Elastic Modulus Prediction for Manufactured Sand Concrete Using Fuzzy Set and Neural Network

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Abstract: The application of concrete with manufactured sand instead of natural sand is becoming increasingly prevalent. However, due to the inherent differences in the physical properties of manufactured and natural sand, it is not possible to apply the modulus of elasticity formula for natural sand concrete directly to manufactured sand concrete. Given that the combination of fuzzy rule modelling and neural network technology has been applied to data prediction, a prediction method based on fuzzy set and BP neural network model is constructed for the purpose of predicting the elastic modulus of manufactured sand concrete. The predicted value is then compared with the target value. The results demonstrate that the predictive model exhibits superior performance. The predictive model may serve as a point of reference for analogous studies.

Keywords: BP neural network; elastic modulus, fuzzy set; manufactured sand concrete

1 INTRODUCTION

The accelerated growth of the economy, the expansion of infrastructure and the intensifying focus on environmental protection have resulted in a situation whereby the existing natural sand resources are unable to satisfy the requirements of engineering practice. Consequently, there has been an increase in the utilisation of concrete incorporating manufactured sand in lieu of natural sand on an annual basis [1-6]. The elastic modulus of the manufactured sand concrete represents a pivotal indicator for the assessment of its mechanical properties, and it constitutes a fundamental parameter for the assurance of structural stability and deformation control throughout the construction and operational phases. After a long period of research and practice, the elastic modulus formula for natural sand concrete has been relatively mature and widely used in engineering fields. Due to the differences between the properties of manufactured sand and traditional natural sand, the modulus of elasticity formula for natural sand concrete cannot be applied directly. It is therefore of the utmost importance to ascertain the elastic modulus of the manufactured sand concrete in order to guarantee the quality and durability of the material. Common data prediction methods can be divided into two main categories: statistical methods and machine learning methods. In statistical methods, we use historical data to predict future trends; whereas in machine learning methods, we construct models to learn from historical data and make predictions. Neural network learning is used as a common machine learning method to achieve various complex predictions, given that the BP neural network is a multi-layer feedforward network trained by the error back propagation algorithm [7-11], which is one of the most widely used neural network models. Its efficacy has been demonstrated in a number of contexts, including retrieval for soil moisture in farmland, measurement for vehicle distance, rock engineering system, prediction for shale static elastic modulus, and other examples [7-15]. It can adaptively select the intermediate weights and thresholds, and use gradient search technology to minimize the error mean square between the actual output value and the expected output value of the network model. It is a promising research direction to combine neural networks with fuzzy sets by fuzzing the parameters on the basis of neural networks. Therefore, the manufactured sand concrete's elastic modulus is predicted based on fuzzy set and BP neural network. The fundamental stages of the process comprise the initialisation of the weights and biases, the forward propagation of the input data to generate predictions, the calculation of the discrepancy between the predictions and the true values, the adjustment of the weights and biases by back propagation to reduce the discrepancy, and the repetition of the process until the stipulated conditions for termination are met, such as the attainment of the preset number of iterations or the error threshold. Upon completion of the training phase, the trained network is deployed to make predictions on new data.

2 DATA SAMPLE OF ELASTIC MODULUS OF MANUFACTURED SAND CONCRETE

The replacement rate of manufactured sand and the age of concrete are the factors affecting the manufactured sandconcrete's elastic modulus. C55 concrete's elastic modulus with varying replacement rates of manufactured sand at different ages are collected in Fig. 1.
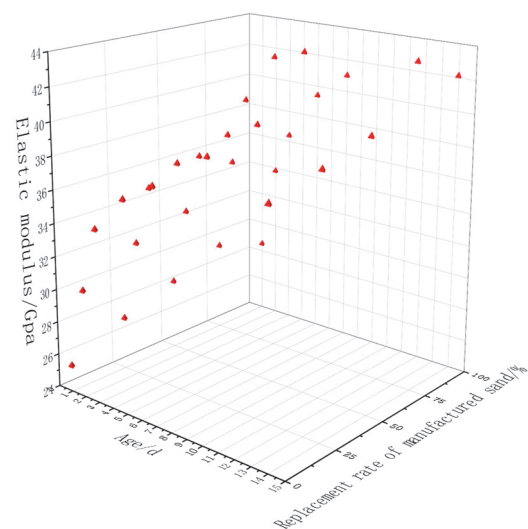

