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Modeling of shear wave velocity in limestone by soft computing methods

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ABSTRACT

The main purpose of current study is development of an intelligent model for estimation of shear wave velocity in limestone. Shear wave velocity is one of the most important rock dynamic parameters. Because rocks have complicated structure, direct determination of this parameter takes time, spends expenditure and requires accuracy. On the other hand, there are no precise equations for indirect determination of it; most of them are empirical. By using data sets of several dams of Iran and neuro-genetic, adaptive neuro-fuzzy inference system (ANFIS), and gene expression programming (GEP) methods, models are rendered for prediction of shear wave velocity in limestone. Totally, 516 sets of data has been used for modeling. From these data sets, 413 ones have been utilized for building the intelligent model, and 103 have been used for their performance evaluation. Compressional wave velocity (V_p), density (γ) and porosity (n), were considered as input parameters. Respectively, the amount of R for neuro-genetic and ANFIS networks was 0.959 and 0.963. In addition, by using GEP, three equations are obtained; the best of them has 0.958R. ANFIS shows the best prediction results, whereas GEP indicates proper equations. Because these equations have accuracy, they could be used for prediction of shear wave velocity for limestone in the future.

1. Introduction

Nowadays, using dynamic methods for quick and precise estimation of elastic constants is common in rock engineering. The nondestructive characteristic of these tests makes them, mostly usable [1]. The most significant mechanical waves that are popular for this purpose are compressional and shear ones. Core preparation for testing is not always easy. Furthermore, high-quality samples are required to carry out a proper test. Sample preparation from intensively weathered or crushed rocks is very important [2]. Thus, indirect determination of a parameter plays a significant role. On the other hand, there are no precise equations for circuitous determination of it; most of them are empirical. Numerous parameters could affect on shear wave velocity, but none of them is considered as empirical ones. Since empirical models used for prediction of shear wave velocity are mathematical and their data are related to a specific formation, they do not generalize to others. Most equations are for sandy formations, and they are not useful for all types of rock units. Therefore, the equations are not comprehensive. This matter makes the selection of equations difficult [2,3]. Because of this reason, many researchers have developed various equations. Most of them are based on experiment, statistics and even intelligent systems.

In order to predict shear wave velocity, neuro-genetic, ANFIS and GEP methods are used in this study. Three models were built according to these three methods. The first model was made based on only one input parameter, V_p, while the second one was created by two inputs, including V_p and γ. Finally, the third model was constructed with three inputs such as Vp, γ and n. Totally, 516 sets of data have been used for modeling. From these sets, 413 ones, 80% of data, have been utilized for training and the remaining (20% of data) was used for test model. Because the accuracy of empirical results is higher than the results obtained from in-situ measurements, empirical ones are used in this research. Data have gained from Khersan 1, Khersan 2, Khersan 3, Ilam Tolombeh Khaneh, Karoon 4, Roodbar Lorestan, Mashkid, Seymareh and Tang-e Maeshooreh dams located in Iran.

2. Previous studies

2.1. Mathematical models for estimation of shear wave velocity

Various methods were introduced to obtain shear wave velocity. Researchers have studied on this subject, like Gassmann et al. [4–13].

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2.1.1. Equations between shear wave velocity and prosity

Equations of velocity-porosity are used in most rock physics issues; they are even utilized in seismic and pore fluids analyses. The equation between shear wave velocity and porosity was introduced by Gassmann [4]. Then, Zimmerman et al. revised the presented equation by Gassmann [14,15]. Some of the empirical equations between porosity and shear wave velocity studies by Wyllie et al. [16–21]. Table 1 compares Eqs. (1)–(4) for water saturated shaly sandstones in 40 MPa effective pressures.

2.1.2. Equations between shear wave velocity and density

Christensen cited that the increase of the amount of density can increases the shear wave velocity [22]. In addition, Irfan and Dearman, by studying on granites, pointed out that the porosity increase leads to be logarithmic decreasing of wave velocity and increasing density the velocity of wave increases exponential [26]. Some of the suggested equations are given in Table 1 (Eqs. (5) and (6)).

2.1.3. Equations between shear wave velocity and compressional wave velocity

Equations between compressional and shear waves velocity are main tools for recognition of lithology and pore fluids. Various investigations were carried out in order to study equations between compressional and shear waves velocity. Generally, the velocity of shear waves is 2/3 of compressional ones [1]. The simplest equation among elasticity waves was defined by Castagna et al. in 1985 (Eq. (11) [11]. The common point among all studies is rendering different equations for various lithologies. Moreover, Eqs. (7)–(13) are used for brine saturated rock [16]. Also, Eqs. (14)–(16) are other ones between shear wave velocity and compressional wave (Table 1).

