Research on Neural Network Evaluation Model for the Implementation Effect of Digital Government Construction Standards

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Abstract. The article studies a model for evaluating the effectiveness of digital government construction standards based on LM backpropagation neural network. Firstly, a fuzzy AHP evaluation index system was established from three aspects and the weight coefficient of the evaluation index was calculated to characterize the impact of the evaluation index on the effectiveness of digital government construction standards; Secondly, based on the LM backpropagation algorithm, a neural network evaluation model is established to reflect the complex nonlinear relationship between the comprehensive evaluation objectives and evaluation index factors of the effectiveness of digital government construction standards; Finally, a comprehensive evaluation of the effectiveness of digital government construction standards is conducted, and the model is reasonable and feasible. With the increase of sample data for evaluating the effectiveness of digital government construction standards, the accuracy of the model evaluation results becomes higher.

Keywords: Digital government construction standards; Evaluation index system; Fuzzy-AHP; LM backpropagation algorithm; Neural network;

1 Introduction

With the increasing maturity of internet technology, the application fields of the new generation of information technology are continuously expanding. The use of the new generation of information technology to build a digital government and promote the digital reform of government departments has become a focus of attention for many scholars. Standardization is a practical activity in which people consciously pursue orderliness [1], with the fundamental goal of establishing the best order and obtaining the best benefits. Standardization, as an important technical foundation [2] for ensuring the construction of digital government norms, is an important technical means to promote more scientific government management, orderly supervision, and more efficient services. It has become an important component of the construction of digital governments at all levels. At the same time, objectively and scientifically evaluating the effectiveness of standard implementation [3] is a key issue in this field. Currently, evaluation based

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on intelligent systems mostly adopts comprehensive evaluation methods.

The paper conducts research on the implementation effectiveness of digital government construction standards and establishes a neural network evaluation model for the effectiveness of digital government construction standards based on LM (Levenberg Marquardt) backpropagation algorithm. The results show that the trained neural network can accurately reflect the objective and complex nonlinear relationship between the comprehensive evaluation values and evaluation indicators of digital government construction standards, It can be used for evaluating the effectiveness of digital government construction standards.

2 Analytic Hierarchy Process Model under Fuzzy AHP

2.1 Fuzzy Comprehensive Evaluation Based on AHP

The weight of evaluation indicators reflects the impact of indicators on the evaluation process and the relative importance between indicators, which is the key to comprehensive evaluation of multiple indicators. The commonly used weight calculation methods include experience evaluation method, comparative weighting method [4], and analytic hierarchy process [5]. Among them, AHP method is a multi-criteria decision-making method that can quantitatively analyze qualitative problems. It can effectively combine subjective and objective judgments, organize various factors of complex problems through hierarchical division, and quantitatively describe the relative importance of each indicator at the same level [6]. Fuzzy AHP is a good means to solve this problem.

2.2 Evaluation Index System for Digital Government Construction Standards

This paper studies and proposes a three-layer evaluation index system of objectives, criteria and indicators. Stratify the evaluation index system into first, second, and third level indicators, as shown in Table 1.

Table 1. Hierarchy of Evaluation Index System

Grade1	Grade2	Grade3
O: Evaluation of standard technical content	**O1:** adaptability	**O11:** The degree to which standards comply with digital government regulations and systems
		O12: Does the structure of the standard need to be adjusted or added or deleted chapters and clauses
		O13: The degree to which the standard structure is reasonable, the provisions are clear, and the terms are rigorous and accurate
		O14: The degree to which the standards are feasible and in line with the actual construction of digital government
	O2: Coordination	**O21:** The standard has the flexibility to adapt to the development of digital government construction