Figure 1 Concrete's elastic modulus with varying replacement rates of manufactured sand at different ages

3 SINGLE FACTOR PREDICTION ANALYSIS

From the data in Fig. 1, it can be seen that the elastic modulus of concrete with manufactured sand is correlated with age and mechanism replacement rate. If only single factor is used to determine the elastic modulus, it will cause great error. For example, the intersection plot of elastic modulus and age in Fig. 2 to Fig. 26, the correlation of various curve fittings is poor. The fitting correlation coefficients for the linear fitting trendlines are between $0.5478 \sim 0.6617$. The fitting correlation coefficients for the exponential function fitting trendlines are between $0.5162 \sim 0.6197$. The fitting correlation coefficients for the logarithmic function fitting trendlines are between $0.8768 \sim 0.9448$. The fitting correlation coefficients for the polynomial fitting trendlines are between $0.914 \sim 0.956$. The fitting correlation coefficients for the power function fitting trendlines are between $0.914 \sim 0.956$. Similarly, the correlation between the manufactured sand's replacement rate and the elastic modulus is also poor. The analysis shows that the prediction of elastic modulus based solely on the age or the manufactured sand's replacement rate is not ideal. This paper attempts to combine the age and the manufactured sand's replacement rate for multi-parameter analysis. Considering the complexity and variability of dimension reduction of multiple parameters and the learning characteristics of BP neural network [10-14], the manufactured sand concrete's elastic modulus is predicted based on BP neural network.
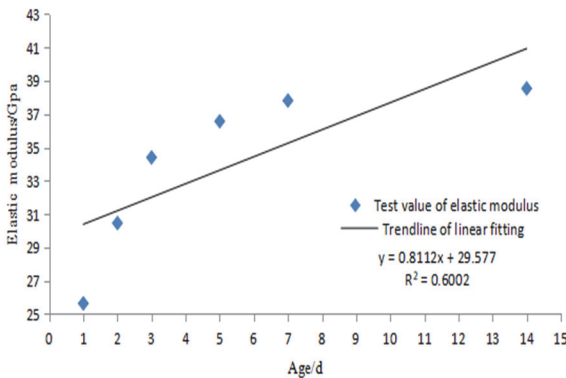

Figure 4 Trendline of linear fitting (Replacement rate of manufactured sand: 50%)
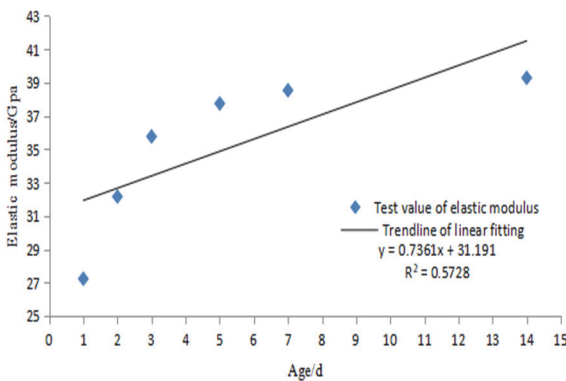

Figure 5 Trendline of linear fitting (Replacement rate of manufactured sand: 75%)

Figure 2 Trendline of linear fitting (Replacement rate of manufactured sand: 0%)

