The weighted connections between neurons send the output of the previous layer neuron to the input of the next layer neuron. The main functions of the neurons are extracting knowledge from training data and storing the learned knowledge as the weights of connections. Figure 3 shows the working mechanism of a neuron in a typical ANN structure.

In the ANN training process, each neuron of the input layer accepts data and multiplies the values by the corresponding weights; then, the results are passed to the hidden layer. In the hidden layer, each neuron receives the transmitted activation signal from the previous layer and generates an output signal through an activation function. The activation signal is the weighted sum of all the signals entering the neuron, which can be represented as:

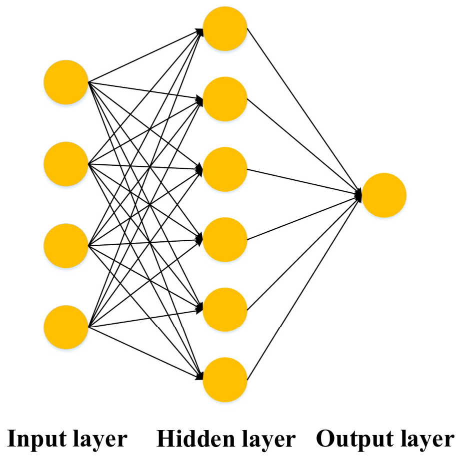

Figure 2. General neural network

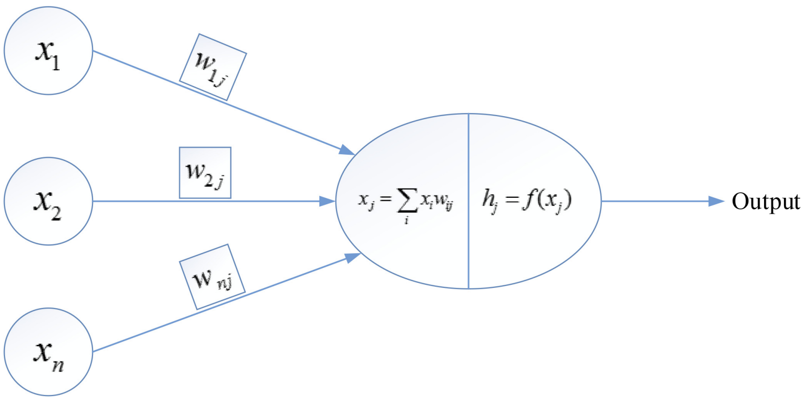

Figure 3. Working mechanism of a neuron in a typical ANN

$$x_j = \sum_i x_i w_{ij} \tag{15}$$

where x_i is the ith input of the input layer; w_{ij} is the weight vector between the ith neuron of the input layer and the jth neuron of the hidden layer; and x_j is the activation signal that neuron j receives in the hidden layer. The neurons of the hidden layer produce an output signal through an activation function. There are many forms of activation functions for hidden layers. One of the most frequently used activation functions is the sigmoid function, which creates a nonlinear dependency between the input signal and output result. The general form of the sigmoid function can be represented as:

$$o_j = f(x_j) = \frac{1}{1 + e^{-x_j}} \tag{16}$$

where o_j is the output of neuron j and x_j is the input for neuron j.

Then, the output is directed to the neurons in the following layer through weighted connections, as denoted in Eqn (17):

$$y_k = \sum_j o_j w_{jk} \tag{17}$$

$$o_k = f(y_k) = \frac{1}{1 + e^{-y_k}} \tag{18}$$

where y_k is input of neuron k in the output layer, w_{jk} is the weight vector of the connection between the jth neuron of the hidden layer and the kth neuron of the output layer and o_k is the predicted data in the output layer. When the signal is passed to the output layer, the output of the activated neurons in the output layer is the prediction set of the ANN model. The mean square error (MSE) is the most widely used error function for ANN models and can be represented as:

$$E(W) = \frac{1}{2} \sum_k (d_k - o_k)^2 \tag{19}$$

where d_k is the actual data for the kth training process and $E(W)$ is the error function. This method involves a forward-propagation training process that aims to compute the global error. Then, a back-propagation process in which the weights are adjusted in a backward manner is implemented to mitigate the transfer of error from the output layer to the hidden layer and then to the input layer to reduce the global error. The adjustment function of the neuron weights of the output layer can be given by:

$$\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial o_k} \times \frac{\partial o_k}{\partial y_k} \times \frac{\partial y_k}{\partial w_{jk}} = -(d_k - o_k) \cdot o_k \cdot (1 - o_k) \cdot o_j \tag{20}$$

$$w'_{jk} = w_{jk} - \eta \frac{\partial E}{\partial w_{jk}} \tag{21}$$

where $o_k \cdot (1 – o_k)$ is the derivative of Eqn (18). $\frac{\partial E}{\partial w_{jk}}$ is the adjusted value of the weight vector of connection between the jth neuron and kth neuron. η is the learning rate of the training process, and w'_{jk} is the new weight vector of the connection between the jth neuron and kth neuron. The weights of the hidden layer are updated in the same way as those of the output layer. The forward transmission of information (from the input layer to the output layer) and the backward feedback of error (from the output layer to the input layer) are repeated to minimize the error.

