Application of artificial neural networks in solving inversion problem of surface wave method on pavements

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Abstract
Surface wave method is an in-situ nondestructive testing procedure for estimation of elastic moduli and layers thicknesses of layered structures such as pavements and natural soil deposits. In this research "Matlab" has been employed for applying artificial neural networks in solving inversion problem of surface wave test dispersion curve and estimating the soil profile. Multi layer neural networks along with back propagation training procedure are used to carry out the required inversion process. The networks are trained using the Steepest Descent Gradient Algorithm, Conjugate Gradient Algorithm and Levenberg – Marquardt Algorithm. Eight training functions have been employed and assessed in three, four and five layer networks. The most optimized network with the least error rate and iteration number for convergence was selected and tested for certainty. By employing the selected optimum network, a number of real cases have been studied and the results obtained have been compared with the available actual data. The results show very good match indicating that the selected back propagation neural network is capable of providing a useful tool for carrying out the inversion process of surface wave method.
Keywords: Surface wave method, artificial neural networks, inversion problem, pavement profile.

1. Introduction

The surface wave method is a new nondestructive Seismic technique for in-situ evaluation of elastic moduli and layers thicknesses of layered systems such as pavements and natural soil deposits. The method is based on the dispersive characteristics of surface (Rayleigh) waves in layered media, i.e., waves of different wavelengths propagate with different velocities. The methodology of the surface wave test is simple and has potential to be fully automated.

The procedure for conducting the surface wave method, which is referred to as spectral analysis of surface wave method by some researchers, can be divided into three phases: (1) data collection in the field; (2) evaluation and construction of the experimental dispersion curve, and (3) inversion of the dispersion curve for determining the stiffness profile of the system. Elastic waves are generated by an impact source on the surface of the system, detected by a pair of receivers, and recorded by an appropriate transient recording device. Fig 1, shows a schematic diagram of the surface wave testing setup. The dispersion curve for a single receiver spacing is obtained from the relationships for phase velocity and wavelength for an arbitrary frequency component. The test is repeated for several receivers spacing to cove a broad range of wavelengths and in two directions to minimize the effects of dipping layers and the internal phase of the instrumentation. The dispersion curves for all receivers spacing and two directions are fully filtered and statically combined to derive an average dispersion curve for the system**.**

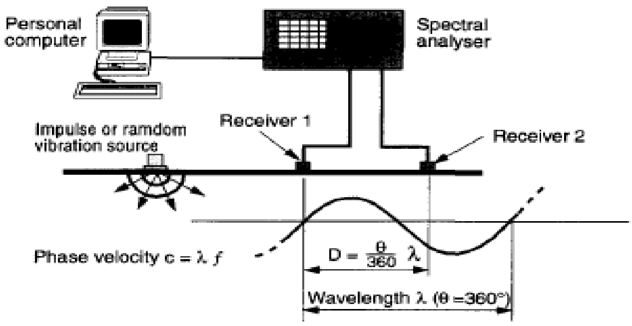

Figure 1: Schematic diagram of surface wave test setup

The objective of the surface wave method is to obtain the experimental dispersion curve that describes the relationship between the velocity of wave propagation (phase velocity) and wavelength (or freguency). Then, through an inversion process the profile of the layers stiffness and thickness of the layered system is obtained. Typical results of the field measurements are shown in Fig 2, Determination of the dispersion curve is a simple and mostly automated task. The inversion process, however, is complex. Most of the inverse techniques developed thus far are based on numerical methods. These methods are almost time–consuming and greatly dependent on the experience of the user. Also the inversion process has been automated for special conditions only, such as pavements and soil profiles where the shear modulus increases with depth. There is a need to develop methods for efficient inversion of the dispersion curve under general conditions.

