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Rock Properties and Seismic Attenuation: Neural Network Analysis

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Abstract—Using laboratory data, the influence of rock parameters on seismic attenuation has been analyzed using artificial neural networks and regression models. The predictive capabilities of the neural networks and multiple linear regresssion were compared. The neural network outperforms the multiple linear regression in predicting attenuation values, given a set of input of rock parameters. The neural network can make complex decision mappings and this capability is exploited to examine the influence of various rock parameters on the overall seismic attenuation. The results indicate that the most influential rock parameter on the overall attenuation is the clay content, closely followed by porosity. Though grain size contribution is of lower importance than clay content and porosity, its value of 16 percent is sufficiently significant to be considered in the modeling and interpretation of attenuation data.

Key words: Attenuation, neural networks, Rayleigh scattering.

1. Introduction

In recent years, attenuation of seismic waves has received considerable attention from the geophysics community. To make full use of acquired seismic data, it is important to interpret seismic attenuation in terms of the physical properties of rock. Such physical properties include for example, porosity, permeability, grain-size and clay content. Knowledge of seismic wave attenuation mechanisms and the causative rock properties are vital for the evaluation and interpretation of field and laboratory seismic data.

The major attenuation mechanisms presently known include matrix anelasticity which involves frictional dissipation resulting from relative motion at solid boundaries and across surfaces of cracks (WALSH, 1966); fluid flow with relaxation due to shear motions at pore fluid boundaries (WALSH, 1969; SOLOMON, 1973); dissipation in a fully saturated rock as a result of the relative motion of the solid frame with respect to fluid inclusions (BIOT, 1956a,b; STOLL and BRYAN, 1970);

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''squirting'' and enhanced intra-crack flow phenomena (MAVKO and NUR, 1975; MAVKO and NUR, 1979); and geometrical effects including scattering off grains and pores (KUSTER and TÖKSÖZ, 1974). Assessing the most influential mechanism for any given attenuation data is still a formidable task.

The factors that cause attenuation and reduction in the velocity of seismic waves propagating through earth materials are also known to control porosity and permeability (KLIMENTOS and MCCANN, 1990). The source of the attenuation data used in this work is obtained from KLIMENTOS and MCCANN (1990). Henceforth in this paper this reference is referred to as KM. The attenuation data measured by KM and the resulting analysis enhance the possibility of predicting porosity and/or permeability from seismic measurements. However the non-separability of the factors affecting both the hydraulic and seismic properties further complicate issues in the sense that other variables such as the clay content and particle size distribution influence the relations, making them inherently nonlinear and complex (HAN *et al.*, 1986). Such complex relations are, however, amenable to artificial neural network (ANN) solutions. KM (1990) used a regression-based empirical model to establish the relation between seismic attenuation and measurable rock properties; porosity and clay content neglecting grain size and permeability. ANNs are an interconnection of processors which mimic the biological activity of the brain. They are particularly useful for solving complex decision problems that are not well understood physically. Unlike traditional regression models incorporating a fixed algorithm to solve a particular problem, neural networks utilize a learning technique to develop an appropriate solution. The associative relationship between input attributes and the specific output parameters is optimized without the constraint of a *priori* information. The computational paradigm of neural networks offers several advantages in solving problems within the geosciences. The importance of ANN in solving a myriad of geophysical problems has been indicated by DOWLA and ROGERS (1995) and MCCORMACK (1991).

In this paper the experimental data obtained and published by KM (1990) are further analyzed to decipher relevant relationships between physical parameters characterizing the rock properties and seismic parameters. The physical parameters include porosity, permeability, grain size and clay content. The seismic parameter considered is attenuation or absorption coefficient. Firstly, the importance of grain size in the overall attenuation is analyzed and assessed and secondly a feed-forward neural network is used to analyze the data and infer relationships between the variables describing the rock and the measured seismic parameter. These relationships are compared with the traditional multivariate regression models as a way of evaluating the strengths and weaknesses of the neural network modeling. Thirdly the relative importance of the different physical rock parameters is assessed to examine its contribution to the overall attenuation process using the neural network weights.

2. Seismic Attenuation and Rock Properties

The relation between seismic attenuation and rock properties is complex. Pore-filling clay materials have important influence on permeability. Clay materials tend to plug the pore throats and hence reduce the ease of fluid transmission, that is, reduce permeability. Measurements of attenuation on synthetic rock by KLIMENTOS and MCCANN (1988) indicate that the compressional wave attenuation is increased by the presence of clay minerals. The attenuation is linearly dependent on the percentage content of the intrapore clay minerals. It is conceivable that if permeability is related to clay content, and compressional wave attenuation is related to clay content, then one would anticipate a relationship between seismic wave attenuation and permeability. In essence rock permeability is expected to contribute to seismic attenuation.

