ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20250312002461
Original scientific paper

Neural Network Identification of the Parameters of Ultra-High-Performance Concrete Bridges

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Abstract: This study focuses on an ultra-high performance concrete bridge, utilizing the natural fundamental frequency and mid-span deflection as input data to construct a backpropagation neural network prediction model. The model inversely identifies two critical material parameters of ultra-high performance concrete - elastic modulus and unit weight - to minimize discrepancies between actual values and design values, thereby establishing a computational model that better approximates the real bridge structure. The results demonstrate the feasibility of the backpropagation neural network prediction model for identifying and correcting structural parameters, with the model exhibiting high prediction accuracy. This approach provides a valuable reference for acquiring actual structural parameters in bridge engineering.

Keywords: backpropagation neural network; bridge engineering; deflection; elastic modulus; natural fundamental frequency; parameter identification; unit weight

1 INTRODUCTION

Ultra-high performance concrete, as a construction material with ultra-high mechanical properties and durability, has garnered increasing attention in bridge engineering [1-6]. Its high compressive and tensile strengths significantly enhance the load-bearing capacity of bridge structures, while its high density and low porosity effectively resist water penetration and harmful chemical ingress, markedly improving durability [7-12]. However, the material composition of ultra-high performance concrete is complex, comprising cement, fly ash, silica fume, fine aggregates, water, superplasticizers, and steel fibers. Fluctuations in the quality of these raw materials directly affect the material performance parameters of ultra - high performance concrete. Additionally, production processes - including mixing, casting, and curing- significantly influence its properties. Currently, there is no unified production standard for ultra-high performance concrete across manufacturers, and variations in production methods or batch-to-batch inconsistencies may lead to substantial disparities in its microstructure and macroscopic performance, resulting in material property variability [13-16]. Such variability introduces uncertainties in structural performance, including load-bearing capacity, deformation characteristics, and durability, which may compromise structural safety and reliability [12-19].

Due to uncertainties in material parameters, ultra-high performance concrete bridges demand refined design and construction control, requiring the identification of suitable parameters to extract performance data that accurately reflects structural behavior. In recent years, the rapid development of artificial intelligence, particularly neural networks, has demonstrated immense potential in structural parameter identification. Neural networks, with their powerful nonlinear mapping and self-learning capabilities, efficiently handle complex input-output relationships, offering novel approaches for parameter identification [20–32]. This study focuses on an ultra-high performance concrete simply supported beam bridge, employing a backpropagation neural network prediction model to identify two critical material parameters-elastic modulus and unit weight-to calibrate design values. This approach establishes a computational model closer to the real bridge structure, yielding more accurate structural calculations and enhancing safety and reliability. Compared to traditional finite element model updating methods, the backpropagation neural network avoids complex mathematical inversion, significantly improving the efficiency and accuracy of nonlinear parameter identification.

2 RESEARCH METHODS

2.1 Study Subjects

This study focuses on a simply supported ultra-high performance concrete beam bridge with a span of 36 meters and a U-shaped cross-section as shown in Fig. 1. The U-shaped cross-section features a beam height of 1.6 meters, a top flange width of 40 centimeters, a web thickness of 15 centimeters, a bottom flange width of 50 centimeters, and a deck thickness ranging from 10 to 40 centimeters. The mid-span cross-sectional properties and material design parameters are detailed in Tab. 1. To achieve precise identification of two critical material parameters - elastic modulus and unit weight - the natural fundamental frequency and mid-span deflection under verification loads were selected as input variables. The natural fundamental frequency, highly sensitive to elastic modulus, serves as a key indicator of structural dynamic characteristics, while mid-span deflection under verification loads reflects the combined effects of elastic modulus and unit weight on structural deformation.

