Prediction of Engineering Parameters Based on Improved Artificial Neural Network

Jiang Shen[1], Ling-ling Li[1], and Dong-ming Lin[2](✉)

[1] Department of Management and Economics, Tianjin University, Tianjin, China

[2] Logistics Center of Shenzhen Power Supply Bureau, China Southern Power Grid, Shenzhen, China

13728662879@163.com, chengzhi0821@163.com

Abstract. The prediction of engineering parameters is crucial for engineering management. This study proposes an improved integrated artificial neural network (ANN) model, combining ANN with AdaBoost algorithm and cost sensitive method to predict engineering parameters. Through the integration of ANN and the set of prediction error threshold and cost value, it not only improves the generalization ability of ANN, but also ensures the scientificity of engineering prediction. The proposed model is applied to predict concrete compressive strength, and compared with artificial neural network, linear support vector machine, support vector regression, multiple linear regression, classification and regression tree. The results show that the mean absolute percentage errors are respectively 14.23%, 16.54%, 30.07%, 17.91%, 31.85%, and 26.08%. Compared with the other five models, the proposed model shows best prediction accuracy. The study shows that the proposed model is superior in engineering prediction.

Keywords: ANN · AdaBoost algorithm · Engineering prediction

1 Introduction

In recent years, Building Information Modeling (BIM) has been widely used in engineering projects. BIM contains a large amount of project information, such as geometric and physical data of components, functional features, etc. As a platform for data integration and sharing, BIM can provide reliable data and result visualization for algorithms [1]. Many researchers have studied the combination of BIM and various algorithms for cost prediction, construction site layout, etc. The capability of Artificial Neural Network (ANN) to perform nonlinear mapping of output from multiple inputs makes them suitable for handling estimation problems in construction that typically involve complex input-output relations [2–4]. ANN demonstrated excellent predictive ability [5–7]. Reference [8] used BP neural network to predict construction cost based on BIM.

In the process of machine learning, the prediction results of ANN depend on its network topology, weights, thresholds and other parameters. Therefore, the results are often unstable. Researchers have optimized the parameters of ANN to improve the

C.-F. Chien et al. (Eds.): *IE&EM 2019*, pp. 21–27, 2020.
https://doi.org/10.1007/978-981-15-4530-6_3

prediction accuracy. Lahiri and Khalfe [9] developed a new hybrid procedure to find the optimum ANN architecture and tunes the ANN parameters. This method incorporated hybrid ANN and differential evolution technique (ANN-DE) for efficient tuning of ANN meta parameters. Jo *et al*. [10] introduced three optimization algorithms to search for the optimal values of the ANN's hyper-parameters. They were random search (RS), tree-structured Parzen estimator (TPE), and hyper-parameter optimization via radial basis function and dynamic coordinate search (FIORD). Lo *et al*. [11] used a parameter automatic calibration (PAC) approach to adjust the training parameters and found the results yielded by the ANN-PAC model were more reliable. Lu *et al*. [12] pointed out that the genetic algorithm (GA) performs better in determining the weighting and threshold of ANN models and is therefore combined with BP to develop this study's ANN model. Although hyperparametric optimization of ANN can improve its prediction accuracy, the optimized ANN model has poor generalization ability. Therefore, when the model is applied to new data sets, and robustness of the model is weak. In order to overcome this problem, Sun and Gao [13] combined AdaBoost algorithm with neural network to overcome the instability of single neural network and provide more accurate and stable prediction for new data sets. AdaBoost algorithm is an iterative algorithm, which is mainly applied to the classification problem [14]. After several years of development, it has been extended to the prediction field [15]. AdaBoost algorithm can improve the prediction accuracy of any given weak predictor.

In this study, AdaBoost algorithm is used to achieve predictors ensemble. ANN is regarded as weak predictor, and the sample weight is adjusted according to the prediction error of ANN. The updated sample weight is used again to train the next new weak predictor, and finally a series of weak predictors are combined, getting a strong predictor and the final output. In order to test the accuracy of the proposed algorithm in engineering prediction, it is applied to the prediction of concrete compressive strength. In order to avoid engineering risks, the prediction error needs to be controlled within a certain range. Therefore, the proposed algorithm is combined with cost sensitive method, threshold value is set for prediction errors.