Attenuation is measured by the decay of a plane wave as it propagates through a rock material and is determined by

$$A(x) = A_0 e^{-\alpha x} \tag{1}$$

where A_0 is the initial amplitude of the propagating wave, $A(x)$ is the wave amplitude after distance x, and α is the attenuation coefficient. The most common measures of attenuation are the dimensionless quality factor Q and its inverse Q^{-1}. The quality factor Q is related to the attenuation coefficient α via the frequency f of the propagating wave and the phase velocity V of the rock medium given by

$$\frac{1}{Q} = \frac{\alpha V}{\pi f - \dfrac{\alpha^2 V^2}{4\pi f}} . \tag{2}$$

Under the low-loss assumption the $\alpha^2 V^2/4\pi f$ term is negligible and is usually dropped. A multivariate statistical relation between attenuation coefficient, the clay content C and the porosity ϕ was obtained by KM (KM model):

$$\alpha = 0.0315\phi + 0.214C - 0.312 \tag{3}$$

with a correlation coefficient of 0.88. However, other important measured parameters, the grain size and permeability were not considered in the modeling process. Grain-size distribution relates to the pore size distribution (ÅBERG, 1992) and hence it is expected to affect permeability and attenuation. One should thus expect the grain size of rock materials to contribute to the overall attenuation of propagating seismic waves. In this work regression equations are developed to predict the attenuation value, using the measured rock parameters as descriptors. These descriptors include the porosity, clay content, permeability and grain size. The regression model relates the attenuation value to the descriptors via the following equation:

$$S = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \tag{4}$$

where S is the computed attenuation value, β_n is the coefficient determined by the regression analysis, and X_n is the value of the descriptor or rock property. KM used only two descriptors ($n = 2$). In this work all the four measured descriptors were used to develop a regression model for comparison with that of the neural network. The resulting regression equation relating attenuation α to the rock parameters is given as:

$$\alpha = 0.432 + 0.011\phi + 0.002K - 0.003D + 0.251C \tag{5}$$

with a correlation coefficient of 0.89, where ϕ is the porosity (percent), K is the permeability (millidarcy), D is the mean grain size (μm) and, C is the clay content (percent). This equation is referred to as the MLR model for the purposes of this paper.

Geometrical spreading, elastic scattering and viscoelasticity are the three frequently described mechanisms by which seismic waves propagating through a rock material become attenuated (JOHNSTON and TÖKSÖZ, 1981). Clay minerals and flow of fluids contribute to the viscoelastic effects while grain-size distributions control the elastic scattering effects. Recent studies by GIST (1994) indicate that the dominant attenuation mechanism is related to the interaction of pore fluids with smaller pores and grain surfaces. This suggests that the contributions from elastic scattering and viscoelastic effects may overlap and hence the need to establish ways of determining the relative importance of each effect.

Fig. 1 illustrates the distribution of different rock parameters for 42 samples of sandstones studied by KM. Though weak correlations exist among some parameters, it is not unreasonable for one to infer that the permeability and average grain size seem to evolve from similar or close distributions and therefore may be correlated. Since the grain sizes of natural earth materials are not uniformly distributed, their relative contribution to the overall attenuation would be significant. None of the attenuation mechanisms described above could be solely responsible for the bulk attenuation and therefore all the causative factors need to be considered. No particular mechanism can be justifiably eliminated from consideration under all the conditions studied in the laboratory and in the field (JOHNSTON and TÖKSÖZ, 1981).

3. *Elastic Wave Scattering and Seismic Attenuation*

The component of wave attenuation due to elastic wave scattering α_s in any medium depends upon the ratio of the seismic frequency (f) or wavelength (λ) to the size of the inhomogeneities (grains). The dependence of attenuation on the frequency and size of the inhomogeneity (D) has been utilized to distinguish three scattering ranges (mechanisms) and can be summarized as (SZILARD, 1982):

Rayleigh region (Rayleigh scattering): $\alpha_s(f, D) \propto D^3 f^4$, $\lambda \gg D$
Stochastic region (stochastic scattering): $\alpha_s(f, D) \propto D f^2$, $\lambda \approx D$
Diffusive region (diffusion scattering) $\alpha_s(f, D) \propto 1/D$, $\lambda \ll D$

The seismic wavelength used in the experiment by KM is on the order of 4500 μm and the average grain size measured has a range of 70–300 μm. We should thus expect a contribution to the overall attenuation from Rayleigh type scattering satisfied by ($D < \lambda/20$) (SZILARD, 1982). A simplified expression for α_s relating to the frequency, medium velocity and size of the inhomogeneities satisfying both Rayleigh and diffusive scattering is given as (BLAIR, 1990):

$$\alpha_s(f) = \frac{C_s}{D}\left(\frac{f}{f_D}\right)^4\left(1 + \frac{f}{f_D}\right)^{-4} \tag{6}$$

where $f_D = K_s(Vp/D)$, K_s and C_s are general constants and V_p is the P-wave velocity of the medium. An attempt was made to fit the attenuation values provided by KM to equation (6) above. Figure 2 shows the measured data from KM and the

