**UDC 550.8.056**

Kh. B. AGHAYEV*, R. H. KULIYEV, Sh. Z. YAQUBOVA

Institute of Geology and Geophysics of ANAS, 119, Ave. H. Javid, Baku, AZ1143, Azerbaijan, tel.: (+994 12) 5105617, e-mail: khagayev@yahoo.com

https://doi.org/10.23939/jgd2020.01.071

# CONSTRUCTION OF A VELOCITY MODEL OF SHEAR WAVE FOR COMPLEXLY STRUCTURED GEOLOGICAL MEDIUM USING NEURAL NETWORK (BY EXAMPLE OF DATA OF THE SOUTH CASPIAN BASIN)

**Object.** Development of a method for predicting a two-three dimensional velocity model of a medium by using a shear wave. Complexly structured geological medium is studied on the basis of geophysical and geological data using an artificial neural network. **Method.** It provides the construction and use of medium models according to geophysical well logging data and other terrestrial geophysical methods. In contrast to existing methods, the proposed method also uses additional data on the medium. They include the thermodynamic state of the medium, stratigraphic confinement of deposits, rock lithology, distribution of data clusters, physical properties of the medium etc. According to the method, one-dimensional models are first constructed on various properties of the medium based on data of complex of well logging. Then, the neural network is studied to predict the shear wave velocity on a set of models. Subsequently, two-three-dimensional models of the medium are constructed according to the results of terresterial geophysical studies. Two-three-dimensional velocity model of a shear wave is predicted by using a complex of these models studied by a neural network. **Results.** Velocity model of shear wave is predicted for complexly structured geological medium of the South Caspian Basin using the method. **Scientific novelty.** It is possible to increase the accuracy and resolution of prediction the medium model by increasing the number of types of data used. **Practical value.** Improving the efficiency of seismic exploration in determining oil and gas saturation, elastic geodynamic state and other physical properties of the geological medium.

*Key words:* seismic exploration; pressure and shear wave; seismic velocity; medium model; prediction; neural network.

## *Introduction*

The results of seismic studies show that the saturation, fracturing, porosity of the rocks, the thermodynamic state and other physical properties of the geological medium have different effects on the kinematic and dynamic parameters of pressure and shear seismic waves [Castagna, et al., 1985; Eberhart, 1989; Puzyrev, 1985; Krief, et al., 1990; Schön, 2015]. For example, changes in temperature and pressure in a medium have different effects on the petrophysical properties of rocks. This feature is often manifested in sedimentary rocks [Eberhart, et al., 1989]. The results of the studies show that if geological medium, its thermodynamic state are more complex, the relationship between the petrophysical properties of the rocks of the medium will be more complicated.

As it is known, two-three dimensional seismic exploration ($2D/3D$) is mainly applied to the reflected pressure wave to study the geological structure of the deep layers of the studied area. If necessary, well logging ($WL$) is also carried out. Single-wave $2D/3D$ seismic exploration is quite effective in the study of relatively simple geological media. However, it is necessary to share data on the reflected pressure ($PP$) and shear ($SS$) waves while studying complexly structured geological medium using seismic $2D/3D$ seismic exploration to increase its efficiency. It is possible to use data on the exchange ($PS$) wave in the absence of data on the $SS$ wave. This necessity is arisen even when the quality and information content of data of seismic exploration is high on $PP$ wave. It is known that, data on the shear wave velocity are necessary information to assess the geodynamic state of a medium [Guliyev et al., 2019]. The necessity of using pressure and shear waves together makes it advisable to use multiwave well and surface seismic surveys, such as: engineering geophysical studies [Burger, et al., 2006; Guliyev, et al., 2019], acoustic well logging ($AWL$) [Ellis and Julian, 2008], vertical seismic profiling ($VSP$) [Meltem, 2016], two ($2D$) and three-dimensional ($3D$) multiwave seismic surveys [Puzyrev et al., 1985; Garotta, 2000] while studying complexly structured geological medium. Multiwave measurements of seismic velocities are also carried out in the laboratory on rock samples [Volarovich et al., 1974].