3.3.2 Dropout regularization method. An ANN model must extract knowledge from training data in the training process to effectively fit new data. However, one of the serious problems of ANNs is overfitting when the training data are not sufficient or overtraining occurs. Overfitting occurs when the mapping function (mainly manifested in the weight vector) generated by the model training process fits the training data set too well, leading to loss of the ability to fit new data and producing only results by heart. Dropout has recently been proposed as a regularization technique to reduce overfitting by changing the neural network structure in the model training process. The working mechanism of this method involves temporarily discarding several neurons together with their weight connections from the neural network training process. In each training process, each neuron is randomly disabled according to the individual Bernoulli distribution with a typical probability p of 50% (Baldi and Sadowski 2014; Meshgi *et al.*, 2017). The weight connections of the retained neurons are trained by back propagation. Figure 4 shows the neuron connection of a fully connected neuron after dropout applied in a fully connected layer with a probability p of 50%.

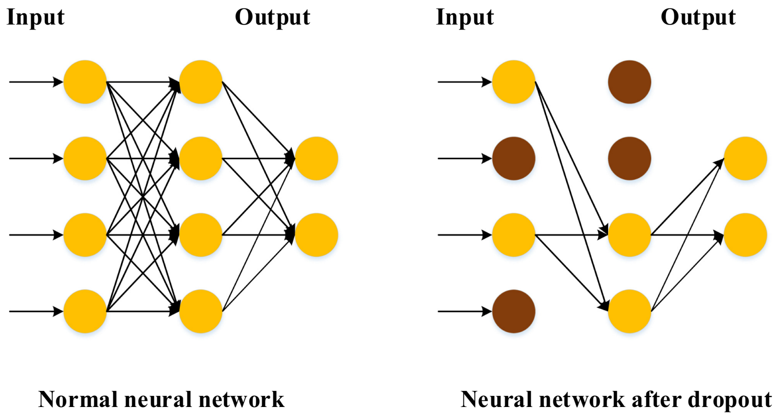

Figure 4.
Dropout applies in a neural network

3.4 Sensitivity analysis using the Garson algorithm

Garson algorithm is a sensitivity analysis method based on the connection weights obtained by the neural network (Chen and Chen 2008). The sensitivity of each of the risk index to the model output was determined using their level of importance (Ayodele *et al.*, 2021). Garson algorithm determines the contribution of each input value to the output value by assigning the hidden layer–output layer connection weight of each hidden layer neuron to the connection weight of each input signal connected to it (Henríquez and Ruz 2018).

4. Result

4.1 Data collection

To investigate resource conflict, a questionnaire survey was issued to experts in project management areas. The questionnaire consisted of two sections asking for general information about the respondents and for respondents to review and indicate the frequency of risk events. The respondents were asked to complete the questionnaires according to their recent participation experiences in projects. A total of 250 questionnaires were sent out to project management practitioners, and 193 responses were received, thus yielding a response rate of 77.2%.

The profile of the respondents is shown in Table 2. The questionnaire is issued to experts in the field of project management, which are included in project management enterprise and academic sector. Academic experts of the survey also often participate in project management practice. The base of the three data items (organization of experts, project management experience of respondents and frequency of parallel multiproject management)

Organization of experts				
Percentage	Project management enterprise 43.52%		Academic sector 56.48%	
Project management experience of respondents				
Percentage	3 years or below 16.58%	3–5 years 7.77%	5–10 years 20.21%	10 years or above 55.44%
Frequency of parallel multiproject management				
Percentage	very low 9.84%	moderately low 22.28%	moderately high 46.63%	very high 21.24%

Table 2.
General information about the experts

in Table 2 is 193 respondents. A total of 56.48% of respondents were scholars studying in project management areas, and 43.52% were practitioners from project management enterprises. A total of 75.65% of the respondents had over five years of experience in project management areas. Over 67.87% of respondents frequently participated in parallel multiproject management. Consequently, the evaluation results of the respondents were considered reliable because the respondents had sufficient experience and frequent involvement in multiproject management; thus, the respondents had adequate knowledge of multiple project management and the associated resource conflict risks.

4.2 Risk evaluation

In this section, a risk evaluation of multiproject resource conflict risk is conducted using the model constructed in the previous section. Because the risk evaluation index system was introduced in the previous section, it is directly implemented in this section without further discussion.

4.2.1 Evaluation criteria determination. The evaluation criteria consisted of five levels that evaluators make evaluation of risk events. All the risk factors were measured on a 5-point Likert scale. In this study, the standard of each risk index was divided into 5 grades, namely, grades 1, 2, 3, 4 and 5, corresponding to risk levels of very low, moderately low, moderately high and very high, respectively. The appraisal set is given by:

$$\begin{aligned} V &= \{v_1, v_2, v_3, v_4, v_5\} \\ &= \{\text{very low}, \text{ moderately low}, \text{ medium}, \text{ moderately high}, \text{ very high}\} \\ &= \{0.2, 0.4, 0.6, 0.8, 1\} \end{aligned}$$

Grade 1 indicates that the risk occurs rarely or almost never occurs; Grade 2 indicates that the risk occurs occasionally and that it does not affect the normal operation of a project; Grade 3 indicates that the risk will occur several times on a regular basis but within the control of the project; Grade 4 indicates that the risk occurs often, resulting in the project being unable to normally continue and Grade 5 indicates that the risk occurs frequently, the project cannot be implemented normally and extensive losses may occur.