		O22: Compliance with standards at all levels
	O3: Progressiveness	**O31:** Advanced level of standards (including industry standards, national standards, and international standards)
S: Evaluation of standard implementation process	**S1:** promotion	**S11:** Flexibility and convenience of obtaining standard queries (transmission channels) **S12:** Have relevant units and departments carried out standard promotion and implementation activities **S13:** Satisfaction with standard promotion **S14:** Are there any derived materials such as guidelines, manuals, and atlases that are compatible with the implementation of the standard
	S2: implement	**S21:** The importance, understanding, and mastery of standards at all levels **S22:** Implementation status of comparison standards (adopted and applied in digital government construction) **S23:** Participation in standard formulation and revision
T: Benefit evaluation of standard implementation	**T2:** economic benefits	**T11:** The impact on regional GDP and its growth rate **T12:** The impact on promoting the development of the digital economy
	T1: People's livelihood benefits	**T21:** The impact on the openness of government data information **T22:** The impact of satisfaction on people's livelihood service experience **T23:** The impact on the intelligence of urban governance **T24:** The impact on transparency in law enforcement and regulation
	T3: ecological benefit	**T31:** The impact on ensuring the rational utilization of resources **T32:** Impact on the ecological environment

2.3 Weight coefficient of evaluation indicators

The process of calculating weights using the AHP method is shown in Figure 1.

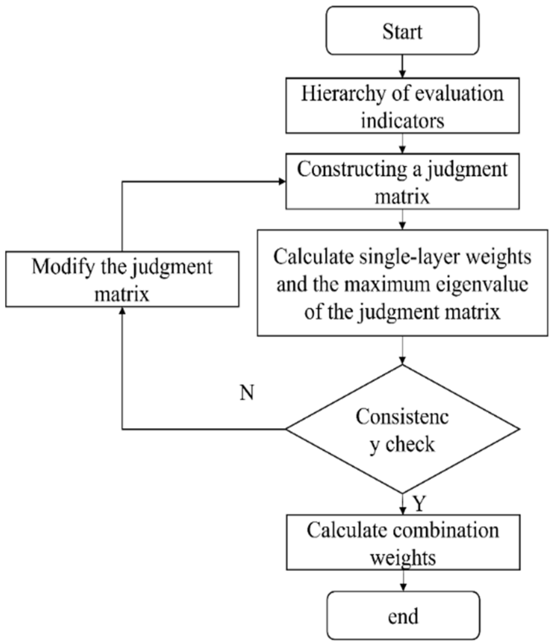

Fig. 1. Weight Calculation Process

The weight coefficient calculation results are as follows

Table 2. Calculation Results of Weight Coefficients

	AO 0.1852			**AS** 0.1562		**AT** 0.6586			**weight**
	O1 0.1221	**O2** 0.0195	**O3** 0.0342	**S1** 0.0961	**S2** 0.0836	**T1** 0.0723	**T2** 0.4023	T3 0.1700	
O11	0.0263	0	0	0	0	0	0	0	0.0263
O12	0.0517	0	0	0	0	0	0	0	0.0517
O13	0.0243	0	0	0	0	0	0	0	0.0243
O14	0.0110	0	0	0	0	0	0	0	0.0110
O15	0.0088	0	0	0	0	0	0	0	0.0088
O21	0	0.0108	0	0	0	0	0	0	0.0108
O22	0	0.0087	0	0	0	0	0	0	0.0087
O31	0	0	0.0342	0	0	0	0	0	0.0342
S11	0	0	0	0.0303	0	0	0	0	0.0303
S12	0	0	0	0.0061	0	0	0	0	0.0061

S13	0	0	0	0.0425	0	0	0	0	0.0425
S14	0	0	0	0.0172	0	0	0	0	0.0172
S21	0	0	0	0	0.0464	0	0	0	0.0464
S22	0	0	0	0	0.0110	0	0	0	0.0110
S23	0	0	0	0	0.0262	00	0	0	0.0262
T11	0	0	0	0	0	0.0573	0	0	0.0573
T12	0	0	0	0	0	0.0150	0	0	0.0150
T21	0	0	0	0	0	0	0.1276	0	0.1276
T22	0	0	0	0	0	0	0.2514	0	0.2514
T23	0	0	0	0	0	0	0.0110	0	0.0110
T24	0	0	0	0	0	0	0.0123	0	0.0123
T31	0	0	0	0	0	0	0	0.0954	0.0954
T32	0	0	0	0	0	0	0	0.0746	0.0746

The ratios CR corresponding to the results in Table 2 are all less than 0.1, which meets the requirements.