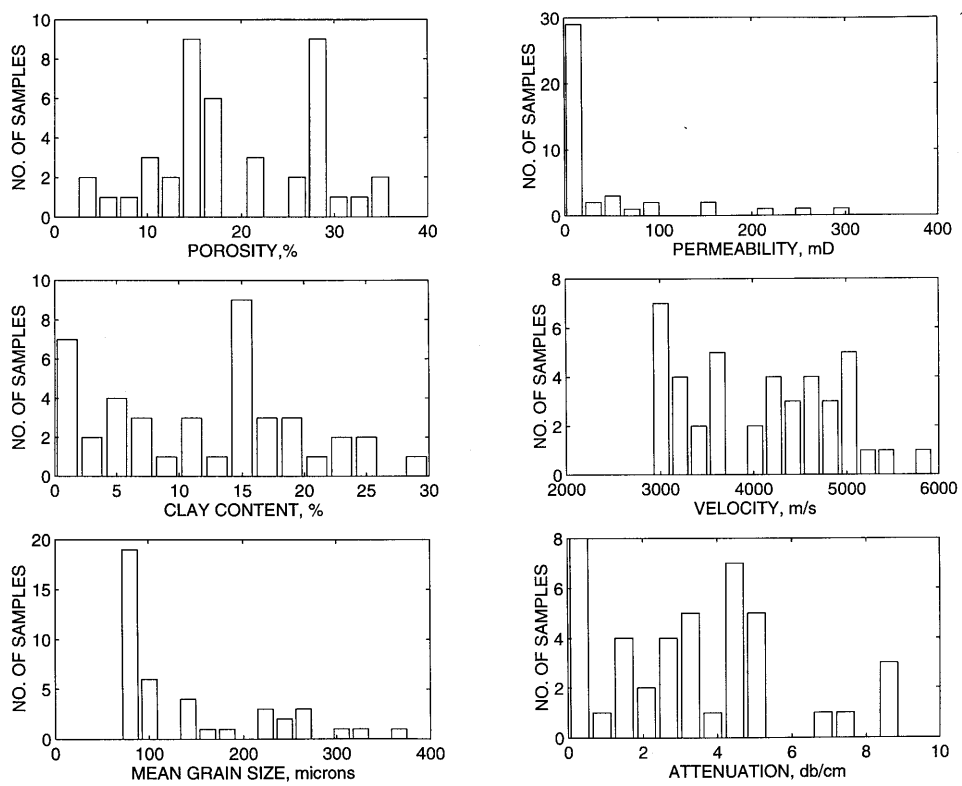

Figure 1
Frequency distribution of various rock and seismic parameters analyzed and measured by KM.

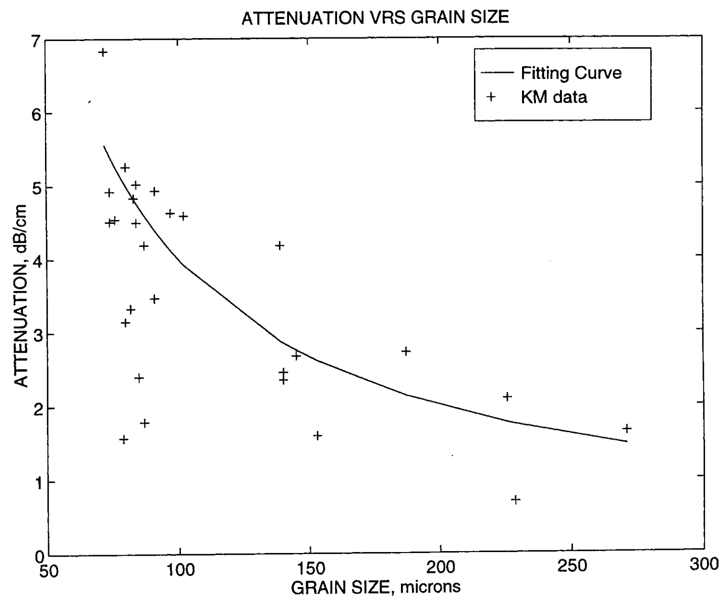

Figure 2
Comparison of model curve relating grain size and attenuation (equation (6)) and attenuation data by KM.

fitted curve, using equation (6) for $K_s = 0.23$ and $C_s = 400$ and a frequency of 1 MHz. The values for the constants are generalized for rocks (Blair, 1990) and their variations are reasonably insensitive to the fitted curve. The quality of the fit as measured by the correlation coefficient is estimated as 0.895. The quality of the fit indicates that the degree of common variation between the data and equation (6) above is significant. This implies that the elastic scattering may usefully contribute to the attenuation data obtained by KM and that grain size as a rock property must be considered.