4.2.2 Weight determination. In this paper, the judgment matrices are obtained by analyzing the answers of 10 selected experts from the questionnaire. For the judgment matrix R of the target layer, six factors from the criteria layer (U_1, U_2, U_3, U_4, U_5 and U_6) are involved. The order of weight values for the six factors is (w_1, w_2, w_6, w_3, w_4 and w_5), indicating that the risk possibility of material resources (U_1) is the highest and that of time resources (U_5) is the lowest. Thus, U is expressed as shown in Table 3:

Hierarchical order: By taking matrix U as an example, the calculation process is presented as follows:

$$M = [M_1, M_2, M_3, M_4, M_5, M_6]^T = [720, 12, 0.25, 0.083, 0.002, 2]^T$$

Table 3. Determination of the judgment matrix R

U	U_1	U_2	U_3	U_4	U_5	U_6
U_1	1	3	4	4	5	3
U_2	1/3	1	2	3	3	2
U_3	1/4	1/2	1	2	3	1/3
U_4	1/4	1/3	1/2	1	2	1
U_5	1/5	1/3	1/3	1/2	1	1/4
U_6	1/3	1/2	3	1	4	1

$$\sqrt[6]{M} = \left[\sqrt[6]{M_1},\ \sqrt[6]{M_2},\ \sqrt[6]{M_3},\ \sqrt[6]{M_4},\ \sqrt[6]{M_5},\ \sqrt[6]{M_6}\right]^T = [2.994,\ 1.513,\ 0.794,\ 0.661,\ 0.375,\ 1.122]^T$$

$$W = [w_1,\ w_2,\ w_3,\ w_4,\ w_5,\ w_6]^T = [0.401,\ 0.202,\ 0.106,\ 0.088,\ 0.050,\ 0.150]^T$$

$$U \cdot W = \begin{bmatrix} 1 & 3 & 4 & 4 & 5 & 3 \\ \frac{1}{3} & 1 & 2 & 3 & 3 & 2 \\ \frac{1}{4} & \frac{1}{2} & 1 & 2 & 3 & \frac{1}{3} \\ \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & 1 & 2 & 1 \\ \frac{1}{5} & \frac{1}{3} & \frac{1}{3} & \frac{1}{2} & 1 & \frac{1}{4} \\ \frac{1}{3} & \frac{1}{2} & 3 & 1 & 4 & 1 \end{bmatrix} [0.401,\ 0.202,\ 0.106,\ 0.088,\ 0.050,\ 0.150]^T = [2.492 \quad 1.267 \quad 0.686 \quad 0.561 \quad 0.315 \quad 0.995]$$

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(UW)_i}{nw_i} = \frac{1}{6} \cdot \left(\frac{2.492}{0.401} + \frac{1.267}{0.202} + \frac{0.686}{0.106} + \frac{0.561}{0.088} + \frac{0.315}{0.050} + \frac{0.995}{0.150}\right) = 6.353$$

$$CI = \frac{\lambda_{\max} - n}{n-1} = \frac{6.353 - 6}{5} = 0.07,\ RI = 1.26$$

$$CR = \frac{CI}{RI} = \frac{0.07}{1.26} = 0.056 < 0.1$$

In this case, the consistency test of matrix U yields an acceptable result. The weight of the criteria layer index has been obtained. The judgment matrix of U_2 is presented in Table 4. The weight determination process is as follows.

$$M = [M_1,\ M_2,\ M_3]^T = [16,\ 0.25,\ 0.25]^T$$

$$\sqrt[3]{M} = \left[\sqrt[3]{M_1},\ \sqrt[3]{M_2},\ \sqrt[3]{M_3}\right]^T = [2.924,\ 0.585,\ 0.585]^T$$

$$W = [w_1,\ w_2,\ w_3]^T = [0.667,\ 0.167,\ 0.167]^T$$

$$CR = 0 < 0.1$$

U_2	U_{21}	U_{22}	U_{23}
U_{21}	1	4	4
U_{22}	1/4	1	1
U_{23}	1/4	1	1

Table 4. Determination of the judgment matrix U_2

According to the above steps, the weights of all factors of index layer can be obtained. The judgment matrix of the index layer is shown in Appendix 1. The results of the weights of index layer is presented in Table 5.

4.2.3 Risk score calculation. Based on the scores given by the respondents for each resource conflict index, the counts of different risk levels can also be obtained. The collected data were divided into 20 groups according to the functions of the respondents in project management. For the first group of data, all respondents used planning functions in project management, as shown in Table 6.

Then, the data were normalized, and the membership matrix of each indicator corresponding to each factor of the evaluation set was obtained, as shown in Table 6.