A source of pressure wave excitation and a special arrangement of geophones are used to obtain data on the geological medium on $PP$ and $PS$ waves in terrestrial multiwave seismic exploration. A special source of shear wave excitation is used along $SS$ wave [Garotta, 2000; Puzyrev, et al., 1985; Robert et al., 2002] in the horizontal direction. In these types of work, seismic waves are recorded using three-component $XYZ$ seismic receivers of displacement. As a result of processing field seismic records, $PP$, $PS$, $SS$ waves are distinguished, and their kinematic, dynamic parameters are determined. Thin-layered $2D/3D$ models of the medium by the velocity of pressure ($V_{PP}^{2D/3D}$), exchange $V_{PS}^{2D/3D}$, shear ($V_{SS}^{2D/3D}$) waves and rock density ($\rho^{2D/3D}$) are deter-mined using seismic inversion [Yilmaz, 2001; Veeken and Silva, 2004] of time section of seismic profile.

Bottom seismic observations ($4C$) are carried out using 4 component $XYZ$ and $P$ (pressure) of seismic receivers in marine multiwave seismic exploration for simultaneous registration of $PP$ and $PS$ waves [Garotta, 2000; Robert et al., 2002; Jack and Rodney, 2005]. We know that the determination of velocity on $PS$ wave due to the asymmetry of its hodograph is a complex and insufficiently correct procedure [Puzyrev et al., 1985]. Therefore, the accuracy of determination of the velocity of $PS$ wave and $SS$ wave on it is lower than that on $PP$ wave. Carrying out specific work of multiwave marine and terresterial seismic exploration, processing of their seismic records is quite complicated and time-consuming. Thus, multiwave seismic exploration, especially $4C$ is carried out rarely. For this reason, it becomes necessary to predict the model of velocity $V_{SS}^{2D/3D}$ involving other methods.

There are various methods, algorithms of prediction the velocity of shear wave along pressure wave. Some of them are given below.

It is widely known that the intensity of the reflected wave along its hodograph depends on the angle of fall of the seismic wave on the reflection boundary and on the ratio of the velocities of pressure and shear waves along the adjacent layers of the medium [Voskresensky, 2001]. $AVO$ ("Amplitude Variation with Offset") conversion of seismic records $2D/3D$ of seismic exploration has been based on this feature [Castagna, et al., 1993; Voskresensky 2001; Qlang, et al., 2018]. Times sections of $AVO$ attributes like "Scaled Poisson's Ratio Change" and "Shear-wave reflectivity $R_S$" carry data on the ratio of pressure and shear wave velocities along the sections. The model is predicted on $V_{SS}^{2D/3D}$ calibrating these sections to shear wave velocities determined on data of multiwave $AWL$, $VSP$ or seismology. However, it should be noted that the reliability of sections of $AVO$ attributes is valid under certain simplified conditions, which may not be acceptable for the studied medium. In addition, the prediction accuracy $V_{SS}^{2D/3D}$ on $AVO$ attributes is limited by the length of the seismic streamer and decreases with increasing depth of the study.

There are other methods in which a model $V_{SS}^{2D/3D}$ is computed using multidimensional empirical dependence between velocities of pressure and shear waves and rock density [Shahoo, et al., 2014; Saeed, et al., 2015]. Empirical dependence is determined on data of multiwave $VSP$, $AWL$ and laboratory measurements of velocities. Then, thin-layered models of layer velocity $V_{PP}^{2D/3D}$ and rock density $\rho^{2D/3D}$ are constructed using the procedure of seismic inversion according to data of $2D/3D$ of seismic exploration on pressure wave. Further, the model $V_{SS}^{2D/3D}$ is calculated using these models according to empirical dependence. It is true if changes in the thermodynamic conditions, lithological composition, saturation, porosity and other properties of the rocks of the medium equally affect the values $V_{PP}^{2D/3D}$ and $V_{SS}^{2D/3D}$ along the seismic profile and in depth. However, this condition is not fulfilled for a real geological medium. It has been revealed that these influences are complex even for rocks of the same lithological composition [Aghayev, 2013; Eberhart et al., 1989]. This feature is often manifested in geodynamically complex geological media consisting of sedimentary rocks. Therefore, this method has a low accuracy in determining the model $V_{SS}^{2D/3D}$. This model can only be used as a priori data on the medium.