4. Neural Networks and Relationship Between Seismic and Rock/Soil Parameters Overview

Artificial neural networks are essentially crude computer models of biological systems with learning capabilities. The networks model such systems by adopting simple rules that govern the interactions between simulated neurons. ANNs are increasingly used to solve a variety of scientific and engineering problems concerned with unknown and varied functional relationships among measured variables. In this paper, ANN is utilized to seek a relationship between seismic attenuation and the parameters characterizing the properties of rocks (grain size, clay content, porosity, permeability). These parameters can be measured or computed independently for a given earth material. However, neither the functional relationship between the seismic and rock parameters nor the possible underlying physical mechanism is known or well understood. At best, we can conceive the relationship to be highly nonlinear given the likelihood of several overlapping attenuation mechanisms. Rather than trying to derive a functional relationship from approximations to theory, an estimate of the functional form is obtained from the measured or computed data themselves. The usefulness of a neural network stems from its adaptability in learning by example and its ability to generalize. In the learning process, the network encodes the generalization of the vital features of the problem into the weights of the network nodes. The information contained in these weights can be used to predict new input patterns. The weights also form a knowledge base that may be exploited to gain insights about the physical system as a whole. Neural networks are useful when searching for particular unknown nonlinear relationships or approximating certain complicated data-generating mechanisms.

Several ANN models have been developed based on different architectures and learning modes. The most popular and widely used model and the one used in this paper is the Multilayer Perceptrons (MLP), an example of which is illustrated in Figure 3. This model can perform complex decision mapping and has wide applications in pattern classifications and function approximation (GARRETT, 1994). The MLP can be trained by several algorithms, for example the backpropa-

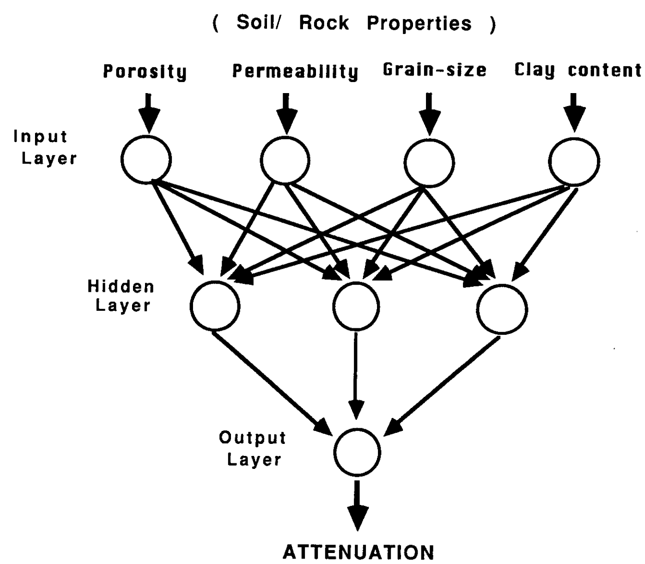

Figure 3
Schematic diagram of a feed-forward artificial neural network with three layers. Input nodes are the rock properties and the output node is the seismic attenuation. Network is designed on the basis of data available from KM.

gation, quasi-Newton method and the Levenberg-Marquardt optimization algorithms. A brief overview of ANN training is described below as details can be found in HASSOUN (1995).

ANN Training

During ANN training, each hidden and output neuron processes its inputs by multiplying each input by its weights. The products are summed and processed using an activation function, usually a sigmoidal function ($f(x) = 1/(1\text{-}e^{-x})$) to produce the output. The neural network learns by modifying the weights of the neurons in response to the errors between the actual and targeted output values. For a given set or vector of N inputs ((x_1, x_2,…x_N) and M outputs (y_1,y_2,…y_M), the output of node j is computed as:

$$y_j = f\left(\sum W_{ij}\ x_i\right) \tag{7}$$

where W_{ij} is the weight of the connection between neurons i and j. The learning rule for the adjustments in the weight between neuron i and j is expressed as

$$\Delta W_{ij} = \eta \delta_j o_i \tag{8}$$

where o_i is either the output of node i or an input, η is a positive constant termed the learning rate and δ_j is an error term of node j. Thus,

$$\begin{aligned} \delta_j &= -\delta E/\delta\,\mathrm{net}_j \\ E &= 0.5 \sum (y_j - o_j)^2 \\ \mathrm{net}_j &= \sum W_{ij}\ o_j \end{aligned} \tag{9}$$

where y_j is the target value for the jth node and o_j is output for the jth node. The value δ is computed as

$$\delta_j = (y_j - o_j)\ o_j\ (1 - o_j) \tag{10}$$

if the node is an output unit, or

$$\delta_j = o_j(1 - o_j) \sum_k \delta_k W_{jk} \tag{11}$$

if the node is not an output unit. In order to improve the convergence characteristics, a momentum gain β is added to the weight correction term to stabilize oscillations during the learning process (HASSOUN, 1995),

$$\Delta W_{i,j}(n+1) = \eta \delta_j o_i + \beta \Delta W_{ij}(n) \tag{12}$$

where n is the iteration index. The training of the network is complete if the convergence of the weighting coefficients has been achieved. The convergence criterion requires that the mean square error at the output must be less than a desired tolerable error.

5. *Neural Network Modeling of Attenuation Data*

Computational Process

Fully connected, three layer, feed-forward neural network was used in this study as shown in Figure 3. As illustrated in the figure, the input layer accepts the rock physical parameters (porosity, permeability, grain size, clay content) which numerically encode the features of each rock. The input signals are weighted as they are transmitted to the nodes of the second layer, the hidden layer. The hidden layer neurons process the data and send signals to the neurons of the output layer. The output layer provides the predicted value; the seismic attenuation.

