MAJOR PROJECT RISK ASSESSMENT METHOD BASED ON
BP NEURAL NETWORK

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Abstract. In order to prevent risks in major projects, it is of great importance to accurately assess risks in advance. Therefore, in this paper, we propose a novel major project risk assessment method with the BP neural network model. Firstly, we propose an index system for major project risk assessment, which is made up of four parts: 1) Schedule risk, 2) Cost risk, 3) Quality risk, and 4) Resource risk. Secondly, we propose a hybrid BP neural network and particle swarm optimization (PSO) model to evaluate risks in major projects. Especially, major project risk assessment results are achieved from the output layers of the BP neural network which is optimized by the PSO algorithm. In our proposed hybrid model, the fitness for each particle is computed through an optimal function, and then the particle can improve its velocity for the next cycle by searching the optimal value. Furthermore, this process should be repeated when the end condition is satisfied. Finally, experimental results demonstrate that the proposed method is able to evaluate risk level of major projects with high accuracy.

1. Introduction. Project management and implementation is a production and consumption process of long cycle and big investment [33]. The internal structure of major project is very complex and it has many relations with outside [21]. In addition, there are many uncertainty factors in the process the major project construction, which may provide many risks to the project and may bring negative influence to the major project [17, 15]. Risk management aims to identify, analyze, quantify the uncertain information which are extruded from the interior and exterior environment of a major project, and then make accurate evaluation of risk management and risk control [13, 1].

The risk in the major project has a complex process, construction and technical requirements, long duration, and great social influence [35]. If we cannot lower the negative influence from project risk, it may directly affect the progress of the project, and then cause serious consequences [27]. Therefore, it is of great importance to study on the major project risk management [18]. Furthermore, with the rapid development of the civilization in modern society, the major project risk management...
is very important, because it may not only reflect the level of project management, but also affect the public image of the corporation’s development [14, 2].

In this paper, we propose a novel major project risk assessment method using the BP neural network. The rest of the paper is organized as follows. In the next section, we propose the related works about BP neural network. In section 3, we formulate the index system for major project risk assessment. Afterwards, we propose a novel major project risk assessment method. Section 5 designs and implements an experiment to validate the effectiveness of the proposed approach. Finally, this paper is concluded in section 6.

2. Related works. In this section, we discuss related works about the applications about BP neural network, which has been successfully in many areas [34, 32]. In particular, back propagation refers to an approach exploited in artificial neural networks to estimate the error contribution of each neuron after a batch of data is processed [31]. In addition, it is utilized by an enveloping optimization algorithm to modify the weight of each neuron, completing the learning process for that case [30].

Xu et al. proposed an improved Back Propagation (BP) neural network model to forecast the temperature of the pavement in winter. Before the construction of the BP neural network model, the authors tried to eliminate chaos and design the regularity of temperature on the pavement surface [29].

Wang et al. proposed a novel wind power range forecasting model based on the multiple output property of BP neural network. In addition, the optimization criterion together with the information of predicted intervals is illustrated as well. Afterwards, an improved Particle Swarm Optimization algorithm is utilized to optimize the BPNN model [25].

Wang et al. propose a fractional gradient descent approach for the back propagation (BP) training of neural networks. In addition, the Caputo derivative is exploited to evaluate the fractional-order gradient of the error defined as the traditional quadratic energy function. Furthermore, experimental results show that the monotonicity and weak (strong) convergence of the proposed algorithm is effective [24].

Wang et al. proposed a two-layer decomposition model and presented a hybrid model based on fast ensemble empirical mode decomposition (denoted as FEEMD), variational mode decomposition (VMD) and back propagation (BP) neural network, which is optimized by the firefly algorithm. This work is unique in the sense that VMD is specifically utilized to decompose the high frequency intrinsic mode functions provided by FEEMD into a number of modes to enhance the precision of the prediction results [22].

Wang et al. proposed a back propagation (BP) neural network model exploiting SR as the input parameter to construct the relation between SR and AT error. Afterwards, the authors exploited the trained BP model to revise the errors in other time period. Next, this work testifies the performance on the datasets in the former research and compared the maximum absolute error, mean absolute error and standard deviation [26].

Su et al. utilized the BP neural network to estimate the physiology index after exercise and to evaluate the human exercise physiology index. Using the analysis of the former BP algorithm, our proposed BP algorithm can effectively integrate particle swarm algorithm to enhance the BP neural network model. Furthermore, the
proposed method can be exploited in college student’s human exercise physiology index and actual human exercises [19].