Recently, the artificial neural networks ($ANN$) are widely used in geophysical studies [Poulton, 2002; Chashkov and Valery, 2011; Aghayev, 2013]. $ANN$ is used to cluster the data and to predict the physical properties of the medium. Methods based on use of $ANN$ have a great opportunity of development. It is mainly due to the fact that $ANN$ has an opportunity of artificial intelligence. It allows determining and taking into account the complex dependences between the petrophysical properties of the medium, their variability, and solving nonlinear and non-stationary problems. Methods using these features are characterized by higher accuracy of prediction of petrophysical properties of rocks, versatility, ease of use, etc.

Methods of predicting the velocity of shear wave using $ANN$ are mainly subdivided into 2 types:

1. Prediction of a one-dimensional shear wave velocity model ($V_S^{1D}$) using multiwave and single-wave well logging data [Shahoo et al., 2014; Eskandari et al., 2004; Saeed et al., 2015; Gholami et al., 2014];
2. Prediction of a two-three-dimensional model $V_{SS}^{2D/3D}$ using data of multiwave well logging and single-wave seismic exploration on pressure wave [Shahoo, et al., 2014; Habib, et al., 2014; Eskandari, et al., 2004; Saeed, et al., 2015; Gholami, et al., 2014].

The "back propagation" algorithm is used to train $ANN$ in both types of methods [Poulton, 2002]. An important requirement of methods is the use of large types of data on the petrophysical properties of rocks whenever possible. In this case, the predicted model of velocity will be more accurate. At the same time, the identity of types of petrophysical properties of rocks used in training and predicting should be ensured.

First, one-dimensional ($1D$) thin-layered models of petrophysical properties of the medium are built based on the data $WL$ and $AWL$ in methods of the 1st type. An aggregate of models $1D$ of the well in which the multiwave $AWL$ is conducted to train $ANN$. Further, using the trained $ANN$, a velocity model of shear wave is predicted according to the data of the well in which a single wave $AWL$ has not been conducted. It may be that, the velocity of shear wave is not measured in some intervals of the depths of the well while working $AWL$. It is possible to predict velocities for the depth interval where $AWL$ has not been carried out.

The methods of type 2 and their various modifications are created from the beginning of the one-dimensional model $1D$ of the petrophysical properties of thin-environment and seismic attribute records using data $WL$, $AWL$ and $2D/3D$ seismic data. $1D$ models refer to the location of the well. These models are used to train the neural network. Then, $2D/3D$ models of the physical properties of the environment are prepared according to the results of terrestrial geophysical studies, including seismic exploration. With the use of $2D/3D$ models and with the use of trained $ANN$, $V_{SS}^{2D/3D}$ is then predicted. In some of these methods, numerous attributes of seismic records [Yilmaz, 2001] are used as additional data to increase the accuracy of velocity prediction. However, an excessive increase in the number of used attributes having low reliability may lead to an increase of the prediction error. It is due to the fact that $ANN$ will “strive” to take into account all the specified types of data with the same weights regardless of their reliability while training and predicting. The main disadvantage of these methods is the insufficient use of various types of geophysical and geological data of the studied medium. Only some data $WL$, $V_{PP}^{2D/3D}$ and various attributes of seismic records $2D/3D$ of seismic exporation are used in methods of the second type to predict $V_{SS}^{2D/3D}$ on neural networks. Since these data do not fully characterize the physical properties of the medium, these methods do not provide the prediction of $V_{SS}^{2D/3D}$ with acceptable accuracy.

It has been noted that $WL$ conducted at internal points of the geological medium allows accurately determining the numerous petrophysical, including acoustic properties of the rocks of the medium [Ellis & Singer, 2007]. As a result of terresterial seismic exploration, gravity exploration, electrical exploration and magnetic exploration, the acoustic, density, electrical and magnetic properties of the rocks of the medium are determined, respectively, in depth and area of study. Each of these methods of ground work allows determining various physical properties of the geological medium with different accuracy, but with lower accuracy than on $WL$.