By systematically varying the elastic modulus, unit weight, and verification load parameters of ultra-high performance concrete, the natural fundamental frequency and mid-span deflection under specific load combinations were calculated. A comprehensive training dataset was generated through extensive computational simulations. A backpropagation neural network was then employed to iteratively train the model using this dataset. Through continuous adjustments of internal weights and thresholds, the network learned the complex nonlinear mapping between input parameters and output responses, enabling efficient and accurate identification of actual elastic modulus and unit weight values [28-40].

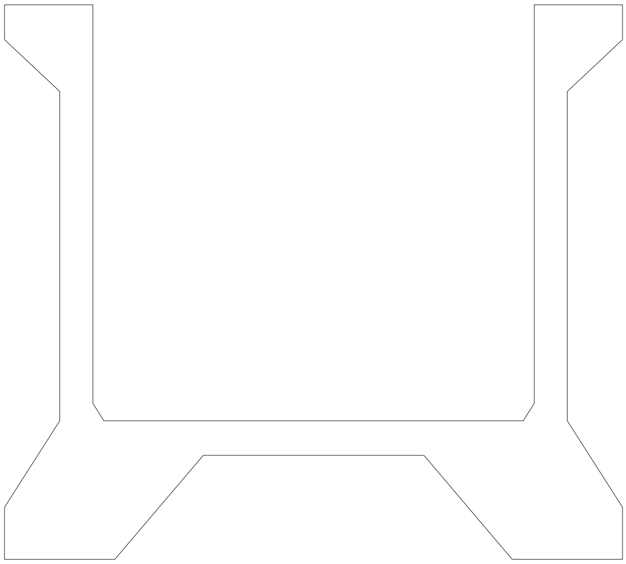

Figure 1 Bridge cross-section form

Table 1 Cross-sectional properties and material design parameters

Parameter category	Parameter name	Numeric value
Cross-Sectional Properties	Moment of inertia I / m^4	0.289
	Area A / m^2	1.3075
Material Properties	Elastic Modulus E /MPa	45200
	Unit Weight γ kN/m^3	25

2.2 Parameter Identification using Backpropagation Neural Network

The Backpropagation Neural Network, fully termed as the Backpropagation Neural Network, belongs to the category of multilayer feedforward networks trained via the error backpropagation algorithm [23-29]. During the training process with sample data, the Backpropagation Neural Network continuously adjusts the connection weights and thresholds between the input layer and hidden layer nodes [27-35]. Its operational principle lies in reducing the error function through gradient descent, with the ultimate goal of minimizing the mean squared error between the network's actual output and the expected output [32-40]. Among various neural network learning algorithms, the Backpropagation Neural Network is widely applied in fields such as function approximation, model classification, data compression, and time series prediction. This network features a simple structure, ease of implementation, robust nonlinear mapping capabilities, and high architectural flexibility.

A neural network consists of three fundamental layers: the input layer, hidden layer, and output layer. These layers are interconnected through weighted parameters. Essentially, all neural networks can be conceptualized as frameworks built upon these three layers and their interlayer weights, with differences primarily arising in the number of hidden layers and node configurations. The input layer serves as the entry point for data, accepting variables that characterize the dataset. Inputs may be single variables or combinations of multiple variables. The hidden layer handles data computation and nonlinear transformations, while the output layer generates the final predictive results.

The weight parameter plays a vital role in the whole neural network system, serving as critical links between layers. The learning process of a neural network fundamentally revolves around optimizing these weights and biases, including those from the input layer to the hidden layer and from the hidden layer to the output layer. Through iterative training, the network continuously refines these parameters until an optimal solution - representing the best parameter combination for practical application - is identified.