Peng et al. constructed a multi-body dynamics model of the steering system and achieved the random road spectrum of 4 wheels through mathematical model. In addition, GA-BPNN algorithm was presented in this work to optimize the structural thickness of key parts on the steering system [16].

Ma et al. utilized the BP neural network predictive model for the determination of supercritical water heat transfer coefficient. Particularly, in this work, a study has been made to determine effect of varying certain parameters such as heat flux, mass flux, pipe diameter and pressure on the heat transfer coefficient of supercritical water [12].

Apart from the above works, BP neural network has also been used in other areas, such as Thermal error compensation of high-speed spindle system [11], Multimedia course-ware evaluation [10], Prediction of high-speed grinding temperature of titanium matrix [8], Sensor-less free space optics communication [7], Macroeconomic forecasting [6], Predicting of MODIS Leaf Area Index Time Series [5], Micro-clearance electrolysis-assisted laser machining [30], Identification and Adjustment of Guide Rail Geometric Errors [4], Prediction on the cutting process of constrained damping boring bars [3], Prediction of cut size for pneumatic classification [28], Temperature Sensing Research [23], and UGI Gasification Processes [9].

3. **Index system for major project risk assessment.** The identification of basic risk factors of major projects is conducive to the establishment of risk evaluation index system, and it is an important cornerstone of the construction of evaluation index system. According to the design principle of index system, in this section, we aim to design an index system for major project risk assessment by fully using the above risk identification methods, and considering the actual development situation of major projects. Then, through extensive communication with relevant experts and scholars and the developers of major projects, we listen to their opinions and suggestions on how to construct the evaluation index system. Structure of the index system for major project risk assessment is shown in Fig. 1.

As shown in Fig. 1, the proposed index system is mainly made up of four parts: 1) Schedule risk, 2) Cost risk, 3) Quality risk, and 4) Resource risk. Schedule risks may greatly influence the process of major project, and it contains Schedule flexibility, Project scale, Requirement clarity, Technical complexity. Cost risks are corresponding to cost plan of the major project, several factors are included: Cost elasticity, Certainty of the implementation conditions, Purchasing conditions and environment. Quality risks affect project quality, requirement fulfillment, and customer satisfaction. Resource risk influence several aspects, such as project personnel, capital and equipment allocation and project support. In detail, resource risk contains: Quality standard, Leader plan feasibility, Project document integrity, Configuration management effectiveness, Non functional requirements.

4. **The proposed method.** Artificial neural network (denoted as ANN) is made up of two modes: 1) training mode, and 2) learning mode. In the training mode, input information is transmitted to the input layer. In addition, a neuron of the ANN can compute the weighted sum of inputs and then transmit it via a transfer function to obtain the output. Transfer function used in ANN is defined as follows.

\[
f(x) = \frac{1}{1 + e^{-x}}
\]  

(1)
Then, the output of a neuron is transmitted to the inputs of all neurons of the next layer, and the output layer generates the final results of the ANN.

As the net error generated by the ANN is lower than the one in the current iteration, we introduce the back propagation (BP) algorithm to solve this issue. In the BP neural network, the cumulative error is utilized to revise the weight. Afterwards, each weight in the BP neural network is given as follows.

\[
\Delta w_{ij} (t) = \mu \frac{\partial E(t)}{\partial w_{ij}} + \nu \Delta w_{ij} (t - 1) \tag{2}
\]

\[
w_{ij} (t + 1) = w_{ij} (t) + \Delta w_{ij} (t) \tag{3}
\]

where \(\mu\) denotes the parameter of the leaning rate, and parameter \(\nu\) refers to the momentum factor and \(t\) denotes the iteration index.

BP artificial neural network denotes the most popular utilized neural network. The BP neural network contains three modules: a) input layer, b) hidden layer and c) output layer [12][13]. Framework of the BP neural network is given in Fig.2 as follows.

The BP neural network requires a lot of continuous non-linear excitation functions:

\[
F(n_{et}) = \left(1 + e^{-n_{et}}\right)^{-1} \tag{4}
\]
where the variable $net_{jk}$ is calculated as follows.

$$net_{jk} = \sum_{i=1}^{N} w_{ji} \cdot OT_{ki} + \theta_j$$  \hspace{1cm} (5)$$

$$OT_{ki} = \left( 1 + \exp \left( - \sum_{i=1}^{N} w_{ji} \cdot OT_{ki} - \theta_j \right) \right)^{-1} \hspace{1cm} (6)$$

The parameters of the output layer are estimated as follows.

$$\omega_{kj} = (t_{kj} - OT_{kj}) \cdot OT_{kj} \cdot (1 - OT_{kj}) \hspace{1cm} (7)$$

In addition, the parameters of the hidden layer are estimated as follows.

$$\omega_{kj} = OT_{kj} \cdot (1 - OT_{kj}) \cdot \sum_{m=1}^{M} \omega_{km} \cdot \gamma_{uj} \hspace{1cm} (8)$$

To illustrate the idea of the proposed algorithm, process of the BP neural network algorithm is illustrated in Fig. 3.