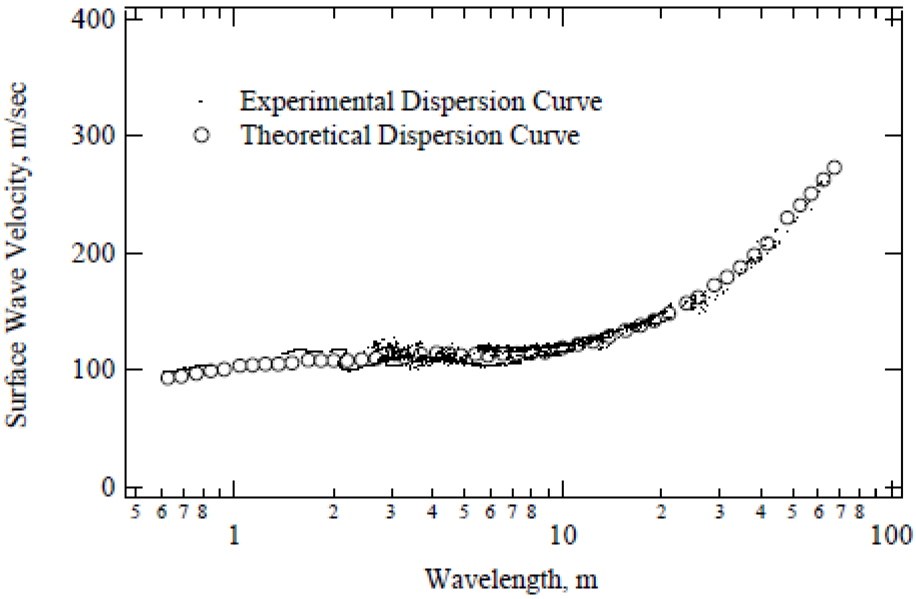

Figure 2: Typical results of surface wave field, measurement

2. ARTIFICIAL NEURAL NETWORKSS

Artificial neural networks are biologically inspired analogues of the human brain. They are composed of many operationally simple but highly in interconnected processing units. The processing units themselves have certain functional similarities to biological neurons, and their organization bears at least superficial resemblance to the organization of neurons in the brain.

The type of calculation performed by a neural network is determined by the architecture of the network. The most common architecture used for mapping, classification and forecasting is the multilayer, feed-forward network (Hecht–Nielsen 1989). These networks consist of several layers of processing elements. The processing elements pass information in the form of signal patterns from the input layer of the Network through a series of hidden layers to the output layer. The signals travel along connections whose strengths are adjusted to amplify or attenuate the signal as it propagates through the network. Each prosing element sums the signals arriving at its inputs from the previous layer, performs a nonlinear transformation on the collective signal, and passes the transformed signal on to each of the processing elements in the succeeding layer. Thus, the output signal pattern that results from a given input signal pattern is uniquely determined by the distribution of connection strengths throughout the network. In that respect, the "knowledge" contained in the network is stored as the connection strengths.

The neural network gains its knowledge through training. Training of feed–forward networks is commonly accomplished using a supervised learning method. In supervised learning, a set of training examples (consisting of input–output pairs) is iteratively presented to the network. The in put signals are propagated through the network, and the resulting outputs are compared to the target out puts. A learning algorithm is employed to adjust the connection strengths so as to minimize the differences between the calculated and target outputs.

The back propagation learning algorithm has become the de facto standard for training multi-layer, feed-forward networks. After each training example is presented to the network, the differences between the calculated and target output patterns are computed and propagated backwards through the network using the existing network connection strengths. The individual connection strengths are then adjusted in the direction that reduces the error apportioned to them. If training is successful, after many iterations (using training examples each time or reusing a limited set of training examples in a different order), the connection strengths attain values that globally minimize the output error (commonly mean) for all inputs.

3. NEURAL NETWORK TRAINING

Back propagation and general regression neural network models are trained using a training set. This training set consists of training patterns, each of which is a data pattern consisting of input variables and correct output variables. The inputs in these models are the dispersion curves data. The dispersion curves used to instruct the neural networks are synthetic dispersion curves constructed using the exact dynamic stiffness matrix method developed by Kausel & Roesset (1981) and computerized by Manochehri(2003).