3 DESIGN OF NETWORK SAMPLE DATA
3.1 Acquisition of Sample Data

By systematically adjusting parameters such as the material's elastic modulus, unit weight, and verification load, the natural fundamental frequency and mid-span deflection of the bridge structure were calculated. The verification load was applied as a uniformly distributed load along the entire span. The calculation formulas are as follows:

$$f = \frac{\pi}{2l^2}\sqrt{\frac{EI}{m}} \tag{1}$$

$$v = \frac{5qL^4}{384EI} \tag{2}$$

where: f - Natural fundamental frequency / Hz; v - Mid-span deflection /m; E - Elastic modulus / MPa; I - Moment of inertia of the cross-section /m^4; m - Mass per unit length / kg/m; q - Uniformly distributed verification load along the span length / N/m; L - Span length /m.

To obtain training samples, 100 sets of elastic modulus and unit weight data were randomly generated within ±30% of their design values, based on the possible parameter ranges. Similarly, 100 sets of verification load data were generated within ±30% of the maximum displacement-equivalent live load. These generated data were substituted into Eqs. (1) and (2) to calculate the corresponding natural fundamental frequency and mid-span deflection.

The calculated natural fundamental frequency, mid-span deflection, and corresponding load data were used as input values for the neural network, while the associated elastic modulus and unit weight parameters served as output values for network training. Partial sample data are listed in Tab. 2.

Table 2 Partial sample datas

Input values			Output values	
Natural Fundamental Frequency / Hz	Mid-Span Deflection / m	Verification Load / N/m	Elastic Modulus / MPa	Unit Weight / kN/m^3
0.033	2.102	17609	40850	25.594
0.042	2.436	22570	41030	18.173
0.029	2.238	21232	55790	31.620
0.029	2.245	19607	50720	28.195
0.039	2.093	19744	38100	23.854
0.034	2.192	22883	51230	30.119
0.028	2.243	18911	50880	28.373
0.029	2.256	14531	37330	19.511
0.052	1.830	22109	31900	26.474
0.036	2.074	22711	47930	31.641
0.047	1.952	19772	31860	22.788
0.037	2.041	21929	44800	30.397
0.032	2.712	20759	49510	17.586
0.044	2.166	20601	35180	20.026

Table 2 Partial sample datas (continuation)

Input values			Output values	
Natural Fundamental Frequency / Hz	Mid-Span Deflection / m	Verification Load / N/m	Elastic Modulus / MPa	Unit Weight / kN/m³
0.026	2.381	16161	47400	22.780
0.034	2.389	20621	46120	21.891
0.039	2.633	24601	47490	17.962
0.029	2.474	18707	48720	21.506
0.039	1.997	17370	33890	23.205
0.032	2.399	24512	58670	28.617
0.021	2.343	15903	58610	30.145
0.029	2.508	22142	58730	25.880
0.033	2.228	22809	51570	29.236
0.028	2.600	16881	45400	17.540
0.020	2.768	14475	54910	18.974
0.027	1.854	14042	39090	32.352
0.040	1.953	18149	34330	24.824
0.038	2.377	21402	42190	19.932
0.030	2.588	22606	57160	23.323
0.021	2.291	14988	54870	29.454
0.039	2.130	20058	38570	23.228
0.023	2.377	17566	57630	28.638
0.020	2.203	14196	52480	30.590
0.047	1.869	21536	35010	28.060
0.026	2.236	18172	51990	29.261
0.026	2.388	20454	58590	28.863
0.039	2.337	24519	47310	23.726
0.023	2.637	17305	55800	21.703
0.040	2.192	22650	42590	24.392
0.028	1.973	15229	41390	30.001

3.2 Normalization of the sample data

Raw sample data exhibit varying dimensions and value ranges, which may negatively impact subsequent model training and analysis. Normalization transforms the data into a unified scale and distribution, enhancing model performance and stability. To standardize all sample data under a consistent reference framework and ensure efficient training of the backpropagation neural network, this study employs the max-min normalization method. The calculation formula is as follows [23]:

$$X^* = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

where: X^* - Normalized value; X - Original sample data value; $X_{\max}$ - Maximum value of the dataset; $X_{\min}$ - Minimum value of the dataset.

