Estimation on concrete trench barrier effect: a hybrid experimental method based on neural network model

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Abstract

In this paper, the neural network is introduced as the basic model, and the barrier effect of the vertical seismic wave amplitude is estimated by the three dimensional concrete trench. The back propagation training method is adopted in the paper. The main procedure includes inputting the related parameters of trench barrier seismic wave, analyzing by the pre-processed method and factor algorithm, and selecting six parameters such as the trench section, the distance between the epicenter and the trench, the immersed depth in the foundation and the in-filled material property, etc. The disadvantage of the node numbers and the network learning, which is made by the previous trial-and-error method, should be improved by the Cascade Correlation learning procedure, the automatically adjusted learning speed ratio and the inertia factor algorithm. In addition, the neural network should be built up and taken the average vertical amplitude as the output value. The experiment results show that the built neural network model can simulate the barrier effect of the vertical seismic wave amplitude analyzed by the three dimensional concrete trench, and its accuracy of the predicted results is better.

Keywords: neural network, vibration, seismic waves, trench

1 Introduction

The operation of the traffic, construction or machines may cause the vibration in the surface, and the noise of the vibration may be spread to the nearby regions, which may make the nearby residents feel uncomfortable and the precise instruments in the nearby structures may cause interference. In recent years, the influence on the surrounding environment by the vibration is taken seriously. How to obstruct the spreading of the vibration and how to make the influence on the nearby regions' surface vibration reduce to the minimum has became a hot issue. The trench set between the epicenter and the surface on the protected regions is always used as the barrier of the seismic wave in many ways for obstructing the seismic wave. In this paper, the research can be divided into two parts: the research on the field test [1] and the analysis of the mathematical model [2]. The research on the field test consumes the massive manpower and material resources, and it has a narrow scope of the application, so the method of the mathematical model is usually used to do the research. The aspect has many researches, mainly obtaining the analytic solution or the approximating solution, but the situation is limited to the pure soil medium and the simple geometry [2, 3].

The numerical method is used to analyze the complex structure system and the boundary state, such as the finite difference method [4], the finite element method [5] and the boundary element method [5-9]. The vibrating problem in the boundary element method is shown by the boundary integral equation with the infinite fundamental solution, and the reciprocal theorem for its fundamental solution can automatically meet the requirements of the infinite radiation condition [12] and has to face the boundary of the medium domain, which is the free surface, and the interface surface and the trench surface can be cut through the boundary element. Its procedure of the element discrimination is compared with other value methods, including small unknown numbers. Therefore, the memory space of the calculator can be saved. As for the problem of the barrier on the seismic wave, the boundary element method is widely applied to the condition of caring about the surface vibration, and the comparative research achievements have been introduced [5, 10]. After organizing the comparative research achievements, the scholars introduce some simple regression formulas for obtaining the influence of obstructing the seismic wave by the trench [8]. The experience formulas obtained in the statistic methods is not enough for changing trench design data that it is largely restricted in the practical application. The mainly problem is that there are many parameters to influence the barrier of the seismic waves by the trenches, and the parameters cannot be considered simultaneously, the interaction effects among the parameters are still a complex and unknown mathematical behavior. Therefore, the related researches on obstructing the seismic wave by the trenches effectively are limited [3-8]. The past researches mainly focus on the plain strain two-dimensional problems for the three dimensional analysis is difficult with long calculating time and many memory space in the calculator and its analysis is just restricted to the techniques of dealing with the singular integral. The three dimensional value results will be closer to the real life in the actual application, the barrier of the seismic wave can just be used in some special cases, and the designing principle of the trench cannot be set. Therefore, the paper tries to use the value analysis results, which is obtained from the three dimensional boundary element methods, to search for a method with the consideration of many parameters and discuss its feasibility.

In recent years, the neural network has been successfully

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applied to the traditional physical problems, solving and analyzing the complex relations among multiple variables, which are influenced by one another. It is also successfully applied to the Civil Engineering, such as the analysis of the slope stability, the dangerous prediction of the earthquake, the prediction model of the deep excavation, the estimation of the Liquefaction potential and the active control of the structure [12].

According to the spreading of the wave and the refraction theory, the main effect of obstructing the spreading of the seismic wave by the trenches plays an important role in the trench shape, the in-filled material property of the trenches, such as the shear wave velocity. As for the complex problem with a lack of the proper analysis theory or models, the model of the neural network can comprehensively explore its obtained knowledge and data, and can be utilized to assist the experience design [12]. Therefore, the screening effects of vertical amplitude of seismic waves should be employed by the network with its proper potential.