The dispersion curves in the training set can be defined either in terms of dimensionless velocity versus dimensionless frequency or dimensionless velocity versus dimensionless wavelength.

The dimensionless values of the parameters are used to enable application of the database to a much wider range of intermediate neurons (in the hidden layers). Examination of the outputs from the neural network models indicates that these models are capable of matching the dispersion curve inputs with the correct soil profile. The MSE is given by the following:

$$MSE = \frac{\sum(A-P)^2}{n} \quad (1)$$

Where A = actual output value, P = output value by the neural network, and n = number of cases in the training set. The lower values of the MSE indicate that the neural network is working better. Table 1 shows the MSE values for the test set each model.

Table 1: Mean squared error for test set

Model	Learning B.P.	Training Algorithm	Epochs Function	MSE
3 – layer	SDG	traing dx	28750	0.388234
4 - layer	SDG	traing dx	21750	0.29405
5 - layer	SDG	traing dx	19250	0.25504
3 - layer	CG	trains cg	4380	0.099985
4 - layer	CG	trains cg	1592	0.099900
5 - layer	CG	trains cg	1243	0.099966
6 - layer	LM	trainlm	----	----

Eight instructive functions have been used, in–clouding: Batch Gradient Descent (traingd), Batch Gradient Descent with Momentum (traingdm), Steepest Gradient Descent with Variable Learning Rate (traingdx), Fletcher–Reeves Conjugate Gradient (traincgf), Polak-Ribiere Conjugate Gradient (traincgp), Powell-Beale Conjugate Gradient (traincgb), Scaled Conjugate Gradient (trainscg) and Levenberg -Marquardt (trainlm) algorithms. After instructing the network all instructive algorithms have been assessed in three, four and five layer networks. Among these networks, the most optimized one with the least error rate and iteration number to be converged was studied and investigated. It was noticed that the Scaled Conjugate Gradient (SCG) algorithm is the best and fastest one among the others and therefore this algorithm was selected as the optimum one to be utilized in the network training. Levenberg-Marquardt algorithm was also applied but as the network was so large, the computer confronted with run out of memory. Considering the methods to decrease the memory for algorithm, again computer failed to run the program because of great dimensions of network Therefore, according to the Matlab´s recommendation, the other algorithms were used.

Table 2 compares the results between neural network calculations and the actual examining values for 5 test data. Figs 3 and 4 show artificial neural network's results with actual examining data in the form of dispersion curve and plot of soil profile in 5layer network (5 –90–80–70-119) using Conhugate Gradient algorithm in TEST – 1 (for instance).

Table 2: Neural network output parameter's error values

Test Data	d2/d1	d3/d1	Vs2/Vs1	Vs3/Vs1	Vs4/Vs1
TEST -1	5.00	3.50	0.080	0.078	0.074
TEST -2	4.50	4.00	0.078	0.073	0.070
TEST -3	4.00	4.50	0.820	0.079	0.075
TEST -4	4.00	4.00	0.079	0.075	0.072
TEST -5	4.50	5.00	0.084	0.081	0.076

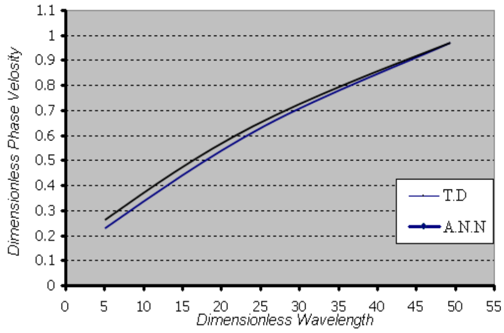

Figure 3: Dispersion curves of neural network results and actual examining data.