Figure 6 Trendline of linear fitting (Replacement rate of manufactured sand: 100%)
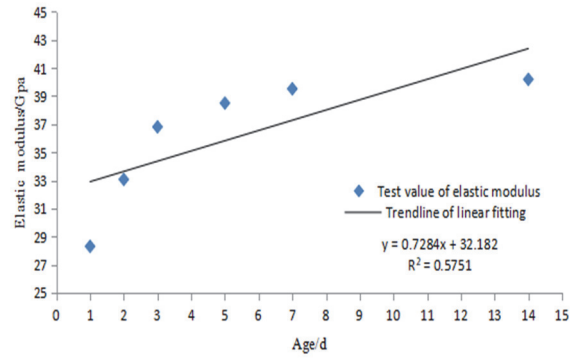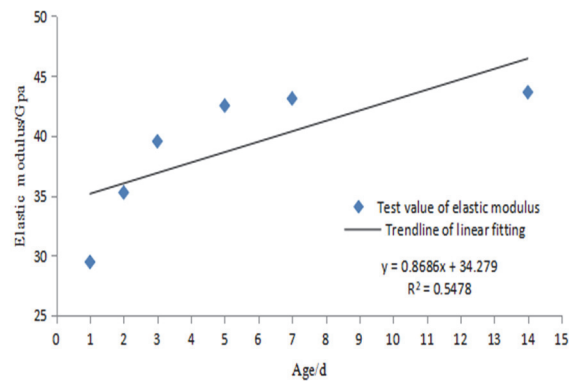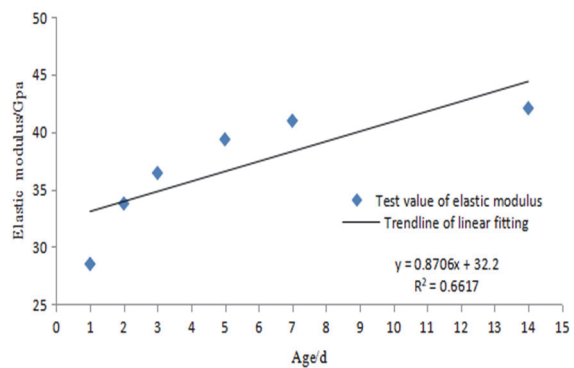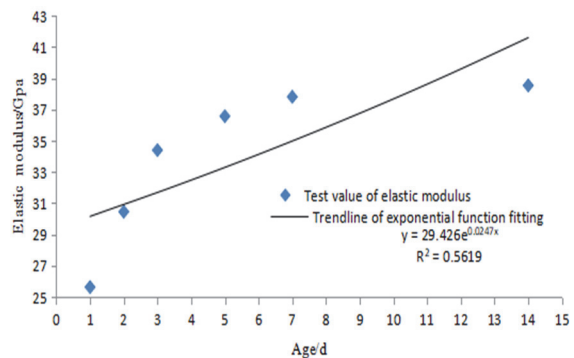

Figure 3 Trendline of linear fitting (Replacement rate of manufactured sand: 25%)

Figure 7 Trendline of exponential function fitting (Replacement rate of manufactured sand: 0%)
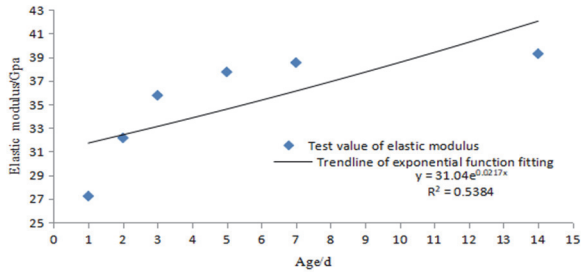
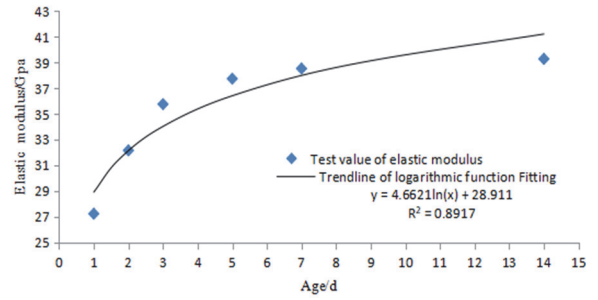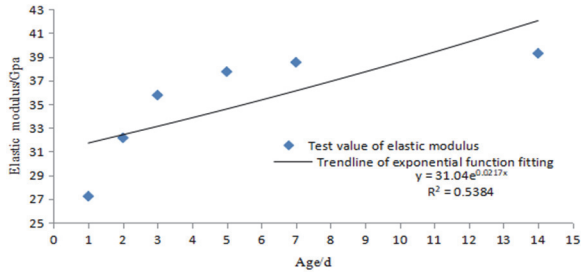**Figure 8** Trendline of exponential function fitting (Replacement rate of manufactured sand: 25%)

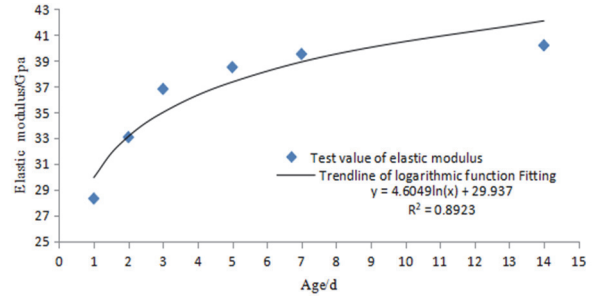**Figure 9** Trendline of exponential function fitting (Replacement rate of manufactured sand: 50%)

