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The Use of the BP Neural Network Model in Risk and Return Assessment of Investment Projects for Engineering Management

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Abstract. This work aims to address the challenge of risk and return assessment in investment projects within the field of engineering management by proposing an innovative evaluation method based on a Back Propagation Neural Network (BPNN). By constructing and training the BPNN model, it successfully predicts the risk levels and returns of projects using a large dataset of historical engineering project data, significantly enhancing the accuracy of predictions and the scientific basis for decision-making. Experimental results show that, compared to traditional evaluation methods, the BPNN model demonstrates clear advantages in prediction accuracy, factor analysis, and decision support. The work also reveals limitations in areas such as data quality, model interpretability, and consideration of external factors, indicating directions for future research. The contribution of this work lies in showcasing the potential applications of artificial intelligence technology in engineering management. Moreover, this work provides new approaches and tools for risk assessment and return prediction of investment projects, with important theoretical and practical value.

Keywords: Engineering Management; Back Propagation Neural Network; Investment Projects; Risk and Return

1. Introduction

In the context of global economic integration, the intensity of market competition has reached unprecedented levels. This not only requires enterprises to have keen market insights but also tests their wisdom and courage in investment decision-making [1-3]. The success or failure of investment projects is directly related to the survival and development of enterprises. Therefore, accurately assessing the risk and return of projects has become a major issue for corporate decision-makers. However, traditional evaluation methods, whether based on subjective judgments from expert experience or on simple financial indicators for quantitative analysis, have significant limitations. In the complex and ever-changing market environment, these methods often fail to capture all the factors affecting project risk and return, significantly reducing their predictive accuracy and reliability [4-7].

In the face of this challenge, the rise of artificial intelligence (AI) technology offers new perspectives and solutions for the evaluation of investment projects. AI, especially developments in the field of machine learning, provides powerful tools for handling complex problems [8-10]. Among various machine learning models, the Back Propagation Neural Network (BPNN) stands out for its strong nonlinear modeling capabilities. BPNN can simulate the working method of human brain neurons through multi-level node connections, thereby achieving precise capture of complex input-output relationships [11-13]. This ability makes it unparalleled in handling problems involving numerous variables, nonlinear relationships, and high-dimensional data.

Specifically, in the risk and return assessment of investment projects, BPNN can integrate various influencing factors, including but not limited to market trends, industry dynamics, technological changes, policy environments, and capital costs. By training the model, it can learn the intrinsic connections between these factors and project risk and return. Compared to traditional evaluation methods, the BPNN model can more comprehensively and deeply reveal the essence of project risk and return, providing more accurate predictive results. Moreover, with the maturity of big data and cloud computing technologies, the training and application of BPNN have become more efficient and convenient, allowing this advanced tool to be promoted and applied more widely [14-17].

The core innovation of this work lies in the systematic application of BPNN to the field of engineering management for the first time, particularly in the risk and return assessment of investment projects. By building a data-driven predictive model, this work effectively addresses the shortcomings of traditional evaluation methods. It provides decision-makers with more precise and comprehensive data support, thereby significantly enhancing the scientific and accuracy of investment decisions. Additionally, the work focuses on optimization strategies and validation methods for the model, ensuring its reliability and practicality, and opening up new directions for theoretical research and practical operations in the field of engineering management.

2. Methods

2.1. Data Collection and Preprocessing

(1) Data Collection. In order to build an efficient and accurate BPNN model, this work initially undertakes extensive data collection. The data sources encompass engineering projects globally, including sectors such as infrastructure construction, energy development, and information technology. Each data record contains detailed project information, such as project scale (typically represented by investment amount), cost budget, expected completion time, technical difficulty rating, market environment assessment, and the project's final actual risk level and return. Notably, the risk levels and returns are used as label data for model training and validation processes during the supervised learning.

(2) Data Preprocessing. Data preprocessing is an indispensable step in constructing machine learning models, directly impacting the model's performance and stability [18-20]. First, the data are cleaned to remove outliers and missing values, improving data quality. Subsequently, numerical features are standardized. Each feature X_i is transformed into $\frac{X_i-\mu}{\sigma}$, where μ is the mean and σ is the standard deviation of the feature. This normalization ensures that all features are on the same scale, preventing any feature with a larger magnitude from dominating the model training results. For categorical features, one-hot encoding is used to convert them into binary vectors, facilitating model processing.