The geological structure, thermodynamic condition, lithology, fracture, oil and gas saturation, acoustic and other rock properties differ significantly in the area of study by complexly structured medium on the same layers. These properties with different reliability and characteristics will be reflected in the values of the measured physical parameters of the medium. Therefore, if more types of information are set by such medium, the prediction of velocity of shear wave will be more accurate. The joint use of data of various geophysical methods can improve the accuracy of prediction of model $V_{SS}^{2D/3D}$. It is due to the fact that in the process of training and predicting, $ANN$ will “strive” to take into account differences in values of geophysical data due to the variability of properties of the medium while moving away from the well, according to which the training $ANN$ has been conducted. It is necessary to increase the number of types of input data set to the input $ANN$ considering it to increase the accuracy of prediction $V_{SS}^{2D/3D}$, especially on complexly structured media. It will provide “more accurate training” $ANN$ and predicting of $V_{SS}^{2D/3D}$. That is, if more diverse data on the studied medium are given at the input of $ANN$, so, the prediction of $V_{SS}^{2D/3D}$ will be more accurate. All this indicates the necessity to develop a new method of prediction of $V_{SS}^{2D/3D}$ on $ANN$ which provides the use of additional data on the geological medium. The foundations of such approach were developed in [Aghayev, 2012]. The method involves the use of various types of data on the studied geological medium. In particular: data and their attributes on $WL$, $VSP$, seismic exploration, electrical exploration, gravity exploration on the geological medium etc. Testing the method showed its effectiveness. There is a necessity to increase its effectiveness while predicting $V_{SS}^{2D/3D}$ for complexly structured media.

### *Method*

An improved version of method of the prediction of shear wave velocity described in [Aghayev, 2012] is presented in this manuscript. The completed procedures of the method designed to increase the effectiveness of the method are described in the proposed manuscript. The sequence of procedures of the method has been described in more detail. Some of its elements are repeatedly given to complete the description of the method.

The models $1D$ and $2D/3D$ are also used on the physical properties of the medium in order The to predict $V_{SS}^{2D/3D}$. The process of predicting a thin-layered model $V_{SS}^{2D/3D}$ mainly consists of the following basic procedures:

- creation of thin-layered $1D$ models of medium properties using data $WL$, $AWL$, $VSP$, their attributes, geological and other data;
- creation of $2D/3D$ models on properties of the medium using data of terresterial geophysical studies and geological data;
- correction of $1D$ and $2D/3D$ models on properties of the medium;
- data clustering of an aggregate of $1D$ models using $ANN$;
- training of neural network using dataset of $1D$ models;
- prediction of $V_{SS}^{2D/3D}$ on set of models $2D/3D$ using the trained $ANN$.

To increase the effectiveness of this method, it has been improved by adding the following procedures:

- Bringing the dispersion of values of $2D/3D$ models to the dispersion of values of $1D$ models within each data cluster. The Implementation of this procedure while calibrating, interpolating, and extrapolating of models;
- correction of prepared $2D/3D$ models of the medium along lines of seismic profiles;
- to increase the influence of values of separate models on the values $V_{SS}^{2D/3D}$ of re-setting these models;
- correction of the predicted model $V_{SS}^{2D/3D}$ based on a thick-layered shear-wave velocity model based on seismological data;
- the use of seismological data to train and predict velocities at depths not opened by wells and areas located away from wells.

The implementation of these additional procedures of the method makes it possible to correct the above mentioned models, especially, $L^{2D/3D}$, $S^{2D/3D}$ and $C^{2D/3D}$. It is advisable in cases of tectonic faults, changes in lithology, saturation, and other properties of the rocks of the medium according to the study area or profile line. An important improvement of the method is to take into account the variability in the area of study of the thermodynamic state of complexly structured geological medium, both in training neural networks and in predicting shear wave velocities.

The types of used data and the main procedures of the method are shown in Fig. 1. The main elements of the method are the following.

**Creation of 1D models of medium properties.** Models are created according to the data of various types of well logs, which allow determining: velocity of pressure ($V_P^{1D}$) and shear ($V_S^{1D}$) waves; density ($\rho^{1D}$); radioactivity ($G^{1D}$); resistance ($R^{1D}$);