3 Neural network evaluation model

3.1 Basic Principles

Construct a three-layer neural network consisting of an input layer, a hidden layer, and an output layer with multiple input neurons [7]. In practical government work, there is often an objective and complex nonlinear relationship between evaluation objectives and evaluation index factors. Traditional linear models can only model linear relationships, and neural networks have strong nonlinear fitting ability, which can better capture complex information in data and improve evaluation accuracy. The nonlinear function is used to characterize the transitive relation between the output and input of each connection node. The neural network can learn, back propagate and correct the sample data according to the set topology structure and transfer method until it meets the given accuracy requirements.

3.2 Establishment of ANN Model based on LM backpropagation algorithm

LM (Levenberg Marquardt) algorithm is a variation of Newton method, which is used to minimize the sum of squares of nonlinear functions. It can also be seen as a combination of the steepest descent method and the Gaussian Newton method (by adjusting damping μ Switching), when the solution is far from the optimal solution, the algorithm is closer to the steepest descent method, slow but ensuring descent; When the solution approaches the optimal solution and the algorithm approaches the Gaussian Newton method, it converges quickly. Its core idea is to replace the calculation of the Hessian matrix with a Jacobian matrix, which improves optimization efficiency and is very suitable for training neural networks using mean square error as the performance indicator [8].

Back propagation algorithm (BP algorithm) is a supervised learning algorithm [9], which is often used to train multi-layer perceptron. The BP algorithm consists of two stages (incentive propagation and weight update) that iterate repeatedly until the network's response to the input reaches the predetermined target range. Incentive propagation includes: (forward propagation stage) feeding training input into the network to obtain incentive response; In the backpropagation stage, the excitation response is subtracted from the target input corresponding to the training input $(\mathrm{t}-\mathrm{a})$ to obtain the response errors of the hidden layer and output layer. The weight update includes: first, multiplying the input excitation and response error by $\left(s^{m^*(a}(\mathrm{m}-1)\right)\big)$ to obtain the gradient of the weight; Then, multiply this gradient by a ratio $\left(\partial^* \mathrm{s}^{m^*(a}(m-1)\right)\big)$ and subtract it before adding it to the weight. The specific steps are as follows:

Step 1: Propagate input forward through the network:

$$\begin{gathered} a^0=p \\ a^{m+1}=f^{m+1}\left(W^{m+1} a^m+b^{m+1}\right), m=0,1, \ldots, M-1 \\ a=a^M \end{gathered} \tag{1}$$

Where p is the input vector, a^m is the output vector of layer m, f^m is the transfer function of layer m, W^m is the weight vector of layer m, and b^m is the offset value of layer m.

Step 2: Backpropagation of sensitivity through the network:

$$\begin{gathered} s^M=-2 F^M\left(n^M\right)(t-a) \\ s^m=F^m\left(n^m\right)\left(W^{m+1}\right)^T s^{m+1}, m=M-1, \ldots, 2,1 \\ F^m\left(n^m\right)=\begin{bmatrix} \dot{f}^m\left(n_1^m\right) & 0 & \cdots & 0 \\ 0 & \dot{f}^m\left(n_2^m\right) & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & & \dot{f}^m\left(n_{s^m}^m\right) \end{bmatrix} \\ \dot{f}^m\left(n_j^m\right)=\frac{\partial f^m\left(n_j^m\right)}{\partial n_j^m} \end{gathered} \tag{2}$$

Where s^m is the sensitivity of layer m, n^m is the response of layer m, and $\dot{f}^m\left(n_j^m\right)$ is the derivative of the transfer function of the j neuron in the m-th layer with respect to n^m.

Step 3: Use the approximate steepest descent method to update the weight and offset values:

$$\begin{gathered} W^m(\mathrm{k}+1)=W^m(\mathrm{k})-\alpha s^m\left(a^{m-1}\right)^T \\ b^m(\mathrm{k}+1)=b^m(\mathrm{k})-\alpha s^m \end{gathered} \tag{3}$$

Where k is the number of iterations.

Step 4: Enter the next input vector p and execute the algorithm's k+1st iteration process. Until the difference between the actual output and the target output reaches an acceptable level (i.e. converges to a certain valve range).