Figure 10 Trendline of exponential function fitting (Replacement rate of manufactured sand: 75%)

Figure 11 Trendline of exponential function fitting (Replacement rate of manufactured sand: 100%)

Figure 12 Trendline of logarithmic function fitting (Replacement rate of manufactured sand: 0%)

Figure 13 Trendline of logarithmic function fitting (Replacement rate of manufactured sand: 25%)

Figure 14 Trendline of logarithmic function fitting (Replacement rate of manufactured sand: 50%)
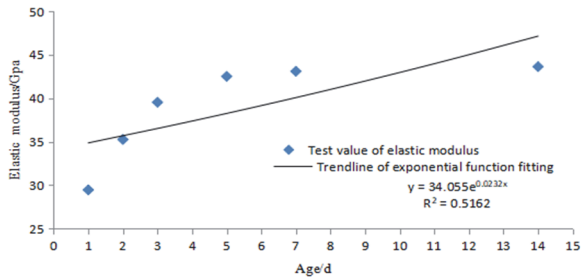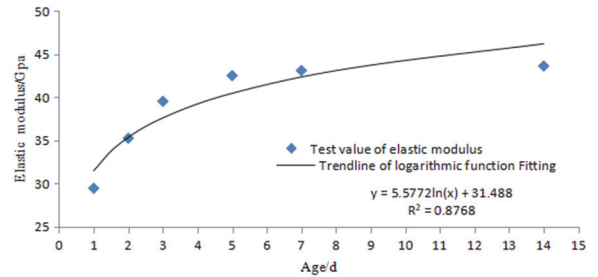

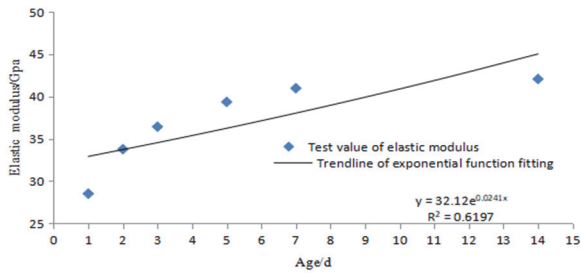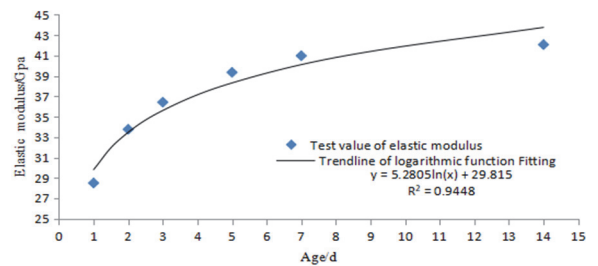**Figure 15** Trendline of logarithmic function fitting (Replacement rate of manufactured sand: 75%)
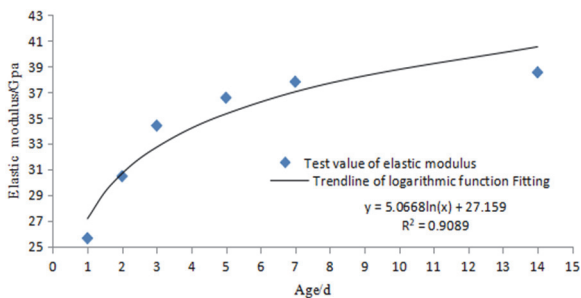

Figure 16 Trendline of logarithmic function fitting (Replacement rate of manufactured sand: 100%)

Figure 17 Trendline of polynomial fitting (Replacement rate of manufactured sand: 0%)

Figure 18 Trendline of polynomial fitting (Replacement rate of manufactured sand: 25%)

Figure 19 Trendline of polynomial fitting (Replacement rate of manufactured sand: 50%)
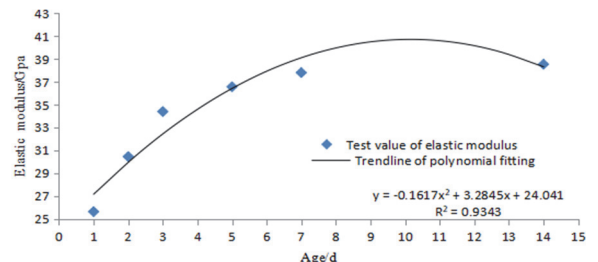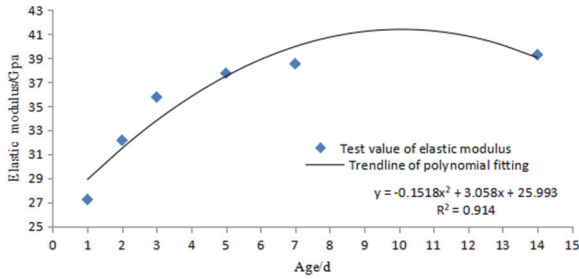