The paper adopts the results, which are about the screening effects of vertical amplitude of seismic waves by the rectangle in-filled trench analyzed by the three dimensional boundary element method, as the basic database, and the neural network model is applied to solve the problem of affecting the complex interactions among parameters [7-11]. The paper aims to build the neural network model based on the machine learning and analyze the control effects of vertical amplitude of seismic waves caused by the three dimensional trench. The paper builds the network training model for using the back-propagation training method as he training principle, and then the built network model should be tested and the results should be analyzed

2 Problem statement

The problem discussed in the paper is that the in-filled trench is used as the mechanism of obstructing the seismic wave, and the obstructing influence of the surface vibration is caused by making the square vibration base from the vertical direction to the harmonic direction. The parameters of the geometric dimension, the parameters of the material property and the dynamic parameters used in the paper is shown as below, where L_r is Rayleigh wavelength. The in-filled trench, whose depth is d and whose width is w, is set in the surface whose distance is 1 or in the surface foundation whose immersed depth is e, and the bearing unit of the foundation has the vertical and harmonic motion. The in-filled trench is mainly to obstruct the Rayleigh wave, so the geometric dimensions in all related parameters, such as the depth, width, distance of the in-filled trench and the immersed depth of the vibrating foundation, take the Rayleigh wavelength L_r, caused by the epicenter, as normalization. The normalized parameters in the problem are the depth parameter $D(D = d/L_r)$, the width parameter $W(W = w/L_r)$, the distance parameter $L(L = 1/L_r)$ and the foundation immersed parameter $E(E = e/L_r)$ in the in-filled trench. The amplitude of the vibration can be reduced through the trench. In order to estimate the screening effects of vertical amplitude of seismic waves, the paper adopts the average amplitude reduction ratio introduced by Beskos [6] to show the result. The average amplitude reduction ratio $\bar{A}_{ry}$ is obtained from the surface amplitude reduction ratio A_{ry} in the proper range (10 times wavelength) after using the trench.

Amplitude reduction ratio A_{ry} is the ration between the surface amplitude after setting the trench and the surface amplitude without setting the trench.

$$A_{ry} = \frac{\text{thevertical amplitude of the surface after using the trench}}{\text{the vertical amplitude of the surface without setting the trench}} . \quad (1)$$

For example, $A_{ry} = 0.3$ represents that the amplitude of the seismic wave after using the trench reduced 70%, and the A_{ry} gets the average value. The average amplitude reduction ratio $\bar{A}_{ry}$ can be obtained as shown in the following equation:

$$\bar{A}_{ry} = \frac{1}{\bar{A}} \int_0^L A_{ry}(x) dA . \quad (2)$$

$\bar{A}$ gets the area covered by the 10 times Rayleigh wavelength after using the trench. $\bar{A}_{ry}$ can estimate the screening effects of vertical amplitude of seismic waves. When $\bar{A}_{ry} < 1$ surface amplitude is reducing, the trench can have the function of obstructing the seismic wave. When $\bar{A}_{ry} > 1$ whose surface amplitude is larger than that one without using the trench, the trench would have the negative effect.

According to the previous references, such as Beskos [6], when $\bar{A}_{ry} < 0.25$, the trench obstructing mechanism has finished the goal of the obstructing control. Therefore, the curves, which are drawn by all influenced parameters to the vertical amplitude reduction ratio $\bar{A}_{ry}$, can directly get the influence of the obstructing effect b the trench affected by all parameters.

3 Value analysis and input variables

The database of the value results in the paper is from the three dimensional boundary element methods. The method analyzes the rigid without quality square foundation with the computer procedure and computes the obstructing effect of the vertical amplitude reduction ratio $\bar{A}_{ry}$ by the harmonic vertical external forces and using the rectangle in-filled trench as the obstructing mechanism.

Where the Rayleigh wavelength is L_r, the width is 0.1 L_r, the distance from the trench center to the foundation center is 5 L_r, the soil shear modulus $G_S = 132\,MN/m^2$, the Poisson ratio $\mu_S = 0.25$, the unit weight $\gamma_S = 17.5\,kN/m^3$, the material damping ratio $\beta_S = 3\%$, the wave velocity of the Rayleigh $V_{RS} = 250 m/\sec$, the shear modulus in the in-filled material $G_C = 34.29 G_S$, the Poisson ratio $\mu_C = \mu_S$, the unit weight $\gamma_C = 1.37\gamma_S$, the material damping ratio $\beta_C = 15\%$, the wave velocity of the Rayleigh $V_{RC} = 1250\,m/\sec$, the vibrating frequency in the strip foundation is 50 Hz, the vertical and harmonic loading amplitude $P_O = 1\,kN/m^2$ and other value parameters. The two dimensional frequency domains in the boundary element method are used to analyze the opening of the rectangle trench and the obstructing effect of the seismic wave to the in-filled trench. Before analyzing the three dimensional values, the paper confirms the precision of analyzing the procedure by comparing the research results on the two dimensional plain strain problems under the situation of the same material property and geometry with Beskos and other scholars because there were no related three dimensional research achievements. The results are similar to the analyzed results by using the three dimensional boundary element value procedures to solve the plain strain problem. The three dimensional boundary element value formula used in the paper has relative accuracy, and the database required in the neural network training is set to be analyzed.