4 TRAINING OF THE BACKPROPAGATION NEURAL NETWORK MODEL

4.1 Parameter Identification Training Model

A three-layer backpropagation neural network with one hidden layer was employed to establish the parameter identification model. Through iterative training, optimal network parameters were identified. The network architecture consists of three input nodes (natural fundamental frequency, mid-span deflection, and verification load), two output nodes (elastic modulus and unit weight), and a hidden layer with 10 nodes. The number of hidden layer nodes was determined empirically through repeated trials, as no explicit formula exists for its determination. Convergence of the network was rigorously validated.

The training process proceeded as follows:

(1) Initialization: The weight matrix and threshold matrix were initialized with random values.

(2) Forward Propagation: Training samples were fed into the network, and actual outputs were computed.

(3) Error Calculation: The difference between actual outputs and target outputs was quantified using a predefined error function.

(4) Backpropagation: Errors were propagated backward through the network to adjust weights and thresholds adaptively.

(5) Termination: Training ceased once the total error met predefined accuracy criteria, yielding finalized network parameters.

4.2 Model Training Results

From the 100 sample datasets, 70 were randomly selected as the training set, and the remaining 30 were reserved as the test set. Through continuous iterative training and adjustments to hyperparameters, the predicted results progressively approached the true values. Consequently, as the number of model iterations increased, the mean squared error (MSE) corresponding to the training curve and the test curve exhibited a consistent decline. To evaluate the training outcomes and assess potential overfitting, a linear regression analysis was performed between the model's output values and their target values. The regression parameters obtained during the training process are illustrated in Figs. 2 to 3. The regression coefficient (R^2) was used as the evaluation metric, where a value closer to 1 indicates better model fit and higher prediction accuracy. The R^2-values for the training set were 0.9954 and 0.9937, demonstrating excellent performance of the trained model.