Figure 20 Trendline of polynomial fitting (Replacement rate of manufactured sand: 75%)
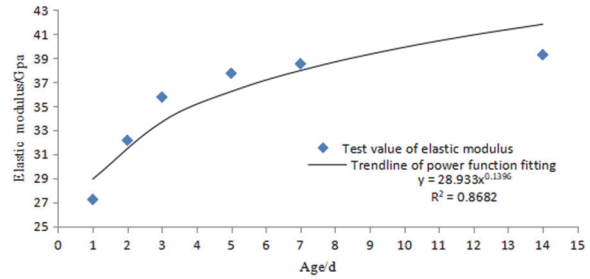

Figure 21 Trendline of polynomial fitting (Replacement rate of manufactured sand: 100%)

Figure 22 Trendline of power function fitting (Replacement rate of manufactured sand: 0%)

Figure 23 Trendline of power function fitting (Replacement rate of manufactured sand: 25%)

Figure 24 Trendline of power function fitting (Replacement rate of manufactured sand: 50%)
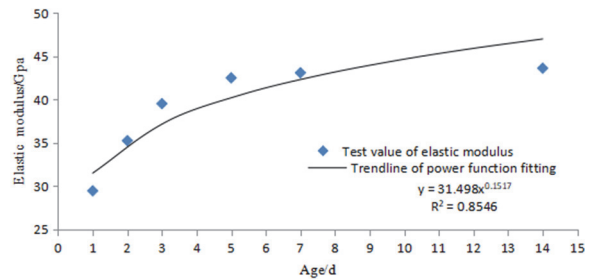
Figure 25 Trendline of power function fitting (Replacement rate of manufactured sand: 75%)
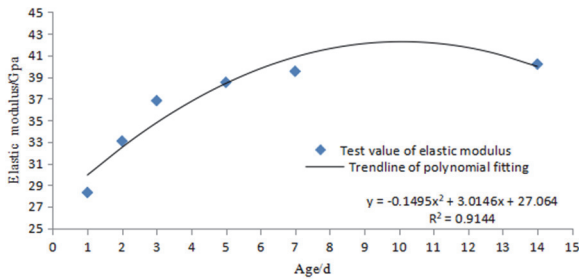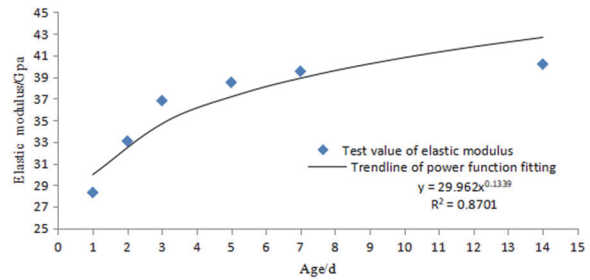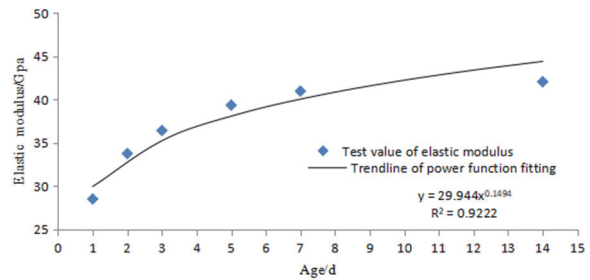

Figure 26 Trendline of power function fitting (Replacement rate of manufactured sand: 100%)
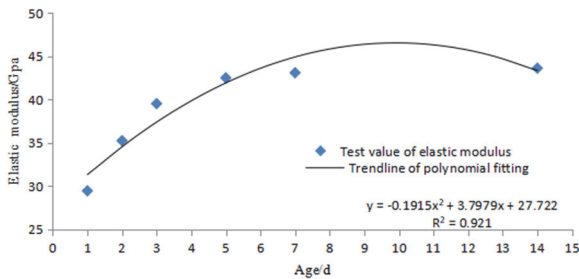
4 BP NEURAL NETWORK PREDICTION ANALYSIS
4.1 BP Network Model