The paper assumes that the contact surface between the soil and the foundation is completely jointed, (when the foundation vibrates, it cannot leave the soil), which means the displacement of the soil in the contact surface is the same as the foundation displacement. The foundation is rigid, and the vibration of the vertical displacement in each element of the contact surface is the same. If the foundation bears the 1 vertical vibration ($u_b = 1e^{i\omega t}$), the surface vibration of the soil when the foundation is in the unit vibration should be obtained. The distance between the vibrated foundation center and the in-filled trench center is *L*, and the $L = 1/L_r$ is 5.0, the semi-width in the vibrated foundation is $B = 0.25L_r$, the vibrated frequency in the foundation is 50 Hz. If the soil media is the medium tight sand, the Rayleigh is $V_{RS} = 250 m/\sec$, the unit weight $\gamma_S = 17.5\, kN/m^3$, the material damping factor $\beta_S = 5\%$. The in-filled trench adopts the concrete as the in-filled material. The property is as follows: Young's flexible modulus $E_C = 11316\, MN/m^2$, the Poisson ratio $\mu_C = 0.25$, the unit weight $\gamma_C = 24\, kN/m^3$ and the material damping factor $\beta_C = 5\%$. In this paper, three-dimensional grooves for vibration-based seismic barrier effect, only for vertical harmonic oscillator state boundary element method used in analysis mode system related literature [5-10] listed eight parameters affecting the normalization, as shown in Table 1. But this study is limited to the groove filling material concrete material, so the shear force to the soil surrounding the groove filling material between the velocities is not changed as the parameters of influence. However, in order to fully understand the filler material parameters on the shock effect of the impact of the barrier, this is only the impedance between the fill material and soil medium exemplary changing grooves and shear wave's division *IR* ratio $S = V_{Ss}/V_{S_t}$ sites and other important parameters to display its seismic amplitude change or site formation conditions after filling the grooves trends affecting the efficiency of the barrier. The impedance ratio is defined as $IR = (V_{Ss} \times \rho_S)/(V_{S_t} \times \rho_t) = (V_{Ss} \times \gamma_s)/(V_{S_t} \times \gamma_t) = S \times M$ (soil material soil shear wave velocity×Unit material weight) / (unit shear wave velocity×filling material filling material weight), impedance ratio *IR* density than $M = \gamma_s/\gamma_t$ (density ratio) [soil medium density ratio of filler material] and velocity ratio $S = V_{Ss}/V_{S_t}$ combination of both [soil medium filler material to shear wave velocity ratio] (velocity ratio). The results show that both the local soil and trench fill material layer trough impedance ratio or difference are more remarkable than the shear wave velocity, the effect of vibration isolation trenches filled the better conclusions. But the rest, such as soil Poisson's ratio μ_S , fill material and soil damping ratio between $\beta_t = \beta_s$, or if one part is related to the size of the grooves on the soil for normalized Rayleigh wave wavelength *Lr*, such as filling the groove geometry parameters (depth $D = d/L_r$, the width $W = w/L_r$, the aspect ratio D/W , the sectional area $A = D \times W$) and depth Buried base ($E = e/L_r$) and the vibration base filling the groove center to center distance ($L = 1/L_r$), etc., for generating a series of numerical analysis result database.

The important degree of the related parameters is obtained from the influence degree of the output values to the surface vertical vibration reduction ratio A_{ry}.

Table 1 represents parts of the results obtained with the analysis of the three dimensional bounder element methods.

4 Neural network model

The paper mainly adopts the concept of the forward network and the basic theory of the back propagation to construct the neural network.

The neural network model is divided into three phases. In the first phase, the structure factor in the neural network is decided by the problem features and the researcher's operating experience, and the parameter types of the input and output can be confirmed on the basis of the related mechanical knowledge. In the second phase, the neural network will take numerical data of network training and testing, in order to find in the first stage to determine the network structure, the best node number of hidden layers and training the number of iterations.

The network training and test through the value data are to find out the network structure, the node numbers in the optimum layer, and the training iteration times confirmed in the first phase. The neural network decided in the first and second phase should be trained again and all value data must be tested through the cross-validation method for improving the accuracy of the network prediction and reaching to the optimum neural network mechanism model.

TABLE 1 Representative training and test example

Number	Type	W	D	S=D/W	A=W×D	L	E	μ_S	β_c/β_s	$\overline{A}_{ry}$
1	T	0.05	0.5	10	0.025	0.4	0	0.25	0.06	0.555945
2	T	0.1	0.5	5	0.05	0.4	0	0.25	0.06	0.456969
3	T	0.15	0.5	3.333	0.075	0.4	0	0.25	0.06	0.396798
4	T	0.2	0.5	2.5	0.1	0.4	0	0.25	0.06	0.355169
5	T	0.05	0.5	10	0.025	0.4	0	0.3	0.06	0.566395
6	T	0.1	0.5	5	0.05	0.4	0	0.3	0.06	0.472504
…	…	…	…	…	…	…	…	…	…	…
849	P	0.1	2	20	0.2	0.8	1	0.25	0.04	0.996274
850	T	0.1	2	20	0.2	0.2	1	0.25	0.02	0.57595
851	T	0.1	2	20	0.2	0.6	1	0.25	0.02	0.486782
852	T	0.1	2	20	0.2	0.2	1	0.25	0	0.515742

In order to check the effects of the network learning, the error function represents the learning quality of the network because there is a certain error between the output value derived from the output neural and the actual expected output values. The goal of building the error function is to make the convergence behavior of the network has certain evidence. The back propagation method in the paper adopts the Levenberg-Marquardt algorithm, and its operation is conducted by the training speed, which is approximating to the second phase. The method can reduce the computing time in each iteration algorithm. The weighted value can be updated with the use of the method and the final error function value can reach to the minimum. If the sum of the error square between the actual value and the expected output value is smaller than a reasonable tolerance value in terms of the whole network error, the learning procedure can be finished.