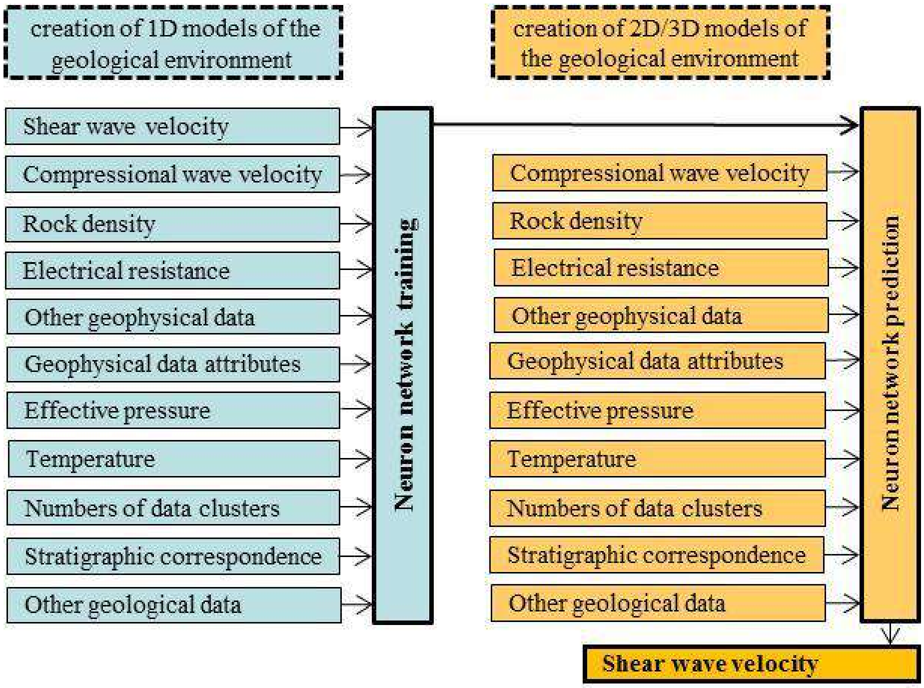


**Fig. 1.** A flowchart of a method of prediction of a velocity model of a medium on shear wave

pressure ($P^{1D}$); temperature ($T^{1D}$). In addition, data determined on $WL$ on oil and gas saturation, porosity etc. can also be used. The method also provides the use of geological models of the medium as well as:

- distribution of rock lithology on the section of the well defined in the form of lithology codes ($L^{1D}$);
- confinement of rock layers of the medium to stratigraphic complexes of deposits ($S^{1D}$);
- distribution of data cluster numbers ($C^{1D}$) along the wellbore;

***Data clustering*** $WL$. The method provides the dismemberment of dataset of $1D$ models into clusters using $ANN$. As a result of clustering, each cluster includes data on the depths of measurements in the well in which rocks with close values of petrophysical properties are located [Poulton, 2002; Chashkov and Valery, 2011; Aghayev, 2013]. Cluster numbers and the distribution of data within them are the same across all $1D$ models. The optimal parameters of data clustering are determined by testing a set of one-dimensional models of the physical parameters of the medium, clustering algorithms, the number of clusters and iterations. It has been revealed that the data are divided into clusters more reliably, in detail, and accurately due to increase in the number of models according to the properties of the medium, clusters, and iterations. The optimality criterion of the selected values of the clustering parameters is the stability of the dependence between various physical parameters of the medium within each data cluster [Aghayev, 2013]. As a result of clustering, $1D$ model of the distribution of cluster numbers ($C^{1D}$) in depth is prepared. This model is used to transfer data on the distribution of data clusters from the well to the seismic profile.

***Creation of*** $2D/3D$ ***models of medium properties.*** A velocity model on pressure wave $V_{PP}^{2D/3D}$ and density of rocks $\rho^{2D/3D}$ is based on the results of seismic inversion [Yilmaz, 2001; Veeken, 2004] of profiles of time sections $2D/3D$. The model of effective pressure ($P^{2D/3D}$) is calculated on the empirical dependence or using models $V_{PP}^{2D/3D}$ and $\rho^{2D/3D}$ considering the depths of the medium. The temperature model of the medium ($T^{2D/3D}$) is calculated on empirical dependence. Models are calibrated to one-dimensional models $P^{1D}$ and $T^{1D}$ built on the databasis of $ANN$. In this case, the dispersion of values of $2D/3D$ models are brought to the dispersion of values of $1D$ models. Then, models of lithology codes ($L^{2D/3D}$), of stratigraphic confinement of deposits ($S^{2D/3D}$) and numbers of clusters of data ($C^{2D/3D}$) are compiled. They are created transferring models $L^{1D}$, $S^{1D}$ and $C^{1D}$ along the seismic profile. Calibration and transfer of models are carried out in according with the positions of the main seismic horizons at each "common deep point" ($CDP$) [Yilmaz, 2001] of the seismic profile.