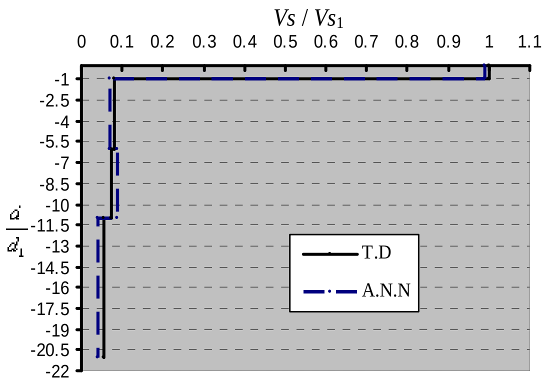

Figure 4: Soil profiles of neural network results and actual examining data

Figs 5 and 6 also show the trained neural network results in company with actual site dispersion curve and soil profile (for instance).

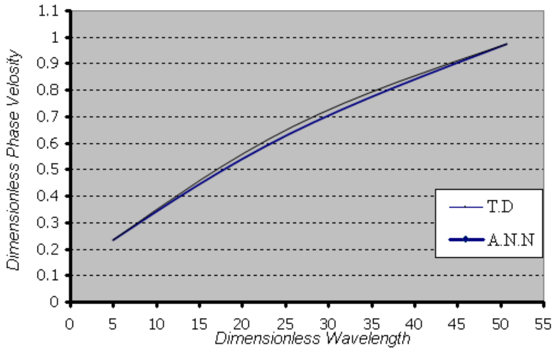

Figure 5: Dispersion curves of neural network results and actual site data.

Soil profiles. The dimensions velocity and dimensionless wavelength are respectively given by the Following relations:

$$V_{phase} = V_{phase} / V_{S1} \quad (2)$$

$$\lambda_{phase} = \lambda_{phase} / d_1 \quad (3)$$

Where V_{s1} and d_1 are the shear wave velocity and thickness of the surface layer, V_{phase} and λ_{phase} are phase velocity and corresponding wavelength in the dispersion curve, respectively.
The training data considered contain a four stratum soil profile, as shown in Table 3. One hundred nineteen training cases were developed each with 76 inputs. All the curves are defined for the same set of 76 dimensionless pair of data (dimensionless wavelength–dimensionless shear wave velocity) in the range from 5–20 with step of 0 .2 for the dimensionless wavelength.

Table 3: Idealized soil profile and layers parameters

Layer No.	Thickness	Shear wave velocity	Mass density	Poisson' s ratio
1	d1	Vs1	ρ1	υ1
2	d1	Vs2	ρ2	υ2
3	d1	Vs3	ρ3	υ3
4	∞	Vs4	ρ4	υ4

The effects of mass density and Poisson s ratio on the dispersion characteristics of surface waves are small. Nazarian & Stokoe (1984) has shon numerically that the effects of these two parameters, in most practical cases, are less than % 5 Therefore, to simplify the inversion process, it is assumed that mass density and Poisson s ratio for each layer are known parameters . Reasonable values are assigned to these parameters based upon past experience. In the present work, these parameters have been assumed to be v = 0.4 and p = 2000 kg / m^3. Also shown in Table 4 are the various values required for each of the five output parameter used in the construction of the corresponding dispersion curve of the given soil profile.

Table 4: Output training parameters

d_2/d_1	d_3/d_1	V_{s2}/V_{s1}	V_{s3}/V_{s1}	V_{s4}/V_{s1}
4.00	5.00	0.082	0.079	0.076
4.50	4.00	0.800	0.077	0.074
5.00	3.50	0.079	0.076	0.075
4.50	3.50	0.078	0.074	0.072
4.00	5.50	0.081	0.076	0.074
3.50	4.00	0.076	0.073	0.070