In order to test the effects of the network learning, the paper randomly divides the example into two parts. The first part is used as the training example, and the second part is used as the test example. When the network learning is up to a certain phase or the learning procedure is finished, the test example is input the network for testing the accuracy and the learning effect of the present network.

The effect of the network learning also can be judged by the root mean power error and related factors, other than the error functions

5 The hybrid experimental analysis method in the neural network

The developing procedure of the analysis structure in the neural network is as shown below. The network structure design in the first phase includes feasibility estimation and network planning. The network training in the second phase includes network analysis, system design and the network structure. The network authentication in the third phase includes network testing, system integration, system maintenance and other five parts [13].

The first phase: The network structure design includes feasibility estimation and network planning [11]. The network developed in the paper just has a hidden layer for the layer in the signal hidden layer is enough to approximate to ant continuous functions in terms of the general approximating theorem. The completely connected internal structure is applied in the network structure (the nodes in any layer connect with all nodes in the next layer nodes).

The Levenberg-Marquardt algorithm is adopted in the back propagation learning. The algorithm can reduce the operating time in each iteration algorithm. The input layer consists of eight input variables, and the related variables are as shown in the Table 1. The output layer consists of a signal neuron, and it is determined by the size of the average vertical vibration reduction ratio A_{ry}. The determination of the numbers of the neuron in the hidden layer is decided through the test and error process. The Cascade Correlation learning [17] adopted in the paper builds to the minimum but the optimum numbers of the nodes in the hidden layer. The ranging value of the variables used in the research is also as shown in the Table 2.

TABLE 2 input parameter value scope of statistics

Input parameters (825 cases)					
W		*D*		*S*	
max	0.200	max	2.000	max	40.000
min	0.050	min	0.250	min	1.250
A		*L*		*E*	
max	0.400	max	0.800	max	1
min	0.0125	min	0.200	min	0
μ_S		β_t/β_s		A_{ry}	
max	0.490	max	0.060	max	0.9983
min	0.250	min	0	min	0.2750

5.1 THE FEASIBILITY ESTIMATION OF THE NEURAL NETWORK

In recent years, the neural network has been successfully applied to the traditional physical problems and the Civil Engineering, the problem discussed in the paper has good verification results. All network models are used as the changing conditions and have the complex relations. It is proper to solve the screening effects of vertical amplitude of seismic waves by 3-dimensional in-filled trenches and analyze the complex relations influenced by many variables with the neural network technology. In the meantime, a rapid and reasonable reference is provided in the actual engineering application.

5.2 NEURAL NETWORK PLANNING

The features of the applied problems belong to the analyzed problems, so the proper supervising learning in the back propagation is selected to do the network planning. The back propagation network belongs to the forward teaching network. It consists of many layers, such as input layer, hidden layer, output layer. It is the hierarchical back propagation network and has the representativeness.

The basic unit in the neural network structure is the processing element, also called artificial neuron. The transformation f in the neural network has many types, and the paper adopts three transformation functions to do analysis and comparativeness, that is the linear function, sigmoid function and the sigmoid function.

The second phase: the network training includes network analysis, system design and network structure.

5.3. THE NEURAL NETWORK ANALYSIS

It mainly analyzes the data collection, data variables, data behaviors and data solutions in the problem in terms of the analyzed network. The system analysis in the neural network system can be divided into four procedures.

5.3.1 Information gathering

In order to make the value results apply in many soil materials and field vibrating condition, the paper sorts the relevant research parameters and the reasonable research value range in terms of the previous references, as shown in the Table 2. The paper simulates and analyzes the effect of the seismic wave obstruction to the three dimensional in-filled trench with the boundary element method. The database after being selected has 852 in total, and parts of the data are shown in the Table 1. After the data in the developed network model is randomly selected, the 70% data is used as the training examples, and the other 30% data is used as the testing examples [14]. Later, the collected input vectors and the output vectors are matched. The network can be trained and built.

5.3.2 Data variables

It decides the input variables and the output variables of the problem. As to the analyzed problem, the selection of the input feature is decided from the expert's experience and the statistic analysis. Before the decision, the interaction between the flexible wave and the trench should be understood. According to the previous references, the width *W*, the depth *D*, the depth-width *S D*/*W*, the sectional area *A W D*, the damping ratio between the in-filled material and the soil *t* – *s*, the distance between the foundation center and the in-filled trench center *L*, the foundation immersed depth *E* and the soil Poisson ratio *S* etc. should be analyzed, and their importance is decided by the size of influencing the average vertical vibration reduction A_{ry}.