The use of additional data while training $ANN$ and predicting allows considering:

- in models $T^{2D/3D}$ and $P^{2D/3D}$ change of pressure and temperature on depth and study area;
- in models $L^{2D/3D}$ and $S^{2D/3D}$ change of lithology of rocks and stratigraphic confinement of deposits on depth of the study;
- in models $C^{2D/3D}$ distribution of data clusters on depth.

Each $2D/3D$ model is compiled as separate time section of the seismic profile.

***Alignment of models on parameters.*** The data type on $1D$ and $2D/3D$ models should be the same. $1D$ models are transformed from depth measurement to time ($h \to t$) and with discretization step as in the seismic profile (2ms, 4ms) to ensure the compatibility of these models. At the same time, values on thin layers are averaged within the step of discretization. Transformation $h \to t$ is carried out using a medium model on the average velocity of pressure wave. This model is determined on data $VSP$ or $2D/3D$. As a result of the increase of step of discretization, data approaches of frequency range, which increases the accuracy of prediction $V_{SS}^{2D/3D}$ occur. According to the method $1D$ and $2D/3D$ models should have the same depth range of studies and step of discretization of data as $2D/3D$ models. The depth of the study of $WL$ is less than that of seismic exploration. And $1D$ models should cover the entire range of changes of thermodynamic conditions in the interesting part of the geological section illuminated by the seismic profile. $1D$ models are extrapolated to the required depth range to ensure the same depth interval according to borehole and surface geophysical data. If there are several wells in the studied area, then $1D$ models are interpolated and extrapolated to the seismic profile, taking into account the location of wells and the stratigraphic confinement of layers of the medium.

A software package *GEOPRESS* [Guliyev et al., 2010] has been used while creating $1D$, $2D/3D$ models and preparation of data for working with $ANN$. Data clustering, training $ANN$ and predicting the model $V_{SS}^{2D/3D}$ is carried out using the software *NeuroXL* [http://neuroxl.com/products/excel-cluster-analysis-software].

***Training of*** $ANN$ ***and prediction of velocity model on shear wave.*** Training of $ANN$ takes place determining the relationship between the totality of values of the above mentioned $1D$ models on the medium and $1D$ of velocity model of shear wave. If there are several wells with the same data types in the studied area, then data of all the wells can be used while training. Wells can be remote for several kilometers from the seismic profile. If the studied medium is simpler, this distance can be higher, for example, by several tens of kilometers.

The number of iterations and neural layers are important parameters while training $ANN$. It has been revealed [Aghayev, 2013] that, as the number of iterations increases, the accuracy of prediction increases while testing them. Within the data used, the greatest accuracy has been achieved at 300–500 iterations. The highest accuracy has been achieved at 300–500 iterations within the used data. A further increase in the number of iterations does not significantly affect the prediction error. The accuracy of prediction decreases due to the insufficient number of iterations with an increase in the number of layers of neurons, especially after the 75th. The optimal parameters of prediction are the following: the number of iterations – 500, layers of neurons – 20; the prediction accuracy is 0.95 % within these values. The optimal parameters of prediction are the following: the number of iterations – 500, layers of neurons – 20; the prediction accuracy is 0.95 % within these values. The main reason for the discrepancy between the given and predicted values of velocities is the insufficient number of iterations. It is due to the limitation of "computer time" of the working day. It is hardly possible to achieve the obtained prediction accuracy using multidimensional empirical dependencies. Then, the model $V_{SS}^{2D/3D}$ has been predicted from the trained $ANN$ using the combination of the above mentioned $2D/3D$ models.

Only those data on which there are the same $1D$ and $2D/3D$ models are used while teching and prediction. In training and forecasting, more or less types of data models can be used than indicated in the flowchart of the method while training and predicting (Fig. 1). Prediction accuracy decreases due to decrease in the number of models. It is more significant when there is a good correlation between the velocity of shear wave and the physical properties of the medium on which models are not specified.

