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Comparative Study on Performance of Various Neural Network Algorithms in Construction Project Cost Prediction

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Abstract

Accurate prediction of construction costs is essential to ensure smooth project execution and guarantee economic benefits. The primary objective of this study is to explore the application of neural network algorithms in predicting construction project costs. Specifically, a back-propagation neural network (BPNN) enhanced with the AdaBoost algorithm was tested and compared with traditional BPNN and support vector machine (SVM) models. Simulation results indicated that the AdaBoost-BPNN algorithm converged faster with a smaller mean square error, providing a more accurate prediction (MAE: 0.467, RMSE: 1.118). This study offers valuable insights into the advantages of boosting techniques in neural network models for cost prediction in construction projects.

***Keywords*: Neural networks, Construction cost prediction, AdaBoost, BPNN, SVM.**

1. Introduction

The construction industry plays a pivotal role in economic development, especially in rapidly urbanizing nations like China. With increased investments in large-scale projects, accurately predicting construction costs has become essential to avoid cost overruns and ensure financial sustainability. Traditional cost prediction methods, such as the quota and bill of quantities methods, rely heavily on historical data and market surveys. While they are straightforward to implement, they lack the flexibility to incorporate complex, non-linear factors that may affect project costs. Neural network algorithms, a branch of artificial intelligence, offer an alternative by uncovering hidden patterns in data, enabling more precise predictions. This paper focuses on utilizing BPNN and AdaBoost to enhance the accuracy of construction project cost predictions. Through comparative simulations, the study seeks to evaluate the performance of various models, providing insights for improving cost prediction accuracy.

2. Related Works

Numerous studies have examined the potential of machine learning techniques in construction cost estimation. Rafiei and Adeli (2018) applied advanced machine learning models to predict construction costs, achieving significant improvements over traditional statistical methods. Kumar et al. (2023) reviewed various machine learning algorithms and found that neural networks, particularly ANN, are commonly employed for cost estimation due to their ability to model complex data relationships.

Ye (2021) introduced a particle swarm optimization-enhanced BPNN for construction project cost estimation, demonstrating the algorithm's superiority in reducing prediction errors. Hashemi et al. (2020) provided a comprehensive review of machine learning applications in construction, noting that neural network algorithms, when optimized, outperform classical models in terms of prediction accuracy.

Building on these studies, this paper adopts AdaBoost to enhance the BPNN model, enabling it to overcome the limitations of traditional methods and improve accuracy.

3. The Cost Prediction Algorithm for Construction Projects

3.1 **Factors Affecting Construction Project Costs**

Cost prediction accuracy depends on several factors that influence construction expenses. These factors are divided into two categories: building characteristic indicators and socio-economic indicators. The former includes project size, the number of floors, and structural complexity, while the latter comprises regional economic factors like gross domestic product (GDP), consumer price index (CPI), and average regional wages (Table 1). These variables form the input layer of the neural network model, enabling it to capture the multidimensional aspects of cost prediction.

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3.2 **Neural Network Algorithm**

Traditional cost prediction models struggle to handle large, multidimensional datasets due to limitations in their capacity to model non-linear relationships. Neural networks, specifically BPNN, are better equipped to manage this complexity. The BPNN algorithm operates by feeding relevant cost indicators into the input layer, passing them through hidden layers where non-linear patterns are captured, and finally producing a prediction at the output layer.

However, training a BPNN model requires careful tuning to avoid overfitting or underfitting. One solution is to combine BPNN with boosting techniques like AdaBoost, which helps reduce prediction errors by focusing on misclassified data. Figure 1 illustrates the process of combining weak BPNN predictors using AdaBoost to generate a robust predictive model.

4. Simulation Experiments

4.1 **Experimental Data**

To test the effectiveness of the proposed algorithm, data from 345 construction projects in Henan province, China, were collected. These projects, ranging from 2012 to 2022, included basic decoration tasks for residential units. After filtering based on the defined cost indicators, 300 sample cases were used for the experiments, with 200 samples reserved for training and 100 for testing. Table 2 provides a statistical summary of the dataset, showing a wide range of values for key indicators like building area, floor numbers, and project costs.

4.2 **Experimental Setup**

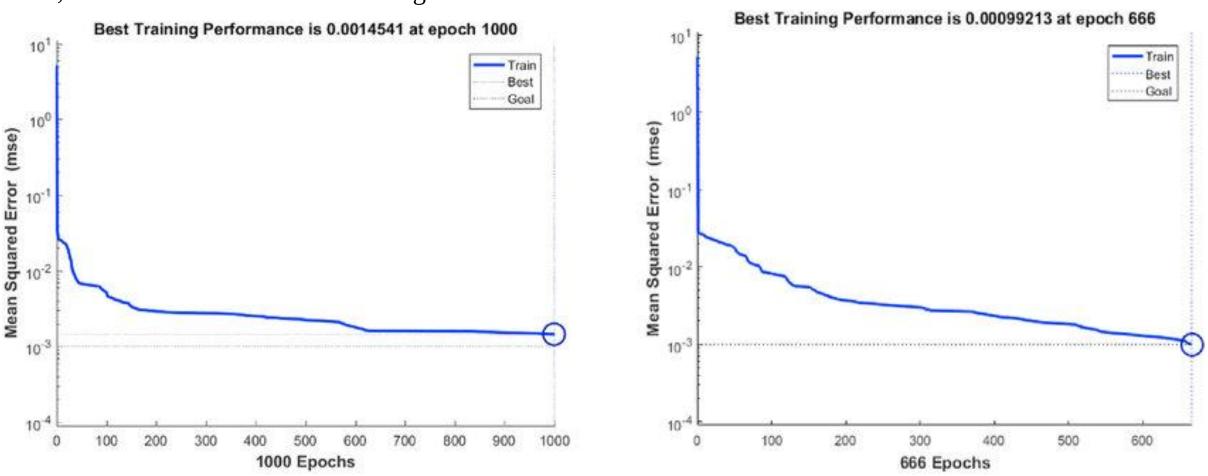
Three prediction models were implemented and compared: traditional BPNN, AdaBoost-BPNN, and SVM. The BPNN structure featured 14 input nodes, two hidden layers with 64 nodes each, and one output node representing the predicted construction cost. The AdaBoost-BPNN model combined 10 weak predictors, adjusting weights based on their errors. The SVM model, on the other hand, used a sigmoid kernel and a penalty parameter of 1.0.