In a fully connected feed-forward network, each neuron is connected to every neuron in the level below it. Each connection has associated with it an adjustable weight as discussed above, which determines how much information is being transmitted from one neuron to the next. The multivariate statistical methods such as used by KM to establish a relationship between some of their parameters characterizing the rock properties and seismic parameters are often complex and require the important parameters to be known for its formulation. The modeling process of neural networks on the other hand is more direct and capable of capturing complex nonlinear interactions between input and output in a physical system. During training, irrelevant input variables are assigned low connection weights which may be discarded from the data. In this work since neural networks are trained on measured laboratory data, they are trained to deal with and handle inherently noisy, inaccurate and insufficient data. The Levenberg-Marquardt (LM) training algorithm is utilized as is has been found to be more efficient and reasonably more accurate than the traditional gradient descent backpropagation (HASSOUN, 1995).

Levenberg-Marquardt Training Algorithm

The Levenberg-Marquardt optimization method provides an alternative and more efficient way of minimizing the sum-square-error E given in equation (9). The backpropagation algorithm is based on the gradient descent technique which has a major drawback of requiring numerous steps before converging to a solution. A reasonable increase in the convergence rate has been noted by HASSOUN, (1995) when the quasi-Newton optimization algorithm is used. An important limitation of the quasi-Newton method on the other hand is that it requires a good initial guess for convergence. The suggested alternative, the Levenberg-Marquardt routine, is essentially an interpolation between the quasi-Newton and gradient descent methods and successfully hybridizes the useful properties of the two methods for optimal performance. The inherent difficulty in selecting the appropriate momentum and learning rate terms in the conventional backpropagation algorithm is overcome in this scheme.

Consider the sum-of-squares error function as above in the form

$$E = \frac{1}{2} \sum_m (\epsilon^m)^2 = \frac{1}{2} \|\epsilon\|^2 \tag{14}$$

where ϵ^m represents the error associated with the mth input pattern, and ϵ is a vector with elements ϵ^m. For small perturbations in the weights W, the error vector can be expanded to a first order via Taylor series expansion

$$\epsilon(W_{\mathrm{new}}) = \epsilon(W_{\mathrm{old}}) + A(W_{\mathrm{new}} - W_{\mathrm{old}}) \tag{15}$$

where W_{old} and W_{new} indicate current and old points in weight space respectively and elements in the matrix A are defined as

$$A_{mi} \equiv \frac{\delta \epsilon^m}{\delta W_i}. \tag{16}$$

Thus the error function defined above can be written as

$$E = \frac{1}{2} \|\epsilon(W_{\mathrm{old}}) + A(W_{\mathrm{new}} - W_{\mathrm{old}})\|^2. \tag{17}$$

If this error function is minimized with respect to the new weights W_{new} we obtain

$$W_{\mathrm{new}} = W_{\mathrm{old}} - (A^T A)^{-1} A^T \epsilon(W_{\mathrm{old}}). \tag{18}$$

The above formula can, in principle, be applied iteratively in an attempt to minimize the error function. Such an approach inherently poses a problem in that the step size (change in weights) could be large in which case the basic assumption (small change in weights) on which equation (17) was developed would no longer be valid. This problem is addressed by the Levenberg-Marquardt algorithm by seeking to minimize the error function while simultaneously trying to keep the step size small enough to ensure that the linear approximation remains valid. To achieve this aim, the error function is modified into the form:

$$E_{\mathrm{mod}} = \frac{1}{2} \|\epsilon(W_{\mathrm{old}}) - A(W_{\mathrm{new}} - W_{\mathrm{old}})\|^2 + \lambda \| W_{\mathrm{new}} - W_{\mathrm{old}} \|^2$$

where the parameter λ governs the step size. Minimization of the modified error with respect to W_{new} gives

$$W_{\mathrm{new}} = W_{\mathrm{old}} - (A^T A + \lambda I)^{-1} A^T \epsilon(W_{\mathrm{old}})$$

where I is the unit matrix.

The weight correction term in the Levenberg-Marquardt scheme is obtained as

$$\Delta w_{ij} = (A^T A + \beta I)^{-1} A^T e \tag{20}$$

where A is the Jacobian matrix of the derivatives of each error from each weight, β is a damping factor which is a scalar and e is an error vector (difference between output and target values). For large values of the damping factor, equation (13) approximates the gradient descent of backpropagation while for small values it leads to the quasi-Newton method. The damping parameter is adjusted according to the nature of changes in the error as learning progresses. In so far as the error reduces, β is made bigger. If the error increases however, β is made smaller. The choice of the damping factor is crucial to the convergence rate and stabililty of the learning process. In this work, the damping factor is chosen as 1.0 percent of the largest singular value in each iteration which provided satisfactory results. In the training process of the network, it took the conventional backpropagation algorithm 30 min to train the network while the Levenberg-Marquardt algorithm took only 6 min. The errors however were comparable, 0.342 for the Levenberg-Marquardt and 0.369 for the conventional backpropagation.