## Database

The method has been tested according to geophysical data of the geological structure, which is located in the oil and gas South Caspian Basin. These structure have anticlinal or diapir shape, a complex geological structure, thermodynamic state complicated by mud volcanoes and faults. Anomalous high reservoir pressure is common here. The study area is a seismically active zone. The sedimentary layer of the medium lithologically consists of an alternation of thin clay and sandy layers. Here the rocks are highly porous, poorly compacted and very sensitive to changes in effective pressure. The rocks of the same layer are in significantly different thermodynamic conditions in different parts of structures. The hypsometric level, temperature and geostatic pressure can differ respectively about 2 km, 60 degrees and 1000 atm within the same strata in the anticlinal and synclinal parts of the structures. There are local and regional tensions of different directions here.

The data $WL$ of one well and $2D$ of the marine seismic profile, which took place near the well have been used while testing the method. The variability and inhomogeneity of petrophysical properties of rocks of the medium along the depth is shown as a "cluster section" [Aghayev, 2013] of the well on 60 clusters (Fig. 2a). Here, clusters with close numbers are observed in the form of bands. Each band indicates the presence of thin layers of rocks in the medium with similar petrophysical properties alternating in depth within the band. The presence of 2–3 bands of clusters in the section at close depths indicate the presense of rocks sharply differing properties at close depths of the medium.

For a visual assessment of the complexity of the dependences between the petrophysical properties of the rocks of the medium, the set of $1D$ models were divided into 10 clusters. The clusters are overlapped in depth in the graph on $AWL$ (Fig. 2. *b*) for a visual assessment of the complexity of the dependencies between the petrophysical properties of rocks of the medium and the reliability of data clustering. It indicates the thin layer of the medium and the presence at close depths of layers of rocks of the medium with sharply different seismic velocities. The results of data clustering indicate the complexity of distribution of values of velocities along the depth of the layers even within the same cluster. The dependence between velocities of pressure and shear waves, the nature of change of velocities are complex and differ in clusters (Fig. 2, *c*). A large dispersion of values of velocities of pressure and shear waves is visible, and even the absence of dependence between them on some clusters (Fig. 2, *c*). Similar dependences are observed between various petrophysical properties of even lithologically identical rocks. These factors indicate that it is necessary to use more different types of data on the petrophysical properties of rocks of the medium for proper training and predicting of velocities on $ANN$. These results indicate the unacceptability of using empirical dependence to predict velocities of shear wave.

## *Results and Discussion*

Prediction of the velocity of two-dimensional model of shear wave is performed in three options:

1. On empirical dependence, on the database of velocities of pressure wave ("option 1");
2. On a neural network, on database on velocities of pressure, shear waves, density of rocks and attributes (instantaneous amplitude, phase and frequency) of a seismic record ("option 2");

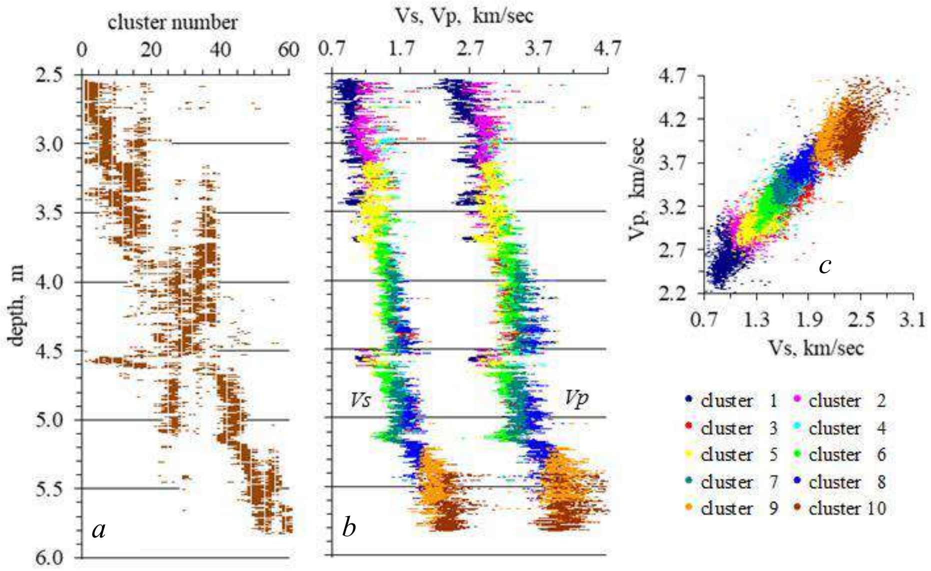


**Fig. 2.** The distribution of numbers of data clusters (a), the change of velocities of waves in depth (b) and the dependence between velocities of waves (c) in clusters