4.3 **Evaluation Criteria**

The performance of the models was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and goodness of fit (R^2). These metrics measure the difference between predicted and actual costs, allowing for a comprehensive comparison of model accuracy and reliability.

5. Experimental Results

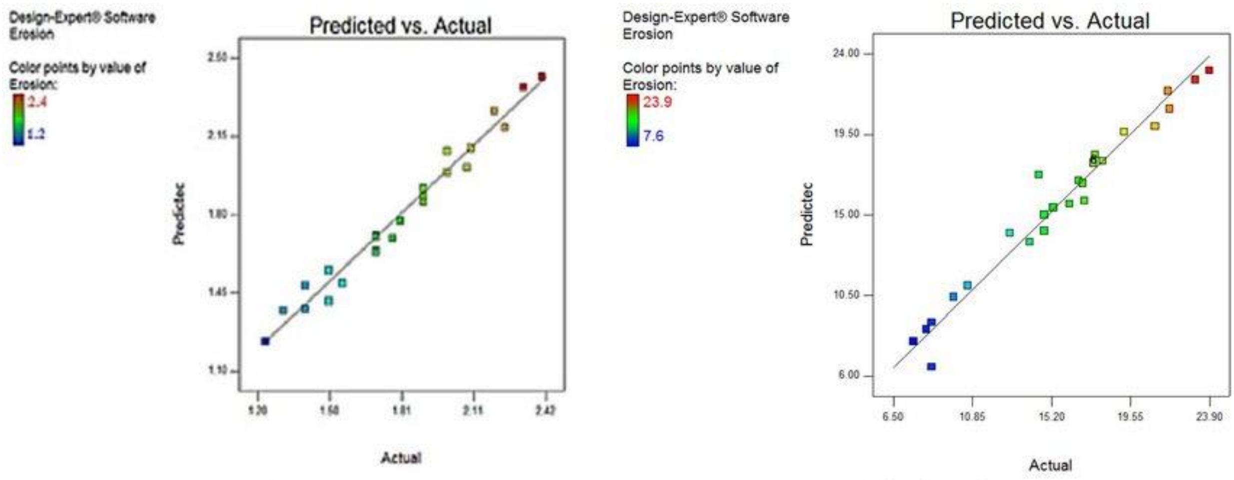
The experimental results demonstrated the superiority of the AdaBoost-BPNN model in terms of prediction accuracy and convergence speed. As shown in Table 4 and Figure 2, the AdaBoost-BPNN algorithm achieved a smaller mean square error and converged to stability faster than both the traditional BPNN and SVM models. Specifically, the MAE of AdaBoost-BPNN was 0.467, compared to 0.603 for traditional BPNN and 0.875 for SVM. The RMSE followed a similar trend, with AdaBoost-BPNN exhibiting the lowest error of 1.118.



(a). MSE of BPNN (b). MSE of GANN

Figure1:Comparison of mean squared error change curve between BPNN and GANN algorithm.

Scatter plots of predicted versus actual costs (Figure 3) further demonstrated the improved performance of the AdaBoost-BPNN model. While all models showed some degree of deviation from the diagonal (representing perfect prediction), the AdaBoost-BPNN scatter points were more concentrated along the diagonal, indicating higher accuracy.



Penetrometer Wind erosion

Figure2: Scatter plot of predicted value vs actual value from RSM design.

6. Discussion

The results of this study highlight the benefits of using AdaBoost to improve BPNN performance in predicting construction project costs. The boosting technique significantly reduces the prediction error by concentrating on samples with larger prediction mistakes, leading to faster convergence and better generalization of the model. While the traditional BPNN and SVM models performed adequately, they were outperformed by the AdaBoost-BPNN model, especially in handling non-linear patterns in the data.

One key observation from the simulations was that SVM, despite its simplicity, struggled with the non-linearity of the data, leading to lower accuracy compared to neural network models. The AdaBoost-BPNN model, by contrast, handled the complexity effectively by combining weak predictors, thus minimizing error in high-variance samples.

7. Conclusions

This paper presented a comparative analysis of neural network algorithms for construction cost prediction, focusing on traditional BPNN, AdaBoost-BPNN, and SVM models. The AdaBoost-BPNN model emerged as the most accurate and reliable, converging faster and with lower prediction errors than the other models. This research demonstrates the value of boosting techniques in improving neural network models, offering an effective solution for cost prediction in construction projects.

While the results are promising, this study was limited by the size of the dataset. Future research should focus on expanding the dataset and applying the model to real-world projects to improve its generalization capability.

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