When using any iterative training procedure, a criterion must be available to decide when to stop the iterations. In this work training continued until the sum-squared error reaches an acceptable value (0.01) for the entire training set or after a fixed number (1000) of training cycles has been reached.

Data Processing and Network Design

The data base used in this work is based on the experimental work provided by KM. As noted by HASSOUN (1995), proper selection of a training set with the right type of data preprocessing and an appropriate number of data points as input to a neural network may outrank the importance of the network design parameters. The input attributes are: (1) porosity, (2) permeability, (3) mean grain size and (4) clay content. The output or target parameter is the measured attenuation.

In designing the network a good training set was first obtained and then processed as input to the net. In the development phase of the design process, the data were divided into two sets. The first set, about 80 percent of the whole data set selected randomly, constitutes the training set used to train the network. The remaining 20 percent, the testing set was used to assess the external predictive abililty of the net. The input values to be supplied to the net were preprocessed by a suitable transformation to lie in the range 0–1. This was deemed necessary as such process tends to improve training of the network (MASTERS, 1993). The differences in the ranges of the various input parameters or attributes may tend to overrule any real importance inherent in the individual attributes. To avoid this, all inputs were scaled so that they correspond to approximately the same input ranges. The normalization techniques used to transform or normalize the input training data x_k (a vector composed of just the kth feature in the training set) in the interval $[\beta, \alpha]$ are expressed as

$$x_k \Leftarrow (\alpha - \beta) \cdot \frac{x_k - x_{\min}}{x_{\max} - x_{\min}} + \beta \tag{20}$$

where $x_{\min}$ and $x_{\max}$ are the respective values of the minimum and maximum elements in the training and the testing data.

For a finite number of examples, the simplest network, the one with the fewest number of weights that satisfies all input-output relations givben by the training set might be expected to have the best generalization properties (DOWLA and ROGER, 1995). The number of examples-to-weight ratio (EWR) in the training process was restricted to values greater than 9 which is close to the value of 10 recommended by DOWLA and ROGER (1995). All computations were performed on the SPARC-20 Unix workstation using the MATLAB programming language.

6. Data Analysis and Discussions

The importance of grain size in the overall attenuation of seismic waves is addressed and analyzed. Even though grain size as a rock property was documented by KM, they did not utilize it in their modeling procedure. In this paper an attempt is made to establish the relevance of elastic scattering due to grain size in the attenuation of seismic waves. The measured physical variables in the form of rock parameters; porosity, permeability, grain size and clay content were included in both multiple linear regression and neural network modeling. In the regression modeling all available data were utilized to obtain the regression coefficients. The resulting equation (equation (5)) was then used to predict the attenuation values given a set of input descriptors or rock parameters. In the neural network modeling, however, part of the data ($\approx 80\%$) was used for training of the network and the remaining used in assessing its external prediction potential.

A plot of the measured versus predicted attenuation values applying the MLR, the neural network and the KM models is shown in Fig. 4. Although the range of the test data set is restrictive, given the limited overall data set and the fact they were chosen randomly, they were deemed sufficient for use as test data. The bench line is the decision line along which the measured and predicted attenuation values are equal. Points falling along or close to this line indicate accurate reasonable predictions. The neural network model predictions matched the measured attenuation values reasonably with a standard error of estimate of 0.57. This is deemed a very good match considering the fact that the neural network has not been exposed to these data values. The MLR model on the other hand has been exposed to the testing data (as the testing data were part of the data used in regression modeling), providing a weaker prediction capability in comparison to the neural network. The

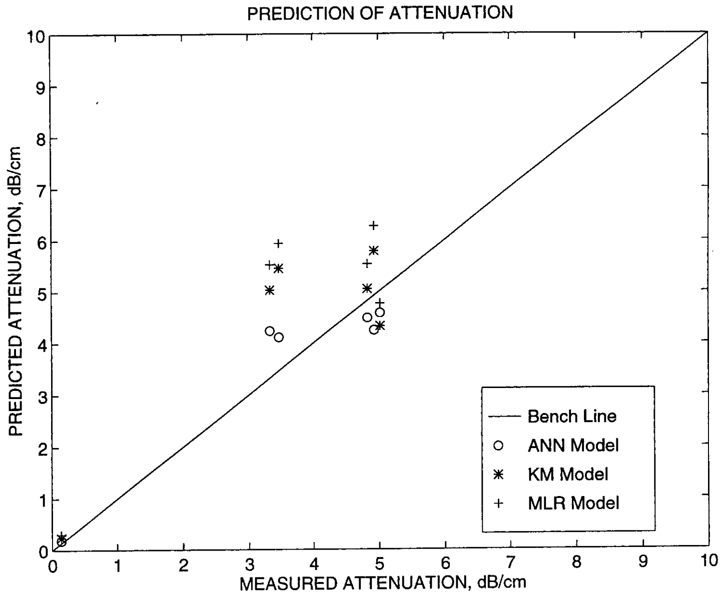

Figure 4
Comparison of prediction capabilities of neural networks and multiple linear regression models.