5.3.3 Data behavior

The data in the paper belongs to the value variables, so it is represented by a processing unit and the data variables are pointed to the processing unit. The data must be reflected in the reasonable area before being processed. The reasonable input value range can be obtained for making the data through the corresponding process. The probability corresponding method adopts parts of the input values' corresponds to the reasonable ranges.

The output value ranges may surpass the neural network and then excite the function values, the saturated situation of the values in the weighted learning would be further caused. The paper adopts the interval corresponding method in the output values to solve the problem.

5.3.4 Data processing

According to the network models, the input vectors and the output vectors should be transformed. The part includes the data analysis and transformation, and the selection of the important parameters. The pure application of the probability corresponding method in the neuron input values and the interval corresponding method in the neuron output values cannot meet the requirement of the interaction among the neurons. Therefore, the paper adopts the non-linear function transformations to solve the special relation among the input neurons, other than the general neurons. Though the function transformed procedure cannot ensure the useless input parameters, it is helpful to the network model. The input parameters can make its original models more generalized by the processing procedures of the function transformation [14]. The preliminary processing functions in the neural network, which are adopted in the paper, are as shown as in the Table 3.

All input parameters are transformed through the preliminary processing function in the Table 3, *K-S* detection method is used to check the goodness of each transformed input parameters. The highest three values after being the complete checking analysis should be used as the important parameter selection base in the neural network in terms of the discretion of the *K-S* detection values.

The proper numbers of the variables should be decided other than selecting the right variables. The paper adopts the genetic algorithm [15] to search for the optimum input parameters and numbers. The paper confirms the width-depth parameter $S = D/W$ in the trench through the fourth power function of the preliminary processing *S_Pwr4*, the area parameter *A* through the hyperbolic tangent function of the preliminary processing *A_Tanh*.

TABLE 3 Convert the input parameter K – S verification value

Input parameters					
W		*D*		*S*	
Before the processing function	Value of $K – S$	Before the processing function	Value of $K – S$	Before the processing function	Value of $K – S$
Rt2	0.7591	Ln x/(1-x)	0.7885	Tanh	0.8931
Linear	0.7591	Linear	0.7885	Pwr4	0.8872
Log	0.7591	Pwr2	0.7885	Linear	0.8837
A		*L*		*E*	
Before the processing function	Value of $K – S$	Before the processing function	Value of $K – S$	Before the processing function	Value of $K – S$
Tanh	0.8778	Pwr2	0.6287	Linear	0.6463
Pwr4	0.8860	Inv	0.6287	Pwr2	0.6475
Linear	0.8778	Linear	0.6287	Log	0.6463
μ_S		β_t/β_s		$\bar{A}_{ry}$	
Linear	0.5652	Log	0.3243	Pwr2	0.9410
Ln x/(1-x)	0.5652	Inv	0.3243	Inv	0.9387
Rt2	0.5652	Linear	0.3243	Log	0.9387

Note: the conversion of input parameters listed in the table in this paper, application of genetic algorithm selection the selection of network input parameters of the basement

The distance parameter L from the foundation center to the in-filled trench center through the linear function of the preliminary processing L_Linear and the square function of the preliminary processing L_Pwr2, the foundation immersed depth parameter E through the linear function of the preliminary processing E_Linear, the damping ratio between the in-filled material and the soil β_t/β_s through the linear function of the preliminary processing β_t/β_s _Linea. After the output parameter and the average vertical vibration reduction ratio $\bar{A}_{ry}$ are processed by the preliminary processing function, the square function of the average vertical vibration reduction ratio $\bar{A}_{ry}$ _Pwr2 is the expected parameter to the network and used as the basis of the network training.

5.4 NEURAL NETWORK SYSTEM DESIGN

5.4.1 Network architecture

This step is to determine network architectures (such as hidden layers, number of hidden layer processing unit, etc.). In the last step of the training, the establishment of application-oriented network program is a trial and error method (trial and error method). The results of the present study show there is no the rules to follow to establish a better network architecture. But in theories, it is enough for perception neural network architecture just taking two-story, with the hidden layer neural meta in addition, then the output of this perception machine can approximate any continuous function, that can be a universal approach device (universal approximate) [16]. Therefore, in this paper, the network topology is determined by the final three-forward networks, which includes the input layer, a hidden layer and output layer.

Another problem lies in the network topology point of decision nodes in the hidden layer, generally usually only be resolved by a trial and error method. But this paper Cascade Correlation study [18] to construct the smallest but best hidden layer nodes. Cascade approach in the implementtation of the Department's use of its training examples herein conjugate gradient (conjugate gradient) as its basis, and adopt various methods to strengthen Cascade improved learning.

5.4.2 Network news

This step is learning parameter determines the network (such as learning rate, the inertia factor, etc.). Learning rate and inertia factor is a network of two of the most important parameters to pass down. These parameters are mainly in the front a back-propagation learning rule of law and the network can improve the convergence rate, but its value is usually determined by trial and error method. However, adding Extend-Delta-Bar-Delta (EDBD) algorithm Minia and Williams [18] proposed in this paper to automatically adjust the learning rate and inertia factor to consider connecting the weighted value of the error function to slow phenomena and jump phenomenon, which enhances learning efficiency back propagation network.