2 Methodology

In order to improve the accuracy of prediction, the AdaBoost algorithm is used to build a hybrid prediction framework containing multiple ANNs. The prediction results of all ANNs are summarized to obtain the final prediction results. The weight of each ANN is controlled by the AdaBoost algorithm. In order to distinguish the importance of different training samples, the weight of the training samples is jointly controlled by the AdaBoost algorithm and the cost sensitive method, and the cost sensitive method is used to set an appropriate threshold for the prediction error. When the error exceeds the threshold, the sample weight needs to be increased on the basis of high cost value, that is, the sample whose prediction error falls outside the threshold has higher prediction cost. When the prediction error is within the set threshold, the sample weight is decreased based on the lower cost value.

In order to ensure the validity and scientificity of the engineering prediction results, the prediction whose error exceeds the set threshold is regarded as a wrong prediction, that is, the prediction result that is too high or too low is unacceptable, therefore, the prediction problem can be converted into classification problem. The prediction results are divided into two categories, one is the correct prediction, the error of which is within the threshold, and the prediction is regarded as $+1$, and the other is the wrong prediction, the error of which exceeds the threshold, and the prediction is regarded as -1. The prediction result is recorded as $(h_i(x_i), y_i)$, y_i is the actual result, $(+1, +1)$ represents that the prediction is correct, and the cost value is C_1; $(+1, -1)$ represents that the prediction is wrong, and the cost value is C_2. The cost of $(+1, -1)$ is higher than $(+1, +1)$, that is, $C_2 > C_1$. By combining the AdaBoost algorithm with the cost-sensitive method, the prediction accuracy of ANN is improved.

ANN is applied for prediction. AdaBoost algorithm and the cost-sensitive method are used to adjust the sample weights, and then several ANNs (weak predictors) are combined by AdaBoost algorithm to achieve the high-precision prediction. The calculation steps of the algorithm are as follows:

Step 1. Select the training data set $S_n = \{X_i, Y_i\} = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ $(i = 1, 2, \ldots, n)$. The weight of the sample S_n is $\{W_t(i)\}$ $(t = 1, 2, \ldots, T)$. The initial weight of the sample is $1/n$.

$$\{W_1(i)\} = 1/n \quad (i = 1, 2, \ldots, n) \tag{1}$$

n is the sample size. T is the number of the predictors.

Step 2. Use the predictor H_t to predict the output variable $\{Y_i\}$, and calculate the prediction error $\{E_t\}$.

$$E_t = \sum\nolimits_{i:f_t(x_i) \neq y_i} w_t^i \tag{2}$$

Step 3. Calculate the weight of the predictor.

$$\alpha_t = \frac{1}{2}\ln\left(\frac{1 - E_t}{E_t}\right) \tag{3}$$

Step 4. Update the sample weight $\{W_t(i)\}$. The error threshold value is set to θ.

$$\begin{cases} W_t(i) = \frac{C_i W_{t-1}(i) \exp(-\alpha_t C_i l_t^i)}{Z_t} \\ Z_t = \sum\limits_i C_i W_{t-1}(i) \exp(-\alpha_t C_i l_t^i) \end{cases} \tag{4}$$

$$l_t^i = \begin{cases} 1, f_t(x_i) = y_i \\ -1, f_t(x_i) \neq y_i \end{cases} \tag{5}$$

$$C_i = \begin{cases} C_1, E_t \leq \theta \\ C_2, E_t > \theta \end{cases} \tag{6}$$

Calculating according to the sample weight update formula above can minimize the prediction error with high cost [16].

Step 5. Repeat step 1–4 until all predictors have been executed.

Step 6. Summarize all the predictors in the AdaBoost framework to form the final strong predictor.

$$H = \sum_{t=1}^{T} \alpha_t H_t \tag{7}$$

The engineering parameters are used to predict the concrete compressive strength. The data set used in the experiment is from the UCI database, which include1030 samples. The sample attributes include cement (m^3/kg), blast furnace slag (m^3/kg), fly ash (m^3/kg), water (m^3/kg), superplasticizer (m^3/kg), coarse aggregate (m^3/kg), fine aggregate (m^3/kg) and age (day).