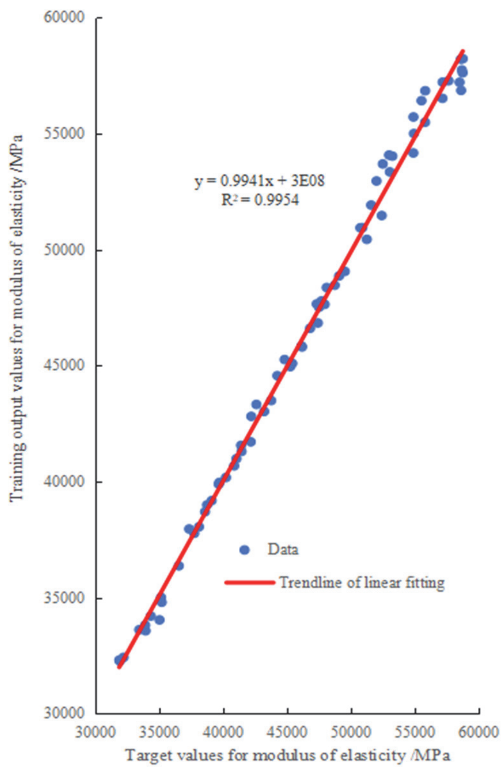

Figure 2 Comparison of training outputs and target values for elastic modulus

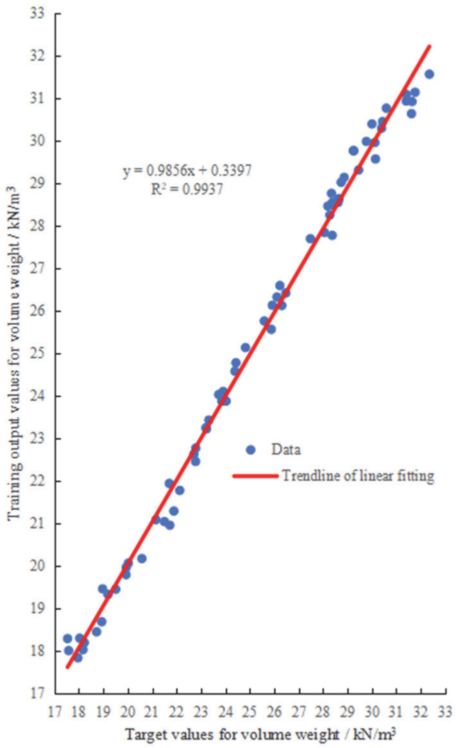

Figure 3 Comparison of training outputs and target values for unit weight

4.3 Model Validation

During the validation process, the model's identified elastic modulus and unit weight values for each sample in the test set were compared point-by-point with predefined target values. The model's feasibility for practical engineering applications was confirmed only when it consistently maintained high accuracy across all evaluation metrics on both the training and test sets.

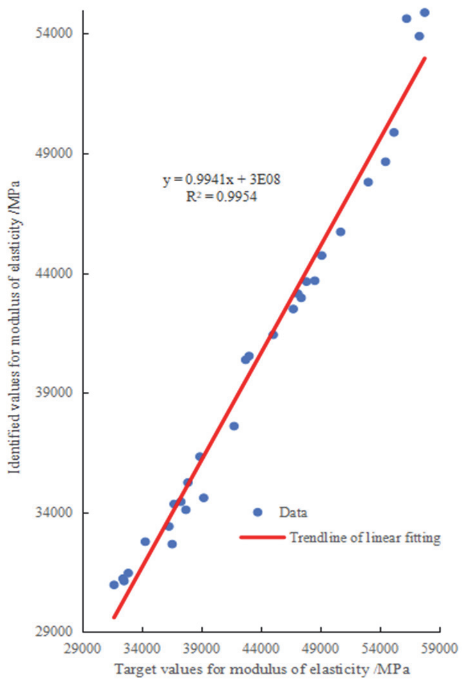

Figure 4 Comparison of identified elastic modulus values and target values

Figs. 4 to 5 detail the validation results on the test set. As shown in the figures, most data points cluster near the 1:1 line, indicating strong agreement between the model's predictions and the target values. The fitting coefficients (R^2) for the two parameters are 0.9954 (elastic modulus) and 0.9113 (unit weight), further validating the reliability of the parameter identification process.

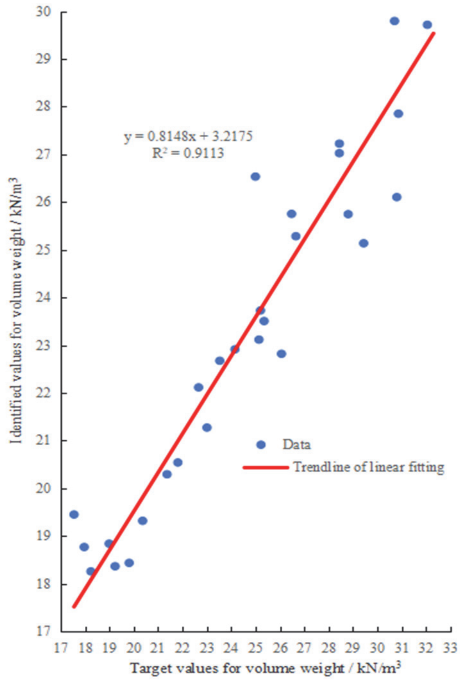

Figure 5 Comparison of identified unit weight values and target values

4.4 Parameter Identification Results

In the validation of the test set described in previous sections, the parameters identified by the Backpropagation Neural Network were compared with the design values, as shown in Figs. 6 to 7. The identified values exhibited significant deviations from the design values overall. If the design values are used for structural verification of the bridge, the verification results will deviate from actual conditions and fail to accurately reflect the structure's load-bearing behavior.