Other parameters: the initial weighting coefficient value is randomly generated and the weighting value for the interval [-1,1] and the learning process is usually conducted once a training example, i.e., an example of each load weight value is updated once.

5.5 CONSTRUCTION OF NEURAL NETWORK

Constructing neural network, via the description above, the issues of this study, its network architecture is three-tier network topology. In the input layer parameters via data preprocessing and post-screening using genetic algorithms are six valid input parameters. In terms of a layer of hidden layer by Cascade Correlation learning tries to select a suitable framework (as shown in Table 4), compare and select a training network for the study of network architecture, the output transfer function for the double bend conversion function, hidden layer processing unit has a network of 39 nodes in the output layer is only one square represents the average vertical amplitude decreased function value ratio $\underline{A}_{ry}$. While between these nodes, which are completely linked, it has a layer of nodes and links between nodes in the next level, there is not a link to a node of the phenomenon. The third stage is the network authentication including network testing, system integration and system maintenance.

TABLE 4 Select Training Network and test results

Training Network 1		**Training Network 2**		**Training Network 3**	
Hyperbolic tangent transfer function		*Linear transfer function*		*Sigmoid transfer function*	
The number of hidden layer processing unit	*Test results correlation coefficient R*	*The number of hidden layer processing unit*	*Test results correlation coefficient R*	*The number of hidden layer processing unit*	*Test results correlation coefficient R*
0	0.8624	0	0.8563	0	0.8627
4	0.8884	5	0.8892	4	0.8982
6	0.8999	10	0.8956	9	0.9111
10	0.9075	14	0.8997	13	0.9148
15	0.9127	19	0.9081	18	0.9158
20	0.9174			22	0.9165
22	0.9188			25	0.9186
24	0.9207				
29	0.9221				
34	0.9235				
39	0.9239				
Select the number of hidden layers handle 39, the correlation coefficient test results R = 0.9239		Select the number of hidden layers handle 19, the correlation coefficient test results R = 0.9081		Select the number of hidden layers handle 25, the correlation coefficient test results R = 0.9186	

5.6 NEURAL NETWORK TEST

The test means the convergence and accuracy of the test class of neural networks. After the neural network learning process, in order to determine the effect of the convergence of how neural networks, and to promote the performance of this class of neural networks, the general practice to all samples divided into two groups, which are used to train a group, while the other group used for testing, and the ratio of the number of training data and testing is usually seven to three ratio of [14]. In this paper, the number of data for training and testing of the network also uses this ratio, and therefore the training data for the 596 pens, and the data part of the test, compared with 256 pens. Due to the untrained data as a test, so you can know this once trained to promote the performance of the neural network model architecture exactly how.

This article uses several methods to assess the test mode, such as: the correlation coefficient *R*, the coefficient of determination R2 (determination coefficient), net correlation coefficient Net-R, the mean absolute error Avg. Abs (the average absolute error), root mean square error RMS accuracy (accuracy) and confidence intervals (confidence interval). In this paper, according to John Wiley & Sons [20] and ISO 5725-1 [20] needs advice and practical aspect of the definition of the output error is 20% accurate, and using a 95% confidence interval for the standard. Network test is divided into the following four stages.

5.6.1 Convergence Test

In the network learning process, errors or energy function is reasonable observation network convergence. In the learning process supervised learning neural networks, the convergence process usually root mean square error to measure. The network convergence test results shown in Table 5. The table can be learned from the network in the learning process and the testing process, the root mean square error of convergence can be reasonable to 0.06, the convergence can be described as good.

TABLE 5 Network convergence test

Sample evaluation	Correlation coefficient R	Net correlation coefficient Net-R	Avg. Abs	Max. Abs.	RMS	Accuracy (20%)	Confidence interval (95%)	Records
All the examples	0.9252	–0.9247	0.0461	0.3101	0.0677	0.9437	0.1318	852
Training examples	0.9270	–0.9263	0.0450	0.3101	0.0670	0.9480	0.1305	596
Debugging Examples	0.9212	–0.9212	0.0485	0.2856	0.0695	0.9336	0.1358	256

5.6.2 Verification test

After the completion of online learning, we analyze the characteristics of network errors, in order to improve network as the basis for learning outcomes. In unsupervised learning neural network learning is completed, the results can be used to do the verification test scatter plot. If the point on the scatter plot are in the diagonal line graph, table validation good results. In addition can also be used to measure the correlation coefficient points on a scatter plot focuses on the degree diagonal line. The midpoint of the scatter plot focused on the degree diagonal line of view, the network validation test results and the correlation coefficient was 0.925, indicating a good validation results.