2.2. Construction of BPNN Model

(1) Network Architecture Design. BPNN is a classic model in the field of machine learning, and its architecture design has a decisive impact on the model's performance. This work carefully designs a BPNN model consisting of three layers: the input layer, a hidden layer, and the output layer, aimed at optimizing the prediction effectiveness of investment project risk and return assessment. Below is a detailed explanation of the functions of each layer, principles for determining node numbers, and overall architecture design strategy. Input Layer Design: The input layer is the first gateway for BPNN to receive external information, with the number of nodes directly corresponding to the number of preprocessed features. This work collects and preprocesses a large number of features related to engineering projects, including project scale, cost, time, technical difficulty, and market environment. Each feature represents a dimension that may influence project risk and return. Therefore, the number of nodes in the input layer equals the total number of these features, ensuring that the model can comprehensively receive and process all relevant information. Determination of Hidden Layer Node Numbers: The hidden layer is the core part of BPNN, responsible for extracting and learning complex nonlinear relationships among input features. The number of nodes in the hidden layer is a hyperparameter that directly affects the model's expressiveness and generalization performance. Too many nodes may lead to overfitting, where the model performs well on training data but poorly on unseen data; too few nodes may cause underfitting, where the model fails to capture the underlying patterns in the data. This work determines the optimal number of hidden layer nodes

through a series of experiments. Specifically, it uses cross-validation methods, tries different numbers of nodes, monitors the model's performance on a validation set, and finally selects the number of nodes that yields the best performance on the validation set. This approach avoids overfitting and ensures that the model adequately learns the complex structure of the data. Output Layer Design: The output layer is the final stage where BPNN outputs the prediction results to the outside world. This work aims to predict the project's risk level and return. Therefore, the output layer is designed to contain two nodes: the first node predicts the project's risk level, and the second node predicts the return situation. This design enables the model to simultaneously handle multi-task predictions, assessing both potential risks the project may face and predicting its potential returns, providing decision-makers with a comprehensive reference basis.

The architecture design of BPNN is a balancing act, considering both the model's complexity and its generalization ability and prediction accuracy. Through careful design of the input layer, hidden layer, and output layer, this work ensures that the model can comprehensively receive and process project feature information, and effectively learn and predict project risk and return. The selection of hidden layer node numbers is validated through experiments, avoiding issues of over-complexity leading to overfitting while ensuring the model adequately learns complex patterns in the data. Overall, such architecture design establishes a solid foundation for the application of BPNN in investment project risk and return assessment, providing decision-makers with scientific, accurate, and comprehensive decision support. Figure 1 depicts the BPNN framework designed.

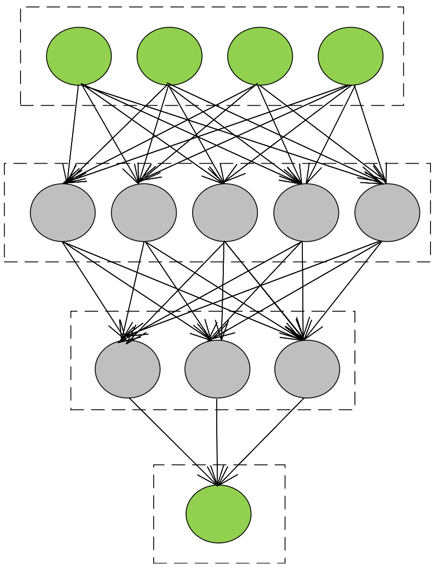

Figure 1: BPNN Framework

(2) Weight Initialization and Forward Propagation. The initialization of weights in BPNN is crucial for the model's convergence speed and final performance. This work adopts Glorot initialization [21], where the weights W_{ij} follow a uniform distribution with a mean of 0 and a variance of $\frac{2}{n_{in}+n_{out}}$. nin and nout are the numbers of nodes in the current layer and the next layer, respectively. During the forward propagation process, the output a(l) of each layer is calculated as follows:

$$a^{(l)} = \sigma(W^{(l)}a^{(l-1)} + b^{(l)}) \tag{1}$$

$W^{(l)}$ and $b^{(l)}$ are the weight matrix and bias vector of layer l respectively, σ denotes the activation function, commonly chosen as the Sigmoid function and ReLU function. This work opts for the ReLU function because it accelerates the training process and mitigates gradient vanishing issues.