On the basis of LM backpropagation algorithm, an ANN model is established, and N sets of project evaluation index values are taken. The two sets of evaluation index boundaries limit the boundary range of the sample data to [30100]. Based on the weight coefficients of each evaluation index obtained, the comprehensive evaluation value Us is calculated as the expected value for neural network learning and training. From the sample data of evaluation indicators, it can be seen that the ANN evaluation model for the effectiveness of digital government construction standards in this article is a three-layer neural network with 23 input neurons, 1 output neuron, and an unknown number of hidden layer neurons. The same network sample data has different values for the number of hidden layer neurons, resulting in different neural networks generated through learning and training. There are many methods for calculating the number of hidden layer nodes. Based on empirical formula, this article calculates the number of hidden layer nodes to be 10.

3.3 Training, Verification, and Testing

A questionnaire survey was conducted to investigate the implementation of digital government construction standards by a total of 42 people in a certain government unit. The scoring results were used as sample data for training, verification, and testing. The three parts accounted for 70%, 15%, and 15%, respectively. The data table is as follows:

Table 3. Sample Data Table

Number	1	2	3	4	5	6	7	…	…	36	37	38	39	40	41	42
O11	90	85	50	85	81	89	76	…	…	59	65	63	72	58	92	93
O12	77	50	91	81	53	95	64	…	…	77	58	77	57	70	74	71
O13	88	95	94	84	59	51	58	…	…	66	61	63	55	74	87	63
O14	86	70	75	95	81	94	54	…	…	55	64	86	63	77	71	63
O15	88	76	53	62	57	75	59	…	…	93	93	94	77	94	65	91
O21	50	72	56	64	57	77	80	…	…	52	50	94	83	84	51	55
O22	62	91	94	95	65	63	58	…	…	58	80	85	89	86	69	65
O31	52	87	54	50	62	93	81	…	…	81	94	87	50	56	72	76
S11	63	70	68	56	93	66	88	…	…	53	89	57	74	63	91	53
S12	86	58	83	60	59	59	94	…	…	52	71	50	71	87	90	63
S13	60	88	70	73	58	56	91	…	…	88	88	81	57	60	69	51
S14	62	95	64	76	78	91	68	…	…	52	63	76	64	87	66	82
S21	79	94	59	77	53	75	88	…	…	82	95	69	62	71	57	57
S22	62	84	78	94	85	76	70	…	…	54	66	76	63	82	66	83
S23	95	53	71	54	83	91	53	…	…	81	59	80	82	71	57	69
T11	77	64	88	55	61	93	80	…	…	52	56	79	61	88	88	70
T12	68	94	50	68	72	78	53	…	…	60	57	73	89	85	56	52

T21	80	72	72	64	64	91	70	…	…	53	80	93	51	57	70	64
T22	54	87	68	80	76	50	79	…	…	71	75	51	86	62	87	81
T23	77	67	53	95	80	60	54	…	…	59	58	70	78	77	80	62
T24	69	86	92	71	64	70	64	…	…	57	92	56	57	83	81	66
T31	54	50	67	86	70	54	87	…	…	74	79	58	86	59	68	60
T32	62	50	92	73	71	74	65	…	…	71	86	62	63	82	58	88
Z	90	85	50	85	81	89	76	…	…	59	65	63	72	58	92	93

The sample data in Table 3 is used to train and test the established neural network to obtain a high-precision digital government construction standard effect price model. This study uses MSE (mean square error: error between output and response) and R (regression R value: correlation between output and response) to describe the effect of mapping input variables to continuous responses. The specific process is as follows:

(1) Take the sample data numbered 1-30 as the training samples, input the neural network with a topology of "23-10-1", and then train the sample data according to the set transmission method for learning, error correction, and other training until the given accuracy requirements are met. The observation value of the training data is 30, MSE is 0.1424, and R is 0.9967.

(2) As a validation of the training network, data from groups 31 to 36 in the sample data were input into the trained network. The observed values of the validation data were 6, MSE was 2.5709, and R was 0.8167.

(3) Using the data from groups 37 to 42 as input, the trained network was tested. The observed values of the test data were 6, MSE was 7.5341, and R was 0.82615.

The R of all data is 0.93671. Based on the analysis in the following figure, it can be concluded that the trained neural network can accurately reflect the objective and complex nonlinear relationship between the comprehensive evaluation value and evaluation indicators of the standard effect of digital government construction, and can be used for the evaluation of the standard effect of digital government construction.