5.6.3 Confirmation test

After completion of online learning, the results of the analysis results of the merits of the network and other network mode or contrast of other technologies. This article will multivariate regression techniques to return to their data, according to the results obtained compared with their advantages and disadvantages. In a multivariate regression analysis, all the parameters and data processing functions without prescreening process and the important parameters, only the original parameter data regression, and the regression equation after the regression coefficients and predict its outcome as shown in Figure 1. Data is shown in Figure 1 multivariate regression analysis found that the width of the groove filled with concrete foundation and soil and fill material Buried damping ratio and other parameters, there are more significant impact on the seismic barrier effect, through its network of input parameters input after the function parameter conversion process and the use of genetic algorithms [10] to search for the best learning results and number of input parameters vary.

Regression analysis in which the main reason why not show off the shape and size parameters of the importance of filling the slot, and that the network parameters by previous treatment, width and depth parameters have been filled with concrete gutters implicit in the deep groove width and basal area ratio among the resulting parameters. Through multivariate regression formula to predict the average error is 0.075, the coefficient of determination was 0.668, root mean square error of 0.103, while the largest relative absolute error was up 164.5%. Therefore, comparison shows that the learning capacity and regression ability of the network model is better than multiple variables techniques.

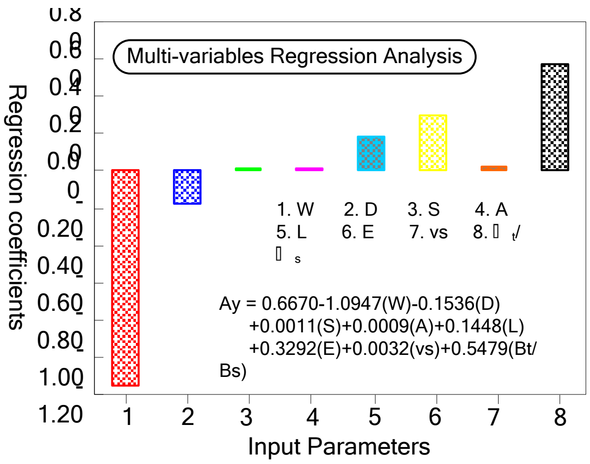

FIGURE 1 multivariate regression analysis

5.6.4 Assessment test

After the system is completed, the results of analysis of the system meet the needs of the target problem. Used to predict problems for supervised learning network, the available statistics [21], the precision and confidence intervals to assess the results of the test system meets the needs of the target problem. All numerical data and the final cross-validation methods enhance the accuracy of the network prediction mechanism to reach the best neural network model. Herein may be apparent from Table 5, the accuracy of the analysis system network output error of 20% and 95% for the 93% confidence interval 0.13, the problem has been to meet the needs of the target.

6 Network systems integration and maintenance and updates

According to the actual needs of the network system, with other systems integrated into a complete problem-solving systems, such as expert systems integration and through knowledge sharing, Convergence, logical, systematic, sustainable, standardization and inference efficiency, precision and reliable technology, the objective of the program, making decisions rationalization, reliable, office automation, rapid technology development and process efficiency, and thus to improve quality, reduce costs, shorten schedules purposes.

Neural network model can be used to simulate complex network links interactions between the different parameters of the actual problem. Different types of geological conditions have different parameters affecting the situation, this paper established a network mode is only used for the mechanical properties of similar geological conditions, and cannot be sure for all geological conditions. Therefore, when the environment changes, neural networks may need to retrain or change the network architecture to adapt to changes in the environment.

7 Evaluation and analysis network

Neural network model to the application level, it can also be classified as a type of empirical formula; with the empirical formula by different neural network model did not make an explicit formula as a result, the corresponding parameters are fully implicit right in the network weights (weighting) in the value of other parameters. To validate the neural network model constructed with learning and predictive capability, we use Gately [22] proposed the concept diagram contribution (contribution graph) and the use of sensitivity analysis to analyze whether this paper constructed a model to assess the impact of the input parameters capabilities. The so-called contribution chart is showing that the contribution of each input parameter of the network results are summed by each connection after the heavy weights of input parameters derived absolute value. According to a rule of thumb, if the value is greater than 5 indicates that the input parameters of very large, if between 0 and 2, then the impact is weaker. Contribution plots can be used to solve common linear (collinear) issue of input variables can also be used to assess the importance of the right input variables, according to this concept, the paper input layer and the hidden layer connection weights obtained by taking the sum of the absolute values obtained its contribution Figure 2, wherein the parametric representation of the number of input variables shown in Table 4. Can be learned from Figure 2, the most influential of the parameters in this paper based on the basis of deeply buried depth and center to center distance between the grooves filled, followed by concrete filled trench aspect ratio parameter, and past scholars concluded similar. However, there is no study in the past about the impact analysis of foundation deep-buried on the barrier effect of vertical amplitude of the seismic impact, but after analysis of the concept of contribution plots, it particularly highlights the impact of the seismic base buried deep vertical amplitude barrier.

Sensitivity analysis is used by the network to determine the small changes in its input parameters affect its output parameter values. Practice is seeking an output value of the function of each of its partial derivatives of each input parameter matrix derived. The results are shown in Figure 3, which can be used to assess the impact of small changes in the output of each input parameter values, while Table 6 series statistical analysis proceeds through all 852 documents, in which the input parameter number for the project is as shown in Table 4. It can be learned from Figure 3 that the area parameters concrete filled trench and groove-based center to center distance between the grooves are more sensitive.