U_1 (0.401)	U_{11}	0.714
	U_{12}	0.143
	U_{13}	0.143
U_2 (0.202)	U_{21}	0.667
	U_{22}	0.167
	U_{23}	0.167
U_3 (0.106)	U_{31}	0.687
	U_{32}	0.186
	U_{33}	0.127
U_4 (0.088)	U_{41}	0.495
	U_{42}	0.285
	U_{43}	0.091
	U_{44}	0.129
U_5 (0.050)	U_{51}	0.667
	U_{52}	0.333
U_6 (0.150)	U_{61}	0.202
	U_{62}	0.106
	U_{63}	0.605
	U_{64}	0.087

Table 5.
Weights of criteria and indexes

	v_1	v_2	v_3	v_4	v_5
U_{11}	0	1	6	4	0
U_{12}	1	2	7	1	0
U_{13}	0	2	7	2	0
U_{21}	1	3	4	2	1
U_{22}	0	5	3	3	0
U_{23}	0	4	3	4	0
U_{31}	1	2	5	2	1
U_{32}	0	4	3	3	1
U_{33}	0	4	3	4	0
U_{41}	3	0	5	1	2
U_{42}	0	3	5	2	1
U_{43}	0	3	5	3	0
U_{44}	1	2	5	2	1
U_{51}	1	2	4	4	0
U_{52}	0	1	6	4	0
U_{61}	0	1	8	2	0
U_{62}	0	3	4	4	0
U_{63}	0	3	4	3	1
U_{64}	0	3	5	3	0

Table 6.
The counts of different risk levels for the first group of data

Combining the obtained weights (Table 6) with the membership matrix (Table 7), the fuzzy logic method can be used to evaluate the indicators at all levels. The data in Table 7 consist of the fuzzy matrix membership R_i values of the six first-level indicators, and the first-level fuzzy evaluation vector E_i of each evaluation indicator can be calculated using the calculation model $E_i = W_i \cdot R_i$ in fuzzy hierarchical evaluation.

The first-level fuzzy evaluation E_1 result for material resources is:

$$E_1 = W_1 \cdot R_1 = \begin{bmatrix} 0.714 \\ 0.143 \\ 0.143 \end{bmatrix}^T \cdot \begin{bmatrix} 0 & 0.09 & 0.55 & 0.36 & 0 \\ 0.09 & 0.18 & 0.64 & 0.09 & 0 \\ 0 & 0.18 & 0.64 & 0.18 & 0 \end{bmatrix}$$
$$= [0.013 \quad 0.117 \quad 0.571 \quad 0.299 \quad 0]$$

The first-level fuzzy evaluation E_2 result for equipment resources is:

$$E_2 = W_2 \cdot R_2 = \begin{bmatrix} 0.667 \\ 0.167 \\ 0.167 \end{bmatrix}^T \cdot \begin{bmatrix} 0.09 & 0.27 & 0.36 & 0.18 & 0.09 \\ 0 & 0.45 & 0.27 & 0.27 & 0 \\ 0 & 0.36 & 0.27 & 0.36 & 0 \end{bmatrix}$$
$$= [0.061 \quad 0.318 \quad 0.333 \quad 0.227 \quad 0.061]$$

The first-level fuzzy evaluation E_3 result for human resources is:

$$E_3 = W_3 \cdot R_3 = \begin{bmatrix} 0.687 \\ 0.186 \\ 0.127 \end{bmatrix}^T \cdot \begin{bmatrix} 0.09 & 0.18 & 0.45 & 0.18 & 0.09 \\ 0 & 0.36 & 0.27 & 0.27 & 0.09 \\ 0 & 0.36 & 0.27 & 0.36 & 0 \end{bmatrix}$$
$$= [0.062 \quad 0.239 \quad 0.398 \quad 0.222 \quad 0.079]$$

Criterion layer	Index layer	Membership R_i v_1	v_2	v_3	v_4	v_5
Material resource(U_1)	U_{11}	0.00	0.09	0.55	0.36	0.00
	U_{12}	0.09	0.18	0.64	0.09	0.00
	U_{13}	0.00	0.18	0.64	0.18	0.00
Equipment resource(U_2)	U_{21}	0.09	0.27	0.36	0.18	0.09
	U_{22}	0.00	0.45	0.27	0.27	0.00
	U_{23}	0.00	0.36	0.27	0.36	0.00
Human resource(U_3)	U_{31}	0.09	0.18	0.45	0.18	0.09
	U_{32}	0.00	0.36	0.27	0.27	0.09
	U_{33}	0.00	0.36	0.27	0.36	0.00
Capital recourse(U_4)	U_{41}	0.27	0.00	0.45	0.09	0.18
	U_{42}	0.00	0.27	0.45	0.18	0.09
	U_{43}	0.00	0.27	0.45	0.27	0.00
	U_{44}	0.09	0.18	0.45	0.18	0.09
Time resource(U_5)	U_{51}	0.09	0.18	0.36	0.36	0.00
	U_{52}	0.00	0.09	0.55	0.36	0.00
Organizational resource(U_6)	U_{61}	0.00	0.09	0.73	0.18	0.00
	U_{62}	0.00	0.27	0.36	0.36	0.00
	U_{63}	0.00	0.27	0.36	0.27	0.09
	U_{64}	0.00	0.27	0.45	0.27	0.00

Table 7. Fuzzy evaluation index matrix of the first group of data

The first-level fuzzy evaluation E_4 result for capital resources is:

$$E_4 = W_4 \cdot R_4 = \begin{bmatrix} 0.495 \\ 0.285 \\ 0.091 \\ 0.129 \end{bmatrix}^T \cdot \begin{bmatrix} 0.27 & 0 & 0.45 & 0.09 & 0.18 \\ 0 & 0.27 & 0.45 & 0.18 & 0.09 \\ 0 & 0.27 & 0.45 & 0.27 & 0 \\ 0.09 & 0.18 & 0.45 & 0.18 & 0.09 \end{bmatrix}$$
$$= [0.147 \quad 0.126 \quad 0.455 \quad 0.145 \quad 0.127]$$