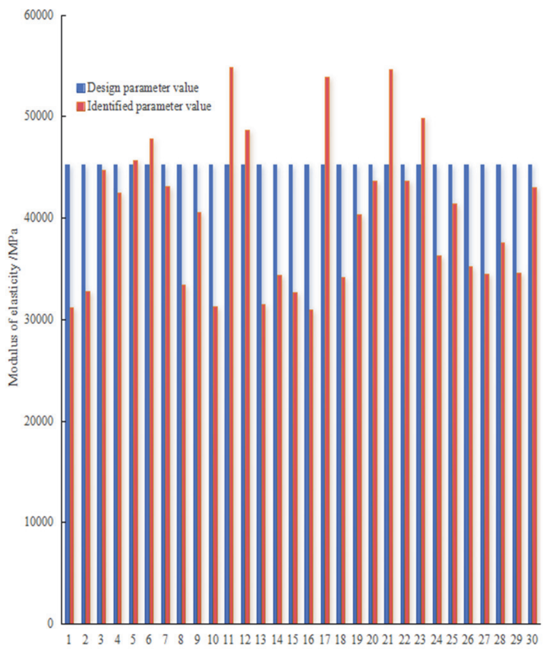

Figure 6 Comparison of identified elastic modulus values and design values

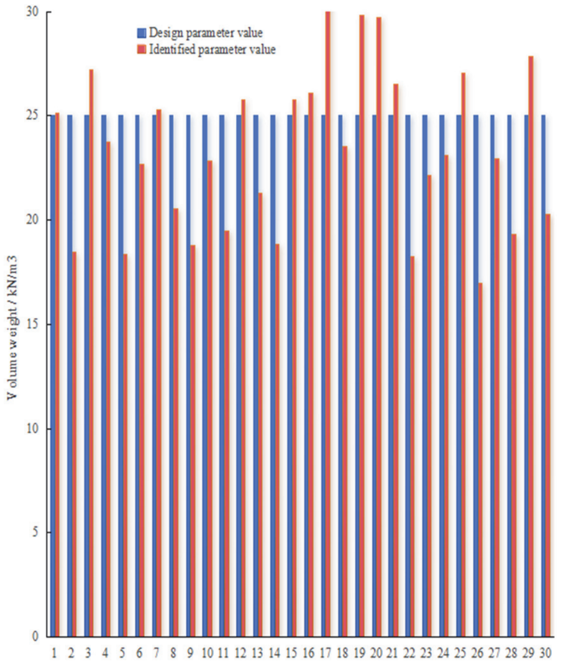

Figure 7 Comparison of identified unit weight values and design values

The frequency and deflection sample values in the test set were treated as test values. Using the parameters of elastic modulus and unit weight identified by the neural network, structural calculations were performed to derive adjusted frequency and mid-span deflection values. These adjusted values were then compared with the corresponding test values (see Figs. 8 to 9). The regression coefficients (R^2) for the comparisons were 0.9836 (frequency) and 0.9822 (deflection), indicating excellent performance of the parameter identification process.

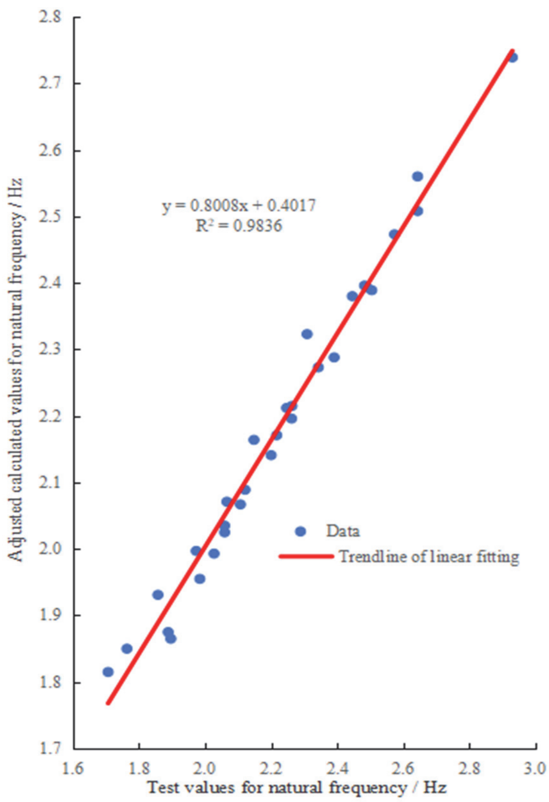

Figure 8 Comparison of test natural fundamental frequency values and calculated values after parameter adjustment