Based on the above analysis, the structure of the BP neural network for major project risk assessment is given in Fig. 4.

Suppose that $n$ refers to number of neurons for an input layer, $k_1, k_2, \cdots, k_s$ denote neurons of the $s$ hidden layers. $m$ refers to neurons for a target output layer. Main ideas of the proposed method are to promote performance of the BP neural network through utilizing particle swarm optimization (PSO) to seek the optimal solutions. The formal description of the hybrid BP neural network and PSO is listed as follows.

Furthermore, we also assume that $C_i = (C_{i1}, C_{i2}, \cdots, C_{iD})$ is the current position for particle $p_i$ and $V_i = (V_{i1}, V_{i2}, \cdots, V_{iD})$ is the current velocity for $p_i$. $B_p = \min\{P_0, P_1, \cdots, P_s\}$ is the best position.
Afterwards, the output vector (denoted as $O$) can be constructed as follows.

$$net_j = \sum_h (w_h y_{hj}) \cdot Z_h - \lambda_{yj}$$  \hspace{1cm} (9)

$$O_j = F(net_j) = \left(1 + e^{-net_j}\right)^{-1}$$ \hspace{1cm} (10)

Afterwards, main differences between various hidden layers are estimated as follows.

$$\phi = Z_h \cdot (1 - Z_h) \cdot \sum_{j=1}^J W_h y_{hj} \cdot Y_j (1 - Y_j) \cdot (T_j - Y_j)$$  \hspace{1cm} (11)

Therefore, errors are computed when the convergence condition is satisfied. Next, the fitness for each particle can be calculated via an optimal function, and then the particle can revise the velocity for the next cycle by seeking the best value. Then, this process should be repeated when the end condition is satisfied. At last, major project risk assessment results are achieved from the output layers of the BP neural network which is optimized by the PSO algorithm.
5. **Experiment.** In this paper, we choose 20 major projects of a famous software development company in China to construct the dataset, among which 12 are utilized to be the training dataset, and others are regarded as the testing dataset. After the BP neural network model has been trained by the training dataset, the risks of major projects in the testing dataset can be computed. In addition, as software project risk is professional, this paper uses the expert scoring method to obtain sample data of index system.

In this experiment, we invite ten experts to evaluate the value of risks for the sample data, in which two business leaders, four project managers, and four project developers. Weights of these three types of persons are set to 1.5, 1.2, and 1 respectively. Furthermore, each index is divided into five grades: 1) lowest risk, 2) lower risk, 3) general risk, 4) higher risk and 5) highest risk. Particularly, these five risk levels are set to five ranges, that is, $(0,0.2)$, $(0.2,0.4)$, $(0.4,0.6)$, $(0.6,0.8)$, and $(0.8,1)$. The lower the risk level represents the lower scoring value. Through the statistical analysis, the index value of the given 8 testing samples (represented as $\{S_1, S_2, \ldots, S_8\}$) are listed in Table. 1 as follows.

As the ground truth, risk scores from experts’ opinion are listed in Table. 2, we compare it with our proposed method. The risk scores from experts’ opinion are illustrated in Table. 2 as follows.

Afterwards, we will test the performance of major project risk assessment using the BP neural network, of which the parameters are given in Table. 3.

Then, we train the proposed BP neural network, and the varying trend of the error rate in the training process is shown in Fig. 5 as follows.