In practical engineering projects, the data of these basic parameter can be directly read from BIM through the API interface using algorithm software, and then analyzed by the algorithm proposed in this paper. In order to test the superiority of the improved artificial neural network, the data set is obtained from the engineering database.

The three-layer ANN model is applied, the number of input neurons is 8, the number of output neurons is 1, the number of hidden layer neurons is 32, the learning rate is 0.2, the number of iterations is 500, and the number of experiments is 25. The error threshold is set to 0.15. The AdaBoost algorithm integrates 10 ANN models. 75% of the total samples are randomly selected as the training set, and the remaining 25% as the test set.

3 Results

Four evaluation indicators are selected to evaluate the performance of the model, namely mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE) and mean absolute percentage error (MAPE).

To obtain comparable experimental results, the same problem is solved by five different methods. AdaBoost-ANN algorithm is compared with artificial neural network (ANN), linear support vector machine (linear SVM), support vector regression (SVR), multiple linear regression (MLR), classification and regression tree (CART) by calculating the values of the prediction error. The experimental results are shown in Table 1.

Table 1. Experimental results of six models

	AdaBoost-ANN	ANN	Linear SVM	SVR	MLR	CART
MAE (MPa)	4.20 ± 0.28	4.85 ± 1.01	8.15 ± 0.35	4.95 ± 0.22	8.24 ± 0.31	7.22 ± 0.32
MSE (MPa2)	33.35 ± 5.36	42.23 ± 16.89	118.96 ± 14.71	45.10 ± 5.01	108.02 ± 7.76	85.97 ± 7.03
RMSE (MPa)	5.75 ± 0.46	6.40 ± 1.11	10.89 ± 0.68	6.71 ± 0.37	10.39 ± 0.38	9.26 ± 0.38
MAPE (%)	14.23 ± 1.16	16.54 ± 3.27	30.07 ± 2.25	17.91 ± 1.75	31.85 ± 2.23	26.08 ± 1.65

It can be seen from Table 1 that the mean absolute error of the AdaBoost-ANN algorithm is reduced by 0.65–4.04 compared with the other five algorithms. In addition, among the other five algorithms, the mean absolute error of the ANN model is the lowest. Similar results are also shown in other indicators. Compared with the other five algorithms the mean square error, root mean square error, and average absolute percentage error of the proposed algorithm are reduced by 8.88–85.61, 0.65–5.14 and 2.31%–17.62%, respectively. Among the other five algorithms, the ANN model outperforms other algorithms. The mean square error is reduced by 8.88–85.61. The root mean square error is reduced by 0.65–5.14. The mean absolute percentage error is reduced by 2.31%–17.62%. Therefore, compared with the other five algorithms, the proposed algorithm has higher prediction accuracy, which indicates that it is superior to the other five algorithms in engineering prediction.

In addition, For SVR, the variance of each evaluation indicator is the lowest among the other five algorithms. For the proposed algorithm, the variance of MAE and MSE is only higher than that of SVR, and the variance of MAPE is the lowest. In addition, the variance of every indicator of the ANN model is the highest.

4 Discussion

Table 1 shows that compared with the other five algorithms, the proposed algorithm has the highest prediction accuracy, and each evaluation indicator of the method is lower, indicating that the proposed algorithm outperforms the other five algorithms and the prediction stability is better. Among the other five algorithms, the ANN model has the best performance in prediction accuracy, but it has the worst performance in prediction stability, which indicates that the ANN model can accurately predict the compressive strength of concrete, but its poor stability can sometimes lead to excessive differences in prediction accuracy, which limits the practical application of the ANN model. Compared with the ANN model, the AdaBoost-ANN algorithm further improves the accuracy of the prediction, and more importantly, it significantly improves the stability of the prediction, and can avoid the situation, to some extent, where the prediction error is large, thus having better generalization ability. The proposed algorithm has higher engineering applicability in practical engineering.