BP neural network model is one of the most widely used instructive training models, and the feedforward neural network including one input layer, one or more hidden layers and one output layer is used as the network structure [10, 13-18]. The neural network flow chart is shown in Fig. 27. BP network continuously updates its thresholds and weights in response to the training data. This ensures that the error function decreases along the negative gradient direction and the training target value tends towards the expected output.
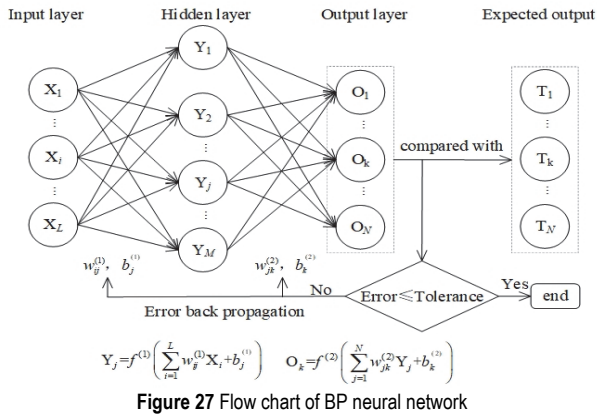
Figure 27 Flow chart of BP neural network

4.2 Structural Design

Taking the substitution rate and age of machine-made sand as input and elastic modulus as output, a three-layer BP network with one hidden layer was used to establish a prediction model. The determination of the number of neurons in a neural network represents a critical issue with direct implications for the performance and complexity of the network. The number of neurons in the input and output layers is typically determined by the specific object or problem under study. The number of neurons in the hidden layer is of critical importance with regard to the performance of the network. An increase in the number of neurons may result in enhanced network performance; however, it may also give rise to overfitting, necessitating a compromise between performance and complexity. Some researchers have proposed empirical formulas to estimate the number of neurons in the hidden layer [7-12]; however, no precise formulas have yet been developed to accurately determine it. In this paper, we determine the number of neurons in the hidden layer through experimentation and tuning. We begin with a smaller number and gradually increase it, observing the change in network performance. After trial calculation, nine is adopted as the number of neurons in the hidden layer. The S-type tangent function, namely tansig, is selected as the activation function of hidden layer neurons and output layer neurons.

4.3 Fuzzification of Input

The fuzzy set is combined with the neural network, and the input of the neural network is converted into fuzzy value by the membership function [19-22].
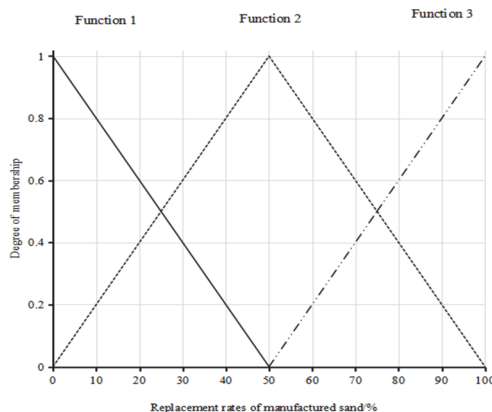
Figure 28 Membership function of replacement rates of manufactured sand

According to the membership function shown in Fig. 28 and Fig. 29, a specific input value is converted into three fuzzy membership input values.
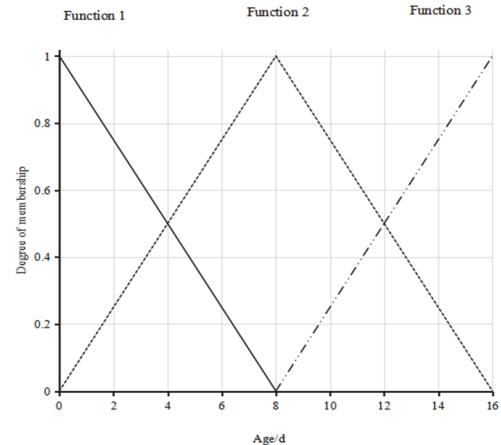
Figure 29 Membership function of ages

4.4 Normalization of Sample Data

The training speed and effect of BP network can be guaranteed by normalizing the sample data and unifying sample data to the same dimension for training and analysis [23-26]. The normalization formula is as follows:

$$X^* = 2 \cdot \frac{X - X_{min}}{X_{max} - X_{min}} - 1 \tag{1}$$

where X, X_{max}, X_{min} and X^* are sample data values, maximum values, minimum values and normalized values respectively.