The first-level fuzzy evaluation E_5 result for time resources:

$$E_5 = W_5 \cdot R_5 = \begin{bmatrix} 0.667 \\ 0.333 \end{bmatrix}^T \cdot \begin{bmatrix} 0.09 & 0.18 & 0.36 & 0.36 & 0 \\ 0 & 0.09 & 0.55 & 0.36 & 0 \end{bmatrix}$$
$$= [0.061 \quad 0.152 \quad 0.424 \quad 0.364 \quad 0]$$

The first-level fuzzy evaluation E_6 result for organization resources is:

$$E_6 = W_6 \cdot R_6 = \begin{bmatrix} 0.202 \\ 0.106 \\ 0.605 \\ 0.087 \end{bmatrix}^T \cdot \begin{bmatrix} 0 & 0.09 & 0.73 & 0.18 & 0 \\ 0 & 0.27 & 0.36 & 0.36 & 0 \\ 0 & 0.27 & 0.36 & 0.27 & 0.09 \\ 0 & 0.27 & 0.45 & 0.27 & 0 \end{bmatrix}$$
$$= [0 \quad 0.236 \quad 0.445 \quad 0.264 \quad 0.055]$$

After evaluating the six first-level fuzzy membership matrices, the next step is to conduct an FCE of the entire system. The fuzzy relation matrix R of the comprehensive evaluation is:

$$E' = \begin{bmatrix} E_1 \\ E_2 \\ E_3 \\ E_4 \\ E_5 \\ E_6 \end{bmatrix} = \begin{bmatrix} 0.013 & 0.117 & 0.571 & 0.229 & 0 \\ 0.061 & 0.318 & 0.333 & 0.227 & 0.061 \\ 0.062 & 0.239 & 0.398 & 0.222 & 0.079 \\ 0.147 & 0.126 & 0.455 & 0.145 & 0.127 \\ 0.061 & 0.152 & 0.424 & 0.364 & 0 \\ 0 & 0.236 & 0.445 & 0.264 & 0.055 \end{bmatrix}$$

By combining the weights of the criteria layer indicators, the result set of the second level of comprehensive evaluation was obtained as follows:

$$E'' = W \cdot E' = \begin{bmatrix} 0.401 \\ 0.202 \\ 0.106 \\ 0.088 \\ 0.050 \\ 0.150 \end{bmatrix}^T \cdot \begin{bmatrix} 0.013 & 0.117 & 0.571 & 0.229 & 0 \\ 0.061 & 0.318 & 0.333 & 0.227 & 0.061 \\ 0.062 & 0.239 & 0.398 & 0.222 & 0.079 \\ 0.147 & 0.126 & 0.455 & 0.145 & 0.127 \\ 0.061 & 0.152 & 0.424 & 0.364 & 0 \\ 0 & 0.236 & 0.445 & 0.264 & 0.055 \end{bmatrix}$$
$$= [0.040 \quad 0.191 \quad 0.468 \quad 0.260 \quad 0.040]$$

$$B = E'' \cdot V^T = [0.040 \quad 0.191 \quad 0.468 \quad 0.260 \quad 0.040] \cdot [0.2 \quad 0.4 \quad 0.6 \quad 0.8 \quad 1]^T = 0.613$$

The value "0" in the evaluation matrix indicates that the value of the membership is equal to 0; that is, no expert considers the risk important at the current risk level. For example, the first group included 11 reviewers. For U_{11}, one individual assigned a v_2 level, 6 individuals assigned a v_3 level, 4 assigned a v_4 level and no one selected v_1 and v_5; therefore, the membership values of v_1 and v_5 are 0. The comprehensive risk assessment score of the first group is 0.613. It indicates that the risk is at Grade 4 which resulting in the project being unable to normally continue. The project manager should compare the risk value of the project with the risk of other project portfolios. Based on this, the priority of risk management should be determined according to the severity of the risk status. Then, resources and management investment should be increased in those high-risk projects to deal with risks quickly.

4.3 Risk prediction

4.3.1 ANN model training. In general, the architecture of the neural network includes the number of layers, numbers of nodes in different layers, type of activation function and learning rate. A three-layer neural network is constructed consisting of an input layer, a hidden layer and an output layer, which is able to approximate arbitrary continuous functions infinitely. The number of nodes in the input layer is set to 19 because the risk indexes are used for risk prediction. The function of this model is to predict the overall risk, so there is 1 node in the output layer. The function of the hidden layer is to extract and remember the useful features and subfeatures from the input patterns to predict the outcome of the network. To construct the optimal performance network, the number of hidden layer nodes is determined by training the network for all the configurations of nodes from 10 to 30. The root mean square error (RMSE between the expected output and network output) and R^2 (squared correlation coefficient between the network input and output) are used to measure the learning ability of the network in the training process. The value of R^2 varies from 0 to 1, and a value close to 1 indicates that the model provides a good fit. The RMSE reflects the extent to which the predicted values deviate from the true values. Table 8 shows the training results.

Notably, the R^2 is greater than 99%, which indicates that the overall network learning ability is very strong. The differences observed for different numbers of hidden nodes were small. To select the network architecture that yields the best performance, the number of nodes in the hidden layer was set to 25. Therefore, a three-layer feedforward back-propagation neural network architecture of 19–25-1 was established.