5 Conclusion

From the perspective of engineering application, in order to reduce the risk of engineering practice and improve the prediction accuracy of engineering parameters, the cost-sensitive method is combined with ANN to set a threshold for the prediction error, and the samples whose prediction errors are beyond the threshold are set to higher cost values, thus ensuring higher prediction accuracy and improving the safety and scientificity of engineering prediction. In order to overcome the dependence of single ANN prediction on hyperparameters and samples, improve the generalization ability of the model and the accuracy of prediction, the AdaBoost algorithm is used to integrate multiple ANNs so as to overcome the dependence of single ANN on hyperparameters and samples and improve the generalization ability of the model. By applying the proposed model to concrete compressive strength prediction and comparing with the experimental results of five other algorithms, it is proved that the proposed model has high precision in engineering prediction.

Combining BIM with ANN provides a new idea for engineering data analysis of BIM project. With the promotion and application of BIM, it will become a new direction for the informatization development of engineering management to combine BIM with algorithms to make full use of the massive data in BIM. By applying the results of data analysis to engineering practice, technical support can be provided for engineering decisions.

There are a large number of engineering parameters in the construction project. This study only uses the compressive strength of concrete as an example to verify the applicability of the improved artificial neural network in engineering prediction. Therefore, in order to meet the actual needs of engineering practice, it is necessary to conduct further research in other engineering parameters in BIM.

Acknowledgment. The research is supported by Shenzhen Power Supply Bureau of China Southern Power Grid commission project: Material Storage and Distribution Management Method Based on Digital Portrait and Intelligent Analysis Technology (grant no. 0918002019 030304WLCP00003).

References

1. Gentili, G.B., Tesi, V., Linari, M., Marsili, M.: A review of BIM-based artificial intelligence methods. J. Graph. **39**(5), 797–805 (2018)
2. Chao, L.C., Skibniewski, M.J.: Neural network method of estimating construction technology acceptability. Constr. Eng. Manage. **121**(1), 130–142 (1995)
3. Boussabaine, A.H.: The use of artificial neural networks in construction management: a review. Constr. Manage. Econ. **14**(5), 427–436 (1996)
4. Boussabaine, A.H., Kaka, A.P.: A neural networks approach for cost flow forecasting. Constr. Manage. Econ. **16**(4), 471–479 (1998)
5. Hossain, K.M.A.: Regression and artificial neural network models for strength properties of engineered cementitious composites. Neural Comput. Appl. **29**(9), 631–645 (2018)
6. Erzin, Y., Cetin, T.: The prediction of the critical factor of safety of homogeneous finite slopes using neural networks and multiple regressions. Comput. Geosci. **51**, 305–313 (2013)
7. Leu, S.-S., Lo, H.-C.: Neural-network-based regression model of ground surface settlement induced by deep excavation. Autom. Constr. **13**(3), 279–289 (2004)
8. Tang, H.-Y., Liu, R.-G., Han, Y., Wang, J.: The construction of project cost prediction system based on 5D-BIM. J. Eng. Manage. **29**(4), 107–112 (2015)
9. Lahiri, S.K., Khalfe, N.: Modeling of commercial ethylene oxide reactor: a hybrid approach by artificial neural network & differential evolution. Int. J. Chem. Reactor Eng. **8**(1) (2010)
10. Jo, Y., Min, K.: Comparative study of the artificial neural network with three hyper-parameter optimization methods for the precise LP-EGR estimation using in-cylinder pressure in a turbocharged GDI engine. Appl. Therm. Eng. **149**(25), 1324–1334 (2019)
11. Lo, D.-C., Wei, C.-C.: Parameter automatic calibration approach for neural-network-based cyclonic precipitation forecast models. Water **7**(7), 3963–3977 (2015)
12. Lu, W., Peng, Y., Chen, X., Skitmore, M., Zhang, X.: The S-curve for forecasting waste generation in construction projects. Waste Manage. **56**, 23–34 (2016)

13. Sun, W., Gao, Q.: Exploration of energy saving potential in China power industry based on AdaBoost back propagation neural network. J. Clean. Prod. **217**(20), 257–266 (2019)
14. Zhong, X.Y., Ling, J.: AdaBoost detector based on multiple thresholds for weak classifier. Comput. Eng. Appl. **45**(19), 160–162 (2009)
15. Ge, Q.F., Feng, X.: Classification and prediction of rockburst using AdaBoost combination learning method. Rock Soil Mech. **29**(4), 943–948 (2008)
16. Sun, Y.: Cost-sensitive boosting for classification of imbalanced data. Pattern Recogn. **40**, 3358–3378 (2007)