standard error of estimate for the MLR model is 1.41. Interestingly, when the permeability and grain size are removed as descriptors, the resulting prediction (KM model) gives a slightly lower standard error of estimate 1.16. A similar analysis using neural networks gave a slightly higher standard error of estimate 0.68. The influence of permeability and grain size has been addressed earlier. Such observations ascertain the pitfalls of linear statistical analysis in nonlinear complex mechanisms such as seismic attenuation. This result emphasizes the usefulness of neural networks in modeling complex nonlinear physical processes. The importance of this result is that all the rock properties do have some level of significant contribution to the overall attenuation of the seismic waves. However, the degree of influence of each rock property may not be obvious. An approach to making an inference on the relative importance or the degree of influence is provided via the neural networks by analyzing the weights of the fully trained network. The procedure is described below.

7. Neural Network Weights and Relative Importance of Individual Input Attributes

The relative importance of the individual input attributes to the overall attenuation was evaluated using a scheme developed by GARSON (1991). Though the

Table 1

Petrographic and compressional wave data for the 42 samples (after KLIMENTOS *and* MCCANN*, 1990)*

Sample No.	Porosity (%) (Helium)	Porosity (%) (Wet-dry)	Perme-ability (mD) (Nitrogen)	Average grain size (μm)	Clay content (%)	P-wave velocity at 40 MPa in m s^{-1}	P-wave attenuation at 40 MPa in dB cm^{-1}
1HM1	30.31	29.81	17.17	74	12.00	3627.00	4.51
1VM1	36.04	35.98	21.16	76	16.00	3121.00	4.54
2V2M1	15.46	20.55	0.05	80	15.00	4152.00	3.15
2H2M1	2.72	3.489	0.00	78	0.00	5934.00	0.01
2V1M1	2.43	2.9	0.00	70	0.00	5835.00	0.08
3H1M1	27.39	32.397	9.30	78	23.00	2952.00	8.92
2H1M1	35.09	35.129	73.26	82	30.00	3108.00	8.48
4HM1	28.04	33.1	10.05	83	20.00	3181.00	4.83
4VM1	28.79	31.02	5.47	84	18.00	3056.00	4.50
5HM1	21.19	23.42	11.42	85	15.00	3700.00	2.40
5VM1	21.73	24.7	7.10	91	22.00	3572.00	3.47
6HM1	27.87	29.943	9.59	84	17.00	2990.00	5.02
6VM1	27.73	30.69	3.50	102	17.00	3090.00	4.59
6VM1	27.12	27.57	0.45	76	25.00	3000.00	8.61
7HM1	22.20	24.84	1.13	91	25.00	3500.00	7.68
8VM1	9.96	11.93	0.01	87	7.00	4705.00	1.79
9HM1	13.47	15.11	0.06	74	14.00	4498.00	4.92
9VM1	17.18	19.05	0.13	72	15.00	4362.00	6.83
9V2M1	16.71	20.48	0.44	79	8.00	4381.00	1.57
10H2M1	26.32	28.83	10.27	82	20.00	3299.00	3.33
10V1M1	33.59	33.249	2.25	80	15.00	3195.00	5.26
11HM1	25.41	27.74	5.78	87	20.00	3314.00	4.19
11VH1	28.87	29.412	7.03	91	23.00	2909.00	4.93
19VM1	27.96	28.543	33.67	139	15.00	3675.00	4.18
33HM1	17.13	18.645	2.21	145	12.00	3933.00	2.68
33VM1	16.65	17.794	0.37	140	12.00	4010.00	2.36
B3BP	14.47	14.783	220.90	242	0.20	4788.00	0.08
B1BP	14.15	15.065	150.70	229	1.00	4960.00	0.70
B2BP	14.37	15.431	255.90	272	1.00	5078.00	0.29
B5BP	15.18	14.518	160.40	260	0.70	4942.00	0.14
B4BP	13.72	15.64	87.65	235	0.50	4950.00	0.09
A1BP	16.50	16.514	41.74	377	15.00	4149.00	3.63
A4BP	16.11	17.06	50.51	312	15.00	4152.00	3.30
A6BP	15.41	16.03	52.42	330	15.00	4246.00	3.38
3H1S1	13.11	12.045	3.67	226	7.00	4666.00	2.10
3H2S1	15.72	16.48	87.55	226	5.00	4564.00	0.47
5HS1	8.96	8.21	0.13	140	6.00	4947.00	2.46
6H1S1	27.33	26.56	305.80	187	5.00	3666.00	2.73
11H2S1	15.13	14.125	11.06	271	4.00	4794.00	1.65
14HS1	11.39	11.98	0.46	153	6.00	4666.00	1.60
14H2S1	5.98	5.45	0.00	97	3.00	5225.00	0.19
15HS1	10.22	9.94	0.16	97	9.00	4895.00	4.63