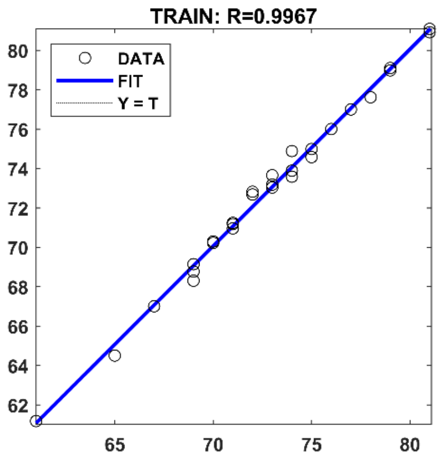

Fig. 2. Training (N=42)

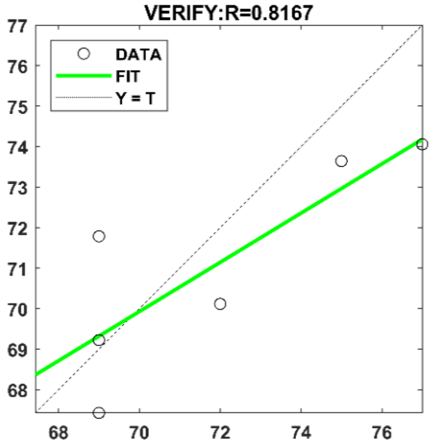

Fig. 3. Verification (N=42)

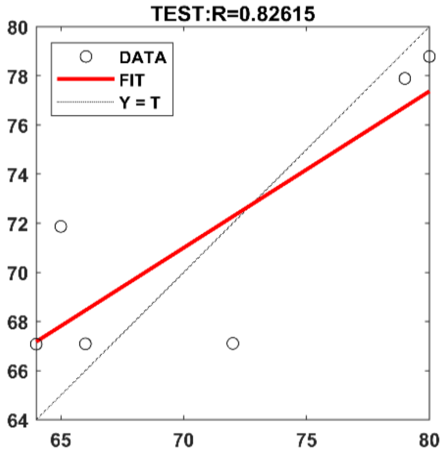

Fig. 4. Test (N=42)

Neural networks have good adaptability and can adjust parameters based on the relationship between input and output, thereby improving evaluation accuracy. They can continuously improve their performance over time. The accuracy of the neural network evaluation model in this article has become increasingly high with the accumulation of sample learning and training in the later stage.

It can be seen from Figure 2, Figure 3, and Figure 4 that when there is sufficient sample size, the training, validation, and testing results all perform very well, with R values close to 1. This indicates that the neural network evaluation model based on LM backpropagation algorithm established in this paper can effectively evaluate the effectiveness of digital government construction standards, and has good robustness. It can further standardize the construction of digital government and provide reference for the next standardization work, Continuously improve the quality of standard formulation and revision, and enhance the usability and practicality of standards.

4 Conclusion

This article is based on the ANN hierarchical evaluation model of LM backpropagation algorithm, and analyzes the effectiveness evaluation example of digital government construction standards. The following conclusions are drawn:

(1) The hierarchical analysis model for the effectiveness of digital government construction standards can systematically analyze the effectiveness of digital government construction standards from three aspects: technical content evaluation, implementation process evaluation, and implementation benefit evaluation. It reflects the hierarchical relationship between evaluation objectives and target layers, criterion layers, and indicator layers in the evaluation index system of digital government construction standard effectiveness, and calculates the weight coefficient of evaluation indicators, And then characterize the proportion of the impact of evaluation indicators on the effectiveness of digital government construction standards.

(2) The neural network evaluation model for the effectiveness of digital government construction standards can reflect the objective and complex nonlinear relationship between the comprehensive evaluation objectives and evaluation index factors of digital government construction standards through learning and training, reducing the subjective factors in the process of evaluating the effectiveness of digital government construction standards. The evaluation results have objectivity and effectiveness.

(3) With the increase of sample data for evaluating the effectiveness of digital government construction standards, the accuracy of neural network evaluation models based on LM backpropagation algorithm has also become increasingly high. Neural networks have good scalability and can increase the number of layers, nodes, and other parameters according to requirements, improving the complexity and performance of the model. At the same time, neural networks can also adapt to different data distributions and tasks by changing network structure and other methods, making it possible to meet more complex real-world government needs.

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