From Fig. 5, we can see that the training process ends at the 4717 step, and then we finish the whole training process. That is to say, the proposed algorithm can achieve fast convergence. The actual results by the proposed method (denoted as BPNN-PSO) and the expectation results are illustrated in Fig. 6, and the BP
Table 1. Testing data of the major project risk assessment problem

|    | S1  | S2  | S3  | S4  | S5  | S6  | S7  | S8  |
|----|-----|-----|-----|-----|-----|-----|-----|-----|
| A1 | 0.135 | 0.154 | 0.228 | 0.190 | 0.218 | 0.184 | 0.208 | 0.252 |
| A2 | 0.145 | 0.216 | 0.195 | 0.221 | 0.140 | 0.287 | 0.210 | 0.243 |
| A3 | 0.139 | 0.138 | 0.363 | 0.270 | 0.139 | 0.306 | 0.151 | 0.274 |
| A4 | 0.427 | 0.520 | 0.599 | 0.582 | 0.633 | 0.618 | 0.535 | 0.587 |
| A5 | 0.451 | 0.510 | 0.638 | 0.605 | 0.639 | 0.616 | 0.630 | 0.571 |
| A6 | 0.156 | 0.210 | 0.493 | 0.167 | 0.305 | 0.393 | 0.219 | 0.289 |
| A7 | 0.241 | 0.215 | 0.390 | 0.185 | 0.214 | 0.334 | 0.334 | 0.169 |
| A8 | 0.371 | 0.319 | 0.343 | 0.208 | 0.179 | 0.397 | 0.380 | 0.356 |
| A9 | 0.385 | 0.419 | 0.312 | 0.220 | 0.303 | 0.323 | 0.356 | 0.117 |
| A10| 0.250 | 0.325 | 0.383 | 0.259 | 0.249 | 0.366 | 0.258 | 0.269 |
| A11| 0.237 | 0.275 | 0.357 | 0.352 | 0.242 | 0.310 | 0.363 | 0.253 |
| A12| 0.339 | 0.349 | 0.325 | 0.333 | 0.321 | 0.328 | 0.309 | 0.329 |
| A13| 0.211 | 0.216 | 0.392 | 0.281 | 0.209 | 0.295 | 0.215 | 0.347 |
| A14| 0.341 | 0.379 | 0.307 | 0.330 | 0.280 | 0.332 | 0.247 | 0.374 |
| A15| 0.171 | 0.182 | 0.319 | 0.213 | 0.148 | 0.348 | 0.150 | 0.195 |
| A16| 0.122 | 0.139 | 0.577 | 0.483 | 0.128 | 0.481 | 0.372 | 0.474 |
| A17| 0.149 | 0.162 | 0.400 | 0.335 | 0.120 | 0.478 | 0.468 | 0.363 |
| A18| 0.164 | 0.225 | 0.320 | 0.284 | 0.212 | 0.351 | 0.332 | 0.398 |
| A19| 0.219 | 0.246 | 0.176 | 0.250 | 0.155 | 0.316 | 0.209 | 0.214 |
| A20| 0.124 | 0.225 | 0.239 | 0.135 | 0.130 | 0.309 | 0.209 | 0.302 |

Table 2. Risk scores from experts’ opinion

| Project | S1   | S2   | S3   | S4   | S5   | S6   | S7   | S8   |
|---------|------|------|------|------|------|------|------|------|
| Expert  | 0.155| 0.189| 0.362| 0.171| 0.158| 0.347| 0.273| 0.301|

Table 3. Parameters of the propose BP neural network model

| ID  | Parameter name                        | Value  |
|-----|--------------------------------------|--------|
| 1   | Number of hidden layer nodes          | 35     |
| 2   | Transfer function type of hidden layer nodes | logsig |
| 3   | Neuron excitation function of output layer | purelin |
| 4   | Training function                     | traiInm |
| 5   | Learning function                     | learnGlm |
| 6   | Maximum iteration number              | 550    |
| 7   | Learning rate                         | 0.00001|
| 8   | Momentum coefficient                  | 0.94   |
| 9   | Error rate of network training        | 0.0001 |

neural network without optimized by PSO (denoted as BPNN) is used to make performance comparison.

Furthermore, error rates of risk assessment for different major projects are illustrated in Fig. 7 as follows.

It can be observed from Fig. 7 that our proposed BPNN-PSO model can effectively assess error rates of risk assessment for different major projects with lower
error rates than BPNN. Because the proposed PSO algorithm provides accurate parameter estimation, and then significantly enhances the accuracy of risk assessment results.

6. Conclusion. This paper presents a major project risk assessment method with the BP neural network model. An index system for major project risk assessment is provided in advance, and four parts are included in this index system: 1) Schedule risk, 2) Cost risk, 3) Quality risk, and 4) Resource risk. Next, we present a hybrid
BP neural network and particle swarm optimization (PSO) model to evaluate risks in major projects. In the end, experimental results show very positive results.

In the future, we will try to conduct the following works:
1) We will discuss how to optimize the proposed index system.
2) We will discuss if deep learning technology can be used in this paper to replace the BP neural network.

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