2.2. Review of using intelligent methods for prediction of shear wave velocity

Numerous researchers have used intelligent methods such as artificial neural networks, fuzzy systems, genetic algorithm, and so on for prediction of shear wave velocity [27–32]. For instance, Rajabi et al. anticipated shear and compression waves velocity in Sarvak reservoir, Iran, by using intelligent methods like fuzzy logic, ANFIS and genetic algorithm [33]. The results obtained are favorable and represent the advantages of these methods.

3. Theory of the methods used

3.1. Neuro-genetic

Neuro-genetic is a combination of artificial neural network (ANN) and genetic algorithms (GA). Having high learning capability and flexibility enables artificial neural network to estimate and predict complicated engineering problems. These networks are utilized in various fields of geotechnics. Researchers use them as appropriate predictor to anticipate different problems.

Multi-layer perceptrons (MLPs) are perhaps the best-known type of network. MLP has a layer structure, consists of at least three hierarchical layers of neurons: an input layer, one or several hidden layer(s) and an output layer [34]. Many types of learning algorithm have been used in the literature. The commonest algorithm used to learn multi-layer networks is "back propagation". Neurons of each layer join another one and activation function is responsible for data transferring.

The first step in training an ANN is to design the network architecture. Design of ANN is specified by the network topology (such as number of hidden layers, number of neurons, and type of transfer functions) and learning rules. These rules specify an initial set of weights, biases, momentum coefficients and learning rates and indicate how they should be adapted during training to improve network performance. Both topology and learning rules are very important and the good selection of those will get better the performance of the network [34]. Trial and error method should be used for optimization of network architecture. Genetic algorithm, a combination system of neuro-genetic could be utilized instead of trial and error method, which is time-consuming. Nowadays, GA is an appropriate tool to search and optimization [35].

Fundamental theories of GAs were established by Holland in the early 1970s [36]. Genetic algorithm has two characteristics: one is a random algorithm, and both selection and reproduction require a random process; second, genetic algorithms are often considered as a population of solutions. Having more than one solution in iteration is beneficial. The algorithm can combine various solutions to obtain the best one. Therefore, it uses all properties of solutions [35,37].

At first, genetic algorithm of a neuro-genetic system works with an initial population of random chromosomes (neural network). Then, main and sub-operators of current generation form the next one in each stage. Chromosome eligibility for transferring to subsequent generation is evaluated target function. By increasing the number of generations, the number of individuals in each generation decreases. Finally, only one chromosome remains, which has

Table 1
Some equations for estimation of shear wave velocity.

No.	Variable	Author(s)	Lithology	Equation type	Equation
1	n, C	Tosaya and Nur [21]	Sandstone	Empirical	$V_s = 3.7 - 6.3n - 2.1C$
2	n, C	Castagna et al. [11]	Sandstone	Empirical	$V_s = 3.89 - 7.07n - 2.04C$
3	n, C	Han et al. [8]	Sandstone	Empirical	$V_s = 3.52 - 4.91n - 1.89C$
4	n, C, P_e	Eberhart-Phillips et al. [20]	Sandstone	Empirical	$V_s = 3.7 - 4.94n - 1.57 + 0.361\ (\mathrm{P_e} - 1.0\mathrm{e}^{-1.67\mathrm{Pe}})$
5	Γ	Christensen [22]		Regression	$V_s = 0.00254\gamma - 3.95$
6	Γ	Diamantis et al. [23]	Serpentine	Regression	$V_s = 298\gamma - 4858$
7	V_p	Pickett [5]	Limestone	Empirical	$V_s = V_p/1.9$
8	V_p	Pickett [5]	Dolomite	Empirical	$V_s = V_p/1.8$
9	V_p	Gastagna et al. [11]	Dolomite	Empirical	$V_s = 0.5832V_p - 0.0777$
10	V_p	Gastagna et al. [11]	Sandstone	Empirical	$V_s = 0.8042V_p - 0.8559$
11	V_p	Gastagna et al. [11]	Mudstone	Empirical	$V_s = 0.8621V_p - 1.1724$
12	V_p	Han et al. [8]	Sandstone	Empirical	$V_s = 0.793V_p - 0.7868$
13	V_p	Gastagna et al. [12]	Limestone	Empirical	$V_s = -0.055V_p^2 + 1.0168V_p - 1.0305$
14	V_p	Anselmetti and Eberli [24]	Carbonate rocks	Empirical	$V_s = 199(\gamma)^{2.84}$
15	V_p	Eskandari et al. [3]		Regression	$V_s = -0.1236V_p^2 + 1.6126V_p - 2.3057$
16	V_p	Brocher [25]		Empirical	$V_s = 0.7858 - 1.2344V_p + 0.7949V_p^2 - 0.1238V_p^3 + 0.006V_p^4$

Note: n = porosity; C = shale volume; P_e = effective pressure; γ = density; V_p = compressional wave velocity; and V_s = shear wave velocity.