The corresponding output for each training case is the soil profile. This profile is described by two thickness ratios, d_2/d_1 and d_3/d_1, and three shear wave velocity ratios,V_{s2} /V_{s1}, V_{s3}/V_{s1} and V_{s4}/V_{s1}.
The training sets were developed so that the dispersion curves matched various combinations of these output parameters. Implementation of the neural network in the field for back calculation of the soil profile using the surface wave method requires the thickness and the shear wave velocity to be known. The experimental dispersion curve is then normalized according to the relations (1) and (2), and input to the neural network. Finally, the neural network provides output defining the soil profile.
A back propagation network is made up of interconnected nodes arranged in at least three layers. The input layer receives the input data patterns, and passes them into the network. The number of input nodes equals the number of input data values. The output layer produces the result. The hidden layers have no direct connection to input or output.
During training, back propagation networks process patterns in a two step procedure. In the first or forward phase

of back propagation learning, an input pattern is applied to the network, and the resulting activity is allowed to spread through the network to the output layer. The desired results are then compared to the actual results produced by the network. This comparison results in an error for each node in the output layer. In the second or backward phase, the error from the output layer is propagated back through the network to adjust the interconnection weights between layers. This process is repeated until the network's output is sufficiently accurate. Back propagation learning is this process of adapting the connection weights. After instruction, a back propagation network can process unknown input data.

An unknown input pattern can be applied, and the network produces a corresponding pattern at the output. In this paper, the Matlab 6.5 software has been used for development of the network and performance of its training, evaluation and assessment. Normal three, four and five layer back propagation network was tested. These networks in company with learning algorithms such as Steepest Descent Gradient (SDG) Algorithm, Conjugate Gradient (CG) Algorithm and Levenberg–Marquardt (LM) Algorithm were used to evaluate the training data. To train the networks, a test set of 35 normalized dispersion curves in company with their soil profile were developed and used. After running the program, the error for each case was calculated and the number of neurons in hidden layers determined. The mean squared error (MSE) was used to evaluate the performance of the network due to different number.

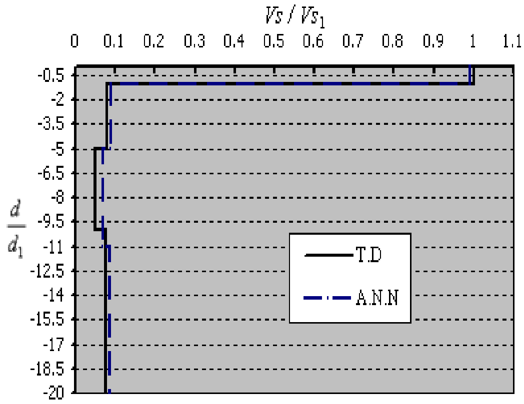

Figure 6: Soil profiles of neural network results and actual site data

These dispersion curve and soil profile have been determined using surface wave test and exploration logs conducted at the site. The site is located at Sacarya in Turkey (Rosenblod & Stokoe 1999). As can be seen from the Figures, the agreement between the calculated neural network results and the actual data is reasonably good. This agreement was also seen in all other cases studied as well. The results indicate that back propagation SCG model with five layers provides good results in analyzing the dispersion data obtained by surface wave method.

4. CONCLUSIONS

Ingestions and results on back propagation neural networks show that these networks are capable of estimating the soil profile under study. The networks studied in this research work inverse the surface waves dispersion curve in order to find out the corresponding four-stratum modeled soil profile.

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According to the observed results, among applied networks in this study, five layer back propagation network with Scaled Conjugate Gradient (SCG) training algorithm produced the best estimation in accordance with these dispersion curves. Using dispersion curves data obtained from the test carried out on real sites to train the neural networks, made it possible to use this method for real sites.

On of disadvantages of neural network methods to inverse dispersion curves is lack of recognition of the soil layer number and it can be removed by training the network according to assumed soil layers . It means that we can not use a trained neural network for four–layer soil system in a five – layer soil profile. In the case of using neural networks for more soil layer profile, we need to increase the training data suitable with that profile. Increasing the range of problem, network will need to learn more complex points which will in turn lead to bigger networks, and several more examples will be needed to train the network. Also faster training algorithms will be required in order complete the set of training data within a reasonable period of time.

5. References

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