The data set obtained from the previous phase was used for training and testing in this study. Then, the 20 groups of data were divided into two subsets, 16 to train the neural network and 4 to test the performance of the resulting model. The evaluation results of respondents from the same function have more structural features due to its similar concerns about the questionnaire, which could facilitate neural network training. In this paper, the network learning rate is set to 0.1. The number of training epochs is set to 500. A logistic transfer function is used as the activation function. To avoid overfitting, the dropout regularization method is applied, and the dropout ratio is set to 0.5. The MSE for training the model is shown in Figure 5.

Generally, the training process can be stopped when the error ceases to decrease or decreases very slowly. The initial error of the network is 0.368. In the 436-epoch training phase, the error is reduced to 0.001, which meets the requirements for model accuracy. When network training is complete, the network is capable of making predictions based on stored knowledge when an unknown example is provided. Next, we will verify whether this network is able to predict risks based on testing data.

4.3.2 ANN model testing. In this section, the trained ANN is verified with testing samples. As in the training process, the evaluation performance of the model was assessed based on the corresponding R^2 and RMSE values. The results of model prediction are shown in Table 9.

The R^2 and RMSE values of the ANN model are 98.3 and 0.8%, respectively. These two indexes indicate that the ANN model has high prediction accuracy for testing

Table 8.
Network performance for different number of hidden nodes in the training process

Nodes of hidden layer	RMSE	R^2
10	0.02475	0.99229
11	0.02456	0.99241
12	0.02499	0.99214
13	0.02445	0.99248
14	0.02467	0.99234
15	0.02459	0.99239
16	0.02473	0.99231
17	0.02492	0.99218
18	0.02479	0.99227
19	0.02505	0.99210
20	0.02463	0.99236
21	0.02483	0.99224
22	0.02469	0.99233
23	0.02486	0.99222
24	0.02519	0.99201
25	0.02437	0.99252
26	0.02506	0.99210
27	0.02531	0.99194
28	0.02464	0.99236
29	0.02478	0.99227
30	0.02476	0.99228

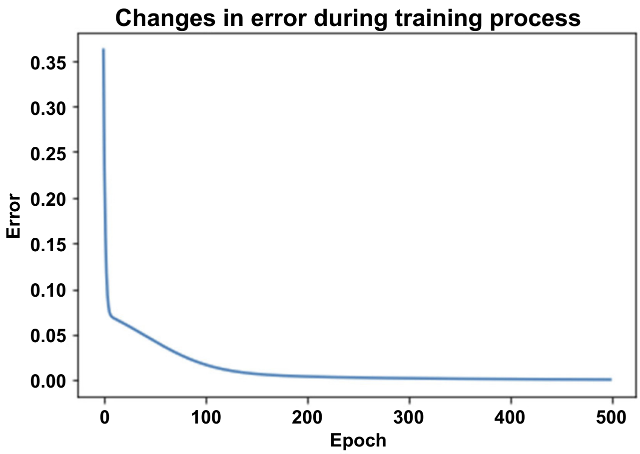

Figure 5.
Mean square error for model training

data. The lowest prediction rate is 98% for the set of testing data, and the average accuracy is 98.75%. Notably, the average prediction rate of the neural network is greater than 98%, even though the training data set is small. Thus, it can be concluded that the developed ANN model can capture the essential components of the underlying nonlinear relevance and is capable of predicting risks appropriately.

4.4 Sensitivity analysis

The sensitivity analysis of the risk factor of the ANN model outputs for the multiproject resource conflict risk based on the Garson algorithm is depicted in Figures 6 and 7(a)-(f).

In Figures 1–6, the risk of multiproject resource conflict was highly influenced by organization resource, and its sensitivity is 21.25%. Similarly, capital resource (U_4), human resource (U_3), material resource (U_1), equipment resource (U_2) and time resource (U_5) possess weights of 20.95%, 16.99%, 15.92%, 15.75%, 9.13%. In Figure 7(a), inferior quality of the materials shared among projects (U_{12}) has the highest importance on material resource risk. In Figure 7(d), insufficient project funding (U_{41}) and poor financial liquidity among projects (U_{44}) significantly influence the capital resource risk collectively. This could be attributed to various factors such as the quantity and speed of capital supply. Meanwhile, defective internal resource management plan (U_{63}) was observed to have the highest importance organization resource risk (Figure 7(f)).

5. Discussion

This paper investigates from a risk management perspective multiproject context resource conflict problem. There is much research on project portfolio resource management. Current work aiming at minimizing the project cycle (Delerue and Sicotte 2020), provides insights in seeking project scheduling plan that meets resource constraints (Zaman *et al.*, 2021; Balouka and Cohen 2019) Notwithstanding their significant contribution, limited academic attention has so far been paid to predict the project resource conflict risk status from an operational perspective for risk loss pre-reduction. As a consequence, there is a need for a method for help project managers monitor the overall project health operation by predicts risk status of multiproject resource conflict.