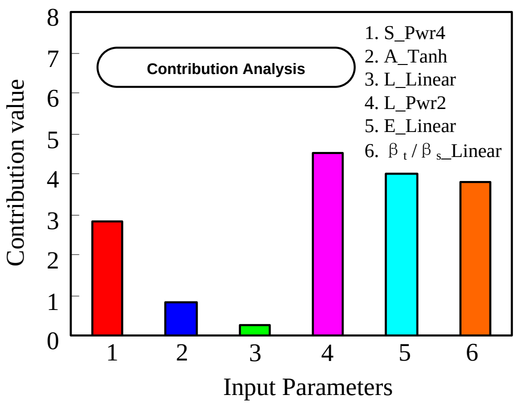

FIGURE 2 The input parameters contribution plot

TABLE 6 Sensitivity analysis of statistics

The sensitivity of the variable name	S_Pwr4	A_Tanh	L_Linear	L_Pwr2	E_Linear	β_t/β_s _Linear
Average value	0.3244	-0.8962	0.7955	-0.8355	0.4171	0.0435
Average of squared error	1.7127	1.4715	1.5189	1.6980	0.6018	0.0435
Variance	1.6094	0.6692	0.8872	1.0011	0.4284	0.0418

Note: This table was approved by all 852 pen case statistics derived

The seismic amplitude groove barrier effect of the problem does not require complex and time-consuming testing process, and eliminates a lot of numerical analysis to calculate the required computer memory and computation time, but cannot provide effective shortcomings reference information immediately. Network input generally is the simple and readily available trench fill material parameters and soil properties and environmental parameters, which can be taken into account the number of interaction parameters. Therefore, for the comparison of the predicted results, the output of the network is fast with high accuracy, the development of these features are favorable factors for the pattern in other application in geotechnical engineering. And it provides the reasonable and rapid economic judgment direction and data for the construction of design engineering reference.

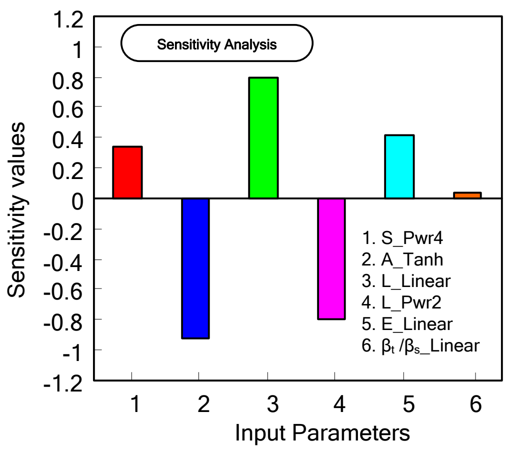

FIGURE 3 the sensitivity analysis

8 Conclusions

This study can be obtained via the following conclusions:

1) neural network model established in this paper simulation analysis boundary element method can fill the grooves in vertical amplitude of the seismic effect on the result of the barrier, and the predicted results of good accuracy, with the promotion of the application.

2) Because seismic amplitude and site conditions (such as the formation of shear wave velocity) are closely related, and if the material filling the grooves with the formation of shear wave velocity difference between the more remarkable, then fill the grooves the better vibration isolation effect. However, in this study the use of the site as a Rayleigh wavelength groove dimensions formalized way to deal with the impact of this parameter formation shear wave velocity and the result of the study trench fill material confined concrete material, this study will be in this filler material shear wave velocity excluding the impact parameter, and the vibration resistance of the other parameters of the groove by genetic algorithms for data processing and screening procedures, using six input parameters should be sufficient, namely concrete tank Goushen aspect ratio, size parameters, vibration source to groove distance Buried deep foundation, damping ratio trenches between the filling material and soil, etc. Recommendations can be added in the future more sites on the three-dimensional formation shear wave velocity change vibration isolation trench filled with case studies for the construction of a complete neural network.

3) Nodes in the hidden layer decisions to Cascade Correlation study, using a variety of possible conversion functions and gradually increase the number of nodes in the program, assessed the results of the network after training in order to adopt the hyperbolic tangent (tanh) conversion function, 39 hidden layer nodes, the correlation coefficient was 0.9239 for the best network architecture.

4) Contribution by the network diagram analysis found that the most influential parameter lower than the average vertical amplitude of the order based on deeply buried depth and distance from the vibration source to fill the grooves, the grooves filled with concrete aspect ratio, resulting from previous scholars similar conclusions; but this article has highlighted the use of the contribution chart analysis Buried deep impact on the basis of vertical amplitude barrier. Display after the completion of construction of neural networks, via the contribution chart analysis, is available in its important influence parameters on the applications of the problem.

5) The sensitivity analysis showed that the area is filled grooves and focal distance to fill the grooves between the centers of the more sensitive.

6) Confirmed test program by the network, in the analysis and processing of complex interactions between multiple variables, learning capacity and regression ability of the network model is better than multiple variables techniques.

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