Table 2

Optimal connection weights

Hidden nodes (1)	Weights: Input #1 (2)	Input #2 (3)	Input #3 (4)	Input #4 (5)	Output (6)
1	−70.5407	89.2112	−221.9069	159.8331	0.3693
2	−31.6879	94.0320	−59.4213	−122.3565	−0.1592
3	58.6875	1.7740	−3.7590	−41.0124	0.2065
4	89.6875	4.4093	−1.1211	−82.3228	−18.5774

scheme is approximate it nevertheless provides one with intelligible and intuitive insights regarding the internal processing of neural networks. The method basically involves partitioning the hidden-output connection weights of each hidden node into components associated with each input node. The weights along the paths linking the input to the output node contain relevant information regarding the relative predictive importance of the input attributes: the weights can be used to partition the sum effects of the output layer. The connection weights of the neural network after training are shown in Table 2. The algorithm for estimating the relative importance is as follows:

1. For each node i in the hidden layer, form the products of the absolute value of the hidden-output layer connection weight and the absolute value of the input-hidden layer connection weight. Perform the operation for each input variable j. The resulting products Γ_{ij} are presented in Table 3.

2. For each hidden node, divide the product Γ_{ij} by the sum of such quantities for all the input variables to obtain Φ_{ij}. As an example for the first hidden node, $\Phi_{11} = \Gamma_{11}/(\Gamma_{11} + \Gamma_{12} + \Gamma_{13}) = 0.1303$.

3. The quantities Φ_{ij} obtained from the previous computations are summed to form X_j. Thus we have for example, $X_1 = \Phi_{11} + \Phi_{21} + \Phi_{31} + \Phi_{41}$. The results are shown in Table 4.

Table 3

Elements of matrix of products Γ_{ij}

Hidden neurode (1)	Input #1 (2)	Input #2 (3)	Input #3 (4)	Input #4 (5)
1	26.000	32.900	81.900	59.000
2	5.000	15.000	9.500	19.500
3	12.200	0.400	0.800	8.500
4	1666.200	81.900	20.800	1529.300

Table 4

Elements of Φ_{ij} *and* X_j

Hidden nodes (1)	Input #1 (2)	Input #2 (3)	Input #3 (4)	Input #4 (5)
1	$\Phi_{11} = 0.1303$	$\Phi_{12} = 0.1648$	$\Phi_{13} = 0.4098$	$\Phi_{14} = 0.2592$
2	$\Phi_{21} = 0.1031$	$\Phi_{22} = 0.3058$	$\Phi_{23} = 0.1932$	$\Phi_{24} = 0.3979$
3	$\Phi_{31} = 0.5589$	$\Phi_{32} = 0.0168$	$\Phi_{33} = 0.0356$	$\Phi_{34} = 0.3887$
4	$\Phi_{41} = 0.5052$	$\Phi_{42} = 0.0248$	$\Phi_{43} = 0.0063$	$\Phi_{44} = 0.4637$
{Sum}	$X_1 = 1.2975$	$X_2 = 0.5122$	$X_3 = 0.6449$	$X_4 = 1.5445$

Table 5

Relative importance of input rock parameters

Result (1)	Input #1 (porosity)	Input #2 (permeability)	Input #3 (grain size)	Input #4 (clay content)
Relative importance	32.43%	12.80%	16.13%	38.64%

4. Divide X_j by the sum for all input variables. The result in terms of percentages provides the relative importance or influence of all output weights attributable to the given input variable. For example, for the first input node, the relative importance is equal to $(X_1/(X_1 + X_2 + X_3 + X_4)) \times 100 = 32.43\%$. For the four input nodes, the results are given in Table 5. It should be noted that the biases are not factored into the partitioning process as they do not affect the outcome of the process (GARSON, 1991).

8. Summary and Conclusions

Using laboratory data of attenuation measurements, relationships between seismic and rock parameters have been modeled using neural networks and regression models. The prediction capability of the neural networks was compared with that of multiple linear regression. Neural networks outperform multiple linear regression in predicting attenuation values with smaller standard errors. The neural network can make complex decision mappings and this capability is exploited to examine the influence of the various rock parameters on the overall seismic attenuation. The results indicate that the most influential rock parameter on the overall attenuation is the clay content, closely followed by porosity. Though grain size contribution is of lower importance than clay content and/or porosity, its value of 16 percent is of enough significance to be considered in the modeling and interpretation of attenuation data. For this data set, the contribution of grain size is of higher relative importance than permeability, which many researchers have considered to bear a significant correlation with seismic attenuation. In large-scale seismic studies, heterogeneities may induce Rayleigh and/or diffusive scattering in addition to that which may be due to fluid flow (permeability). This study may have implications in such attempts to ascertain the relative importance of the various causative rock properties to seismic attenuation.

Using the suggested technique, other factors known to affect seismic attenuation such as temperature and confining pressure may also be incorporated to assess their relative influence on seismic attenuation. Such an analysis could be important in assessing the effect of straining of earth materials on seismic attenuation and subsequent implications in earthquake and explosion studies.

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