Previous studies with a focus on resource allocation and project scheduling indicate that for optimization problems with minimum project cycle as the goal, heuristic algorithms (such

	Actual risk score	Predicted risk score	Percentage error (%)	R^2	RMSE
1	0.602	0.589	−2	0.980	0.008
2	0.630	0.627	−0.5		
3	0.569	0.572	0.5		
4	0.462	0.473	2		

Table 9. Predicted risks vs actual risks for the testing samples

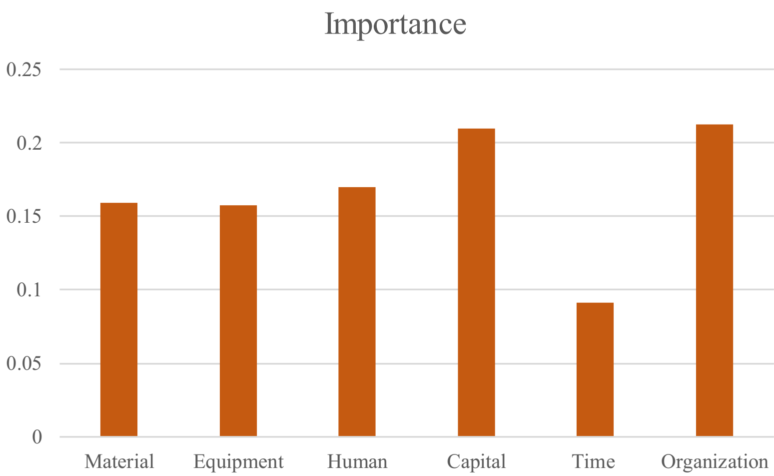

Figure 6. Importance of risk of criterion layer on the ANN predicted

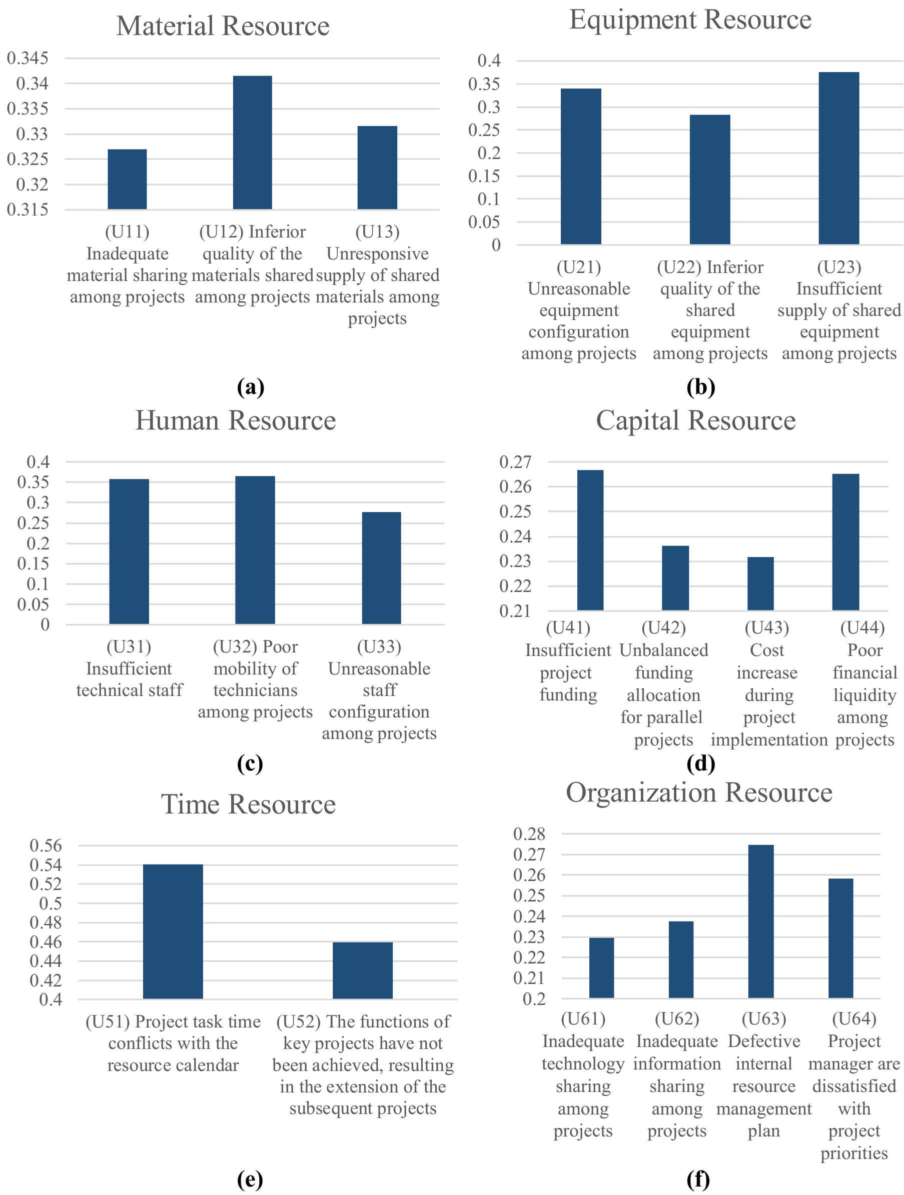

Figure 7.
Importance of risk index on the ANN predicted of (a) Material, (b) Equipment, (c) Human, (d) Capital, (e) Time, (f) Organization resource

as genetic algorithm (Kadri and Boctor 2018), ant colony algorithm (Li and Zhang 2013) and adaptive robust optimization model (Bruni *et al.*, 2017) can search for the optimal solution in a short time, but for risk prediction problem, they can not solve well. However, ANN, with the advantage of abilities of learning and adaptability, is an effective method of dealing with complex nonlinear problem. Hence, this paper presented a novel model for multiproject resource conflict risk prediction based on an ANN. Results suggest that the proposed model through multiple training can predict the risk status of the project with high accuracy. It should be noted that, this study constructed a general risk prediction model based on ANN, and applied risk data from a specific case to validate the model. In a specific project portfolio, the project manager could collect the risk data and train neural networks based on the actual condition of the project portfolio, identify the project portfolios that require priority processing, and then determine the key risk factors affecting the overall risk through sensitivity analysis.