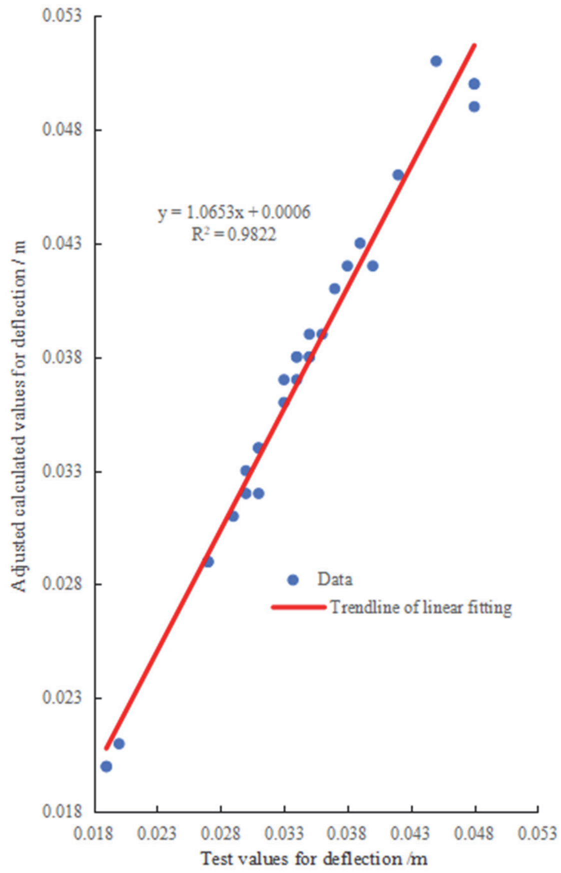

Figure 9 Comparison of test deflection values and calculated values after parameter adjustment

5 CONCLUSION

Accurate identification of bridge parameters is critical for optimizing structural performance and ensuring the long-term safe service of bridges. This study addresses the parameter identification challenge for ultra-high performance concrete bridges by constructing a backpropagation neural network-based model. Through multiple rounds of training and optimization, the model demonstrated high accuracy in identifying two key parameters - elastic modulus and unit weight - with strong performance on both training and testing datasets. These results validate the advantages of neural networks in modeling complex nonlinear relationships and confirm the applicability of the backpropagation neural network for bridge parameter identification.

The sample data in this study were generated using idealized theoretical formulas, focusing solely on the effects of elastic modulus, unit weight, and corresponding loads on natural frequency and deflection. Practical factors such as material heterogeneity, complex cross-sectional geometries, and construction tolerances were not considered. Future research should incorporate finite element simulations to replicate complex real-world conditions or integrate field-measured data to enhance dataset generalizability. Additionally, the model's sensitivity to structural dimensional variations requires further investigation. If deviations between actual bridge dimensions and design values are significant, incorporating geometric parameters into the input layer is recommended to improve identification accuracy.

This study provides an efficient parameter identification tool for construction quality control and health monitoring of ultra-high performance concrete bridges. When using field-measured data to inversely identify structural parameters, measurement errors may introduce deviations in the neural network's input data, potentially degrading identification accuracy. To mitigate such errors, preprocessing techniques such as data filtering and calibration should be applied during the data processing stage.

Acknowledgements

The work was supported by the General Scientific supporting program of Guizhou Province, No. 2021-330.

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