(3) Backpropagation and Weight Updates. The backpropagation algorithm is pivotal in BPNN, calculating gradients of the loss function with respect to network weights, thereby updating weights to minimize the loss. It is assumed that the loss function is L, and the update rule for weights W is:

$$W \leftarrow W - \alpha\frac{\partial L}{\partial W} \tag{2}$$

Where α is the learning rate, which needs to be adjusted appropriately to balance convergence speed and stability. The computation of the gradient $\frac{\partial L}{\partial W}$ follows the chain rule, calculated layer by layer starting from the output layer.

2.3. Model Training and Evaluation

(1) Training Process. The model training is conducted on the training set, aiming to minimize the error between predicted values and actual values, represented by the loss function L. This work employs Mean Squared Error (MSE) as the loss function, defined as:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (3)$$

y_i represents the actual value, $\hat{y}_i$ denotes the predicted value, and N is the number of samples. Model training proceeds through multiple iterations, with each iteration involving forward propagation to compute predicted values and backpropagation to update weights. The iteration continues until the loss function converges or reaches the preset maximum number of iterations.

(2) Model Evaluation. Model evaluation is conducted on an independent test set to assess the model's generalization ability. This work calculates metrics such as the correlation coefficient between predicted and actual values, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and others to comprehensively evaluate the model's prediction accuracy. Additionally, this work performs cross-validation to further validate the model's stability and robustness.

3. Results

3.1. Accuracy of Risk Level Prediction

This work analyzes the accuracy of the model in predicting risk levels. The results are depicted in Figure 2:

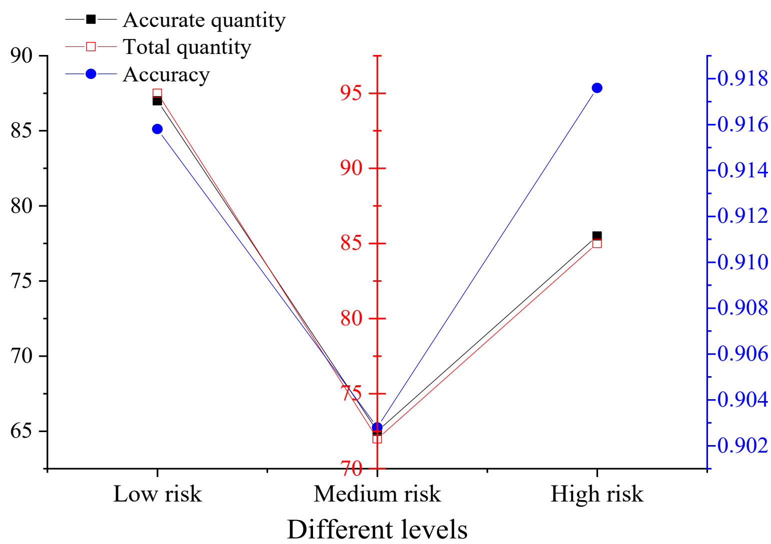

Figure 2: Accuracy of Risk Level Prediction

Figure 2 illustrates the BPNN model's high accuracy in predicting risk levels, particularly achieving accuracy rates exceeding 90% for both moderate and high-risk levels. This indicates the model's effectiveness in capturing critical factors contributing to project risks.

3.2. Prediction of Returns

This work analyzes the errors in predicting returns. Figure 3 presents the results.