Garson algorithm determines the sensitivity of each risk to the overall resource conflict risk. The sensitivity analysis indicates that organization resource and capital resource are more significant variable among all resource risk. This purports that they have have significant influence on the overall risk. Time resource (U_5) have 9.13% sensitivity weight and get the last rank, suggesting lesser sensitivity. Therefore, it may be concluded that the influence of time resource on multiproject resource conflict risk is less, and more attention should be paid to organization resource and capital resource to control the resource conflict risk. In each organization resource risk, defective internal resource management plan is the most significant variable among all organization resource risk. Therefore, as a project manager, it is a need to fully identify the resource requirements of different projects in advance combining the characteristic of project resource sharing. Further, it is important to strictly monitor the execution status of the resource plan during the project process, and adjust the resource plan in time when an exception occurs to the project to ensure the smooth progress of the project. Meanwhile, the project funding and funding liquidity are more significant variable among capital resource risk. Raising project standards during project selection and carefully choosing promising projects for investment can effectively reduce the risk of insufficient funds. To improve the funding liquidity, project manager can increase resource input for profitable project to speed up the realization of project profit targets.

6. Conclusion and future work

Multiproject resource management is the most important part of multiproject management. Resource conflicts among projects are the major cause of poor resource management and will directly affect the normal operation of projects, result in schedule delays and cost overruns, and even lead to project failure. Therefore, the ability to predict multiproject resource conflict risks is critical to many organizations.

To improve risk analysis and risk monitoring, a general model to predict multiproject resource conflict risk is presented in this paper. And a case is supplied to verify the feasibility of the risk prediction model, which could further provide reference for the project managers. Through reviewing the literature on PRM and combining this information expert responses, an evaluation index system for multiproject resource conflict risk is proposed that focuses on the interdependence of multiple project resources. The risk factors that may cause resource conflicts are classified from six perspectives: material, equipment, human, capital, time and organization resource perspectives. To overcome the inherent human subjectivity in this approach, an FCE method is used to transform subjective judgments into quantitative information describing risk. Then, an ANN model is proposed to predict the comprehensive risk score that can describe the severity of risk. In the process of constructing the model, we perform multiple training steps to determine the parameters of the model. To avoid overfitting due to the small size of the training data set, a dropout regularization method was used in the network training process, thereby ensuring the general applicability of the ANN model. Finally, the validation results indicate that for the surveyed sample projects, the multiproject resource conflict risks can be successfully predicted using the ANN modeling technique, with a 98.5% average accuracy. This finding indicates that the model extracted the important knowledge from the risk scores and risk indexes of the resource conflicts from the sample data and made accurate predictions based on unknown data.

Overall, the contributions of this paper are three-fold. (1) First, we explored an important research topic that has received limited attention in the past. The accurate prediction of the risks associated with multiproject resource conflicts can improve resource management and the success rate of projects. (2) Second, we identified the factors that could pose risks related to multiproject resource conflicts and established an evaluation index system for these risks considering the interdependence among project resources to describe the underlying factors that contribute to resource conflict risks. This evaluation index system can help managers discover the potential risk factors in the project management process and provide a reference for other research on the identification and evaluation of resource risks. (3) Third, we proposed an effective model for predicting the risk of multiproject resource conflicts using an ANN. The model can effectively predict complex phenomena with complicated and highly nonlinear performance functions and solve problems with many random variables. Hence, the model could be used to aid multiproject managers in assessing the potential resource conflict risks of their projects.

Our future work will focus on both methodological and application issues. For the methodology, we plan to find better neural predictors and optimization methods for minimizing the prediction errors. From an application perspective, we will increase the sample set size and further assess the generalization capabilities of the network.

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Appendix

Determination of the judgment matrix U_1

U_1	U_{11}	U_{12}	U_{13}
U_{11}	1	5	5
U_{12}	1/5	1	1
U_{13}	1/5	1	1

Determination of the judgment matrix U_3

U_3	U_{31}	U_{32}	U_{33}
U_{31}	1	5	4
U_{32}	1/5	1	2
U_{33}	1/4	1/2	1

Determination of the judgment matrix U_4

U_4	U_{41}	U_{42}	U_{43}	U_{44}
U_{41}	1	3	3	4
U_{42}	1/3	1	4	3
U_{43}	1/3	1/4	1	1/2
U_{44}	1/4	1/3	2	1

Determination of the judgment matrix U_5

U_5	U_{51}	U_{52}
U_{51}	1	2
U_{52}	1/2	1

Determination of the judgment matrix U_6

U_6	U_{61}	U_{62}	U_{63}	U_{64}
U_{61}	1	3	1/4	2
U_{62}	1/3	1	1/6	2
U_{63}	4	6	1	5
U_{64}	1/2	1/2	1/5	1

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