4.5 Model Training

24 of the 30 groups of sample data in Fig. 1 are used as learning sample data. After continuous iterative training, the best training parameters of the model are found.

Figure 30 Regression parameters of learning samples

As shown in Fig. 30, the training output values are linearly fitted with their actual values. The fitting coefficient obtained by fitting output values with the actual values is 1, which indicates that the training model is very effective.

4.6 Model Prediction

Six groups of data in Fig. 1 that did not participate in the network learning were taken as the samples to be predicted. The BP neural network established above is used to predict the elastic modulus of the machine-made sand concrete. In Fig. 31, the prediction 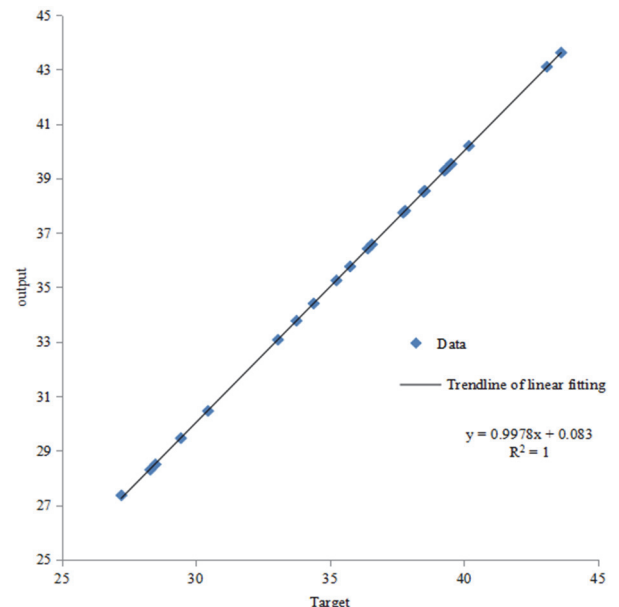results are linearly fitted with the test results, and the fitting coefficient value is 0.9533. It can be seen that the prediction effect is ideal, which indicates that the neural network prediction model is reasonable and feasible.
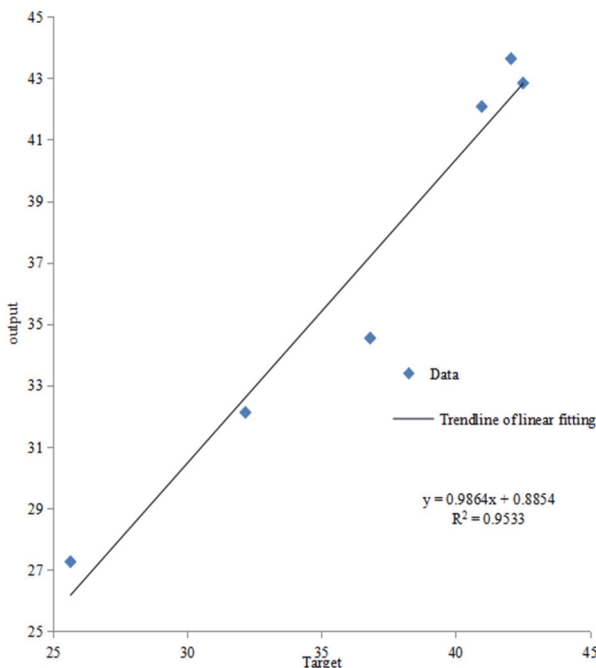

Figure 31 Regression parameters of prediction samples

5 CONCLUSION

Various factors can affect the manufactured sand concrete's elastic modulus. A single factor cannot predict the ideal outcome. Multi-parameter prediction is needed. The training of BP neural network successfully achieved the expected accuracy. The results of the study revealed that the network can be utilized to predict the manufactured sand concrete's elastic modulus. In this paper, the application of BP neural network for predicting the manufactured sand concrete's elastic modulus is mainly studied. It does not take into account the other factors such as the composition, mix proportion, and type of sand. In this paper, only two parameters, namely the replacement rate of manufactured sand and the age of concrete, are considered, and few samples are involved in modeling and inversion. In the future, further parameters affecting elastic modulus can be incorporated into the model, and additional samples can be included in the training set to enhance the model's predictive capabilities.

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