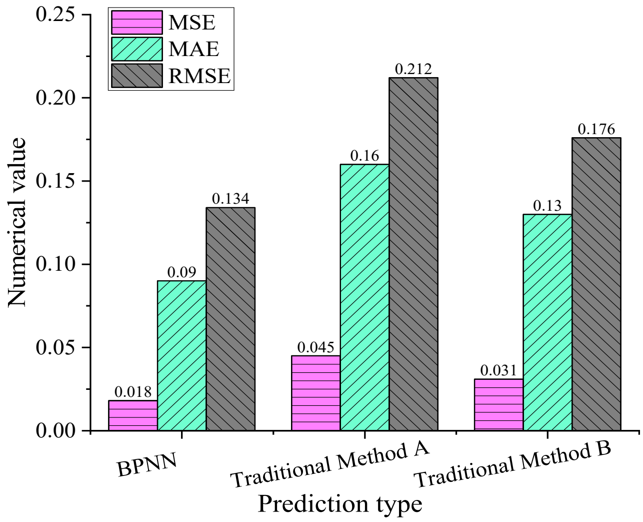

Figure 3: Prediction of Returns

Figure 3 illustrates the performance of the BPNN model in predicting returns. Its MSE, MAE, and RMSE are significantly lower compared to traditional evaluation methods. Particularly noteworthy is the MAE metric, where the BPNN model's error is approximately half that of traditional method A. This highlights the model's substantial advantage in prediction accuracy.

3.3. Sensitivity Analysis of Key Influencing Factors

This work analyzes the sensitivity of key influencing factors in the model. Figure 4 shows the results:

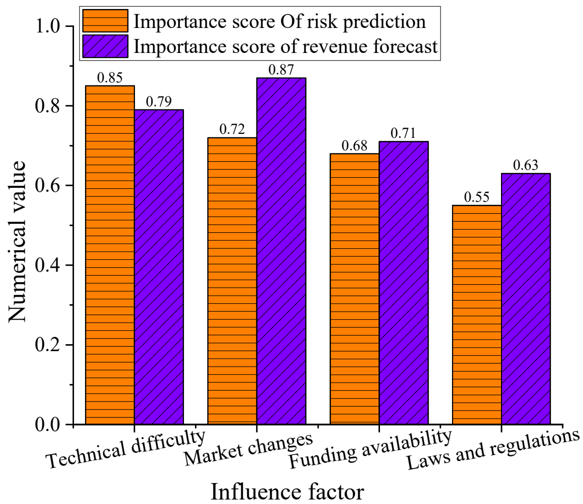

Figure 4: Sensitivity of Key Influencing Factors in the Model

Figure 4 demonstrates that technical difficulty and market changes are the two most critical factors influencing both risk and return predictions. This aligns with intuition and validates the model's rationale. Additionally, the impact of funding availability and legal regulations should not be overlooked, as they partly determine project feasibility and profitability potential. The analysis also reveals the diverse factors and their interactions affecting investment project risk and returns, providing decision-makers with a more comprehensive perspective. By integrating these factors, more accurate project risk assessments can be made, facilitating the formulation of rational investment strategies for sustainable development in complex and dynamic market environments.

4. Conclusion

This work illustrates the substantial potential of AI in enhancing the precision of predictions and the rigor of decision-making in evaluating investment project risks and returns within engineering management. By employing the BPNN model, renowned for its robust data processing capabilities and intricate pattern recognition features, the work significantly improves predictive accuracy and provides profound insights into critical factors influencing project risks and returns. This comprehensive understanding empowers decision-makers with unprecedented insights and robust data support, enhancing the reliability and foresight of investment decisions. The work's strengths lie in three key aspects. First, the BPNN model demonstrates significant superiority over traditional evaluation methods in predicting risk levels and investment returns, particularly evident in critical metrics such as MSE, MAE, and RMSE. Second, the model effectively identifies and quantifies the importance of critical factors like technological complexity and market variations, offering a more comprehensive and detailed perspective for project assessment. Third, by delivering precise prediction outcomes and thorough factor analyses, the BPNN model provides decision-makers with robust data support to formulate strategic decisions amidst complex and dynamic market environments.

Despite these strengths, the work acknowledges certain limitations. Challenges include potential constraints in data completeness and diversity, particularly for specialized projects in specific industries or regions with inadequate data support. Moreover, the risks and returns of investment projects are often profoundly influenced by macroeconomic conditions and regulatory policies. Currently, the model primarily focuses on the characteristics of the projects themselves, with less consideration of external macroeconomic changes. Future research efforts should aim to broaden the sources of data and increase sample sizes to encompass a more diverse range of project types and market environments. Additionally, studies will incorporate more macroeconomic indicators and data on policy changes to enhance the comprehensiveness and predictive accuracy of the model.

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