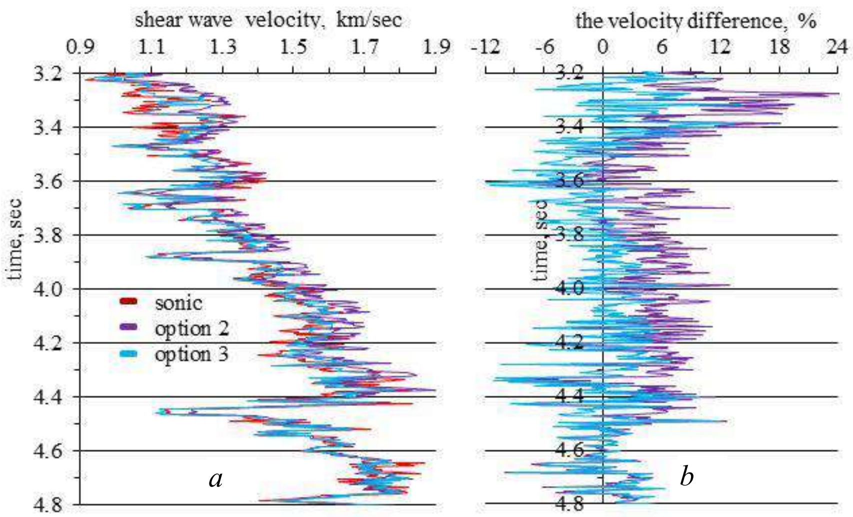


**Fig. 3.** Layer velocities of shear wave (a) and errors in their determination (b)

3. On a neural network, on database as on “option 2” and using additional data on effective pressure, temperature, lithology code, distribution of cluster numbers, stratigraphic confinement of deposits (“option 3”).

The error of values of velocities has been estimated as the difference of velocities according to data of sonic log and predicted on *ANN* (“option 2” and “option 3”). It has been done along the seismic profile *2D* for the *CDP* point, which is the closest to the location of the well. The values of velocities obtained on “option 2” are higher than on “sonic” (Fig. 3a). The average values of absolute values of errors are 5.4 % and 3.3 % on “option 2” and “option 3” respectively. It follows that the use of additional data on “option 3” made it possible to increase the velocity on empirical dependence is 22.5 %. The results of calculation show that, as expected, as the distance from the well, the error of the prediction of velocity increases. If the geological medium is more complex, the gradient of increase of error of the predicted velocity will be greater. This trend can be reduced by using more different types of data on the geological medium.

A thin-layered two-dimensional model $V_{SS}^{2D}$ has been predicted on the profile section remote 13.7 km from the well location. Models $V_{SS}^{2D}$ have been predicted on the above mentioned three “options”. Models are presented in the form of two-dimensional time section (Fig. 4). Resolution of the record in the section is significantly lower than in Fig. 3, *a*. It is due to the limited frequency range of the real seismic signal. The sections in shape are mostly similar but differ in values of velocities.

The section on "option 3" (Fig. 4, *c*) has higher and differentiated in time values of velocities than on "option 1" (Fig. 4, *a*) and "option 2" (Fig. 4, *b*). The sections on "option 2" (Fig. 4, *b*) and "option 3" are slightly more contrast and high-frequency than the sections on "option 1". Higher values of velocities have been obtained in the section on "option 3" at time of 3.8–4.8 sec. This section covers the variability of properties of the geological medium in depth in more detail.

The differences of sections shown in Fig. 4. have been calculated to estimate the error of prediction of velocity. Differences have been calculated from the following three combinations of sections:

- the first, where the "option 3" section has been calculated from the "option 1" section and the result has been divided into "option 1";
- the second, where, from the section "option 1" the section "option 2" is calculated and the result is divided into "option 1";
- the third, where the "option 3" section is calculated from the "option 2" section and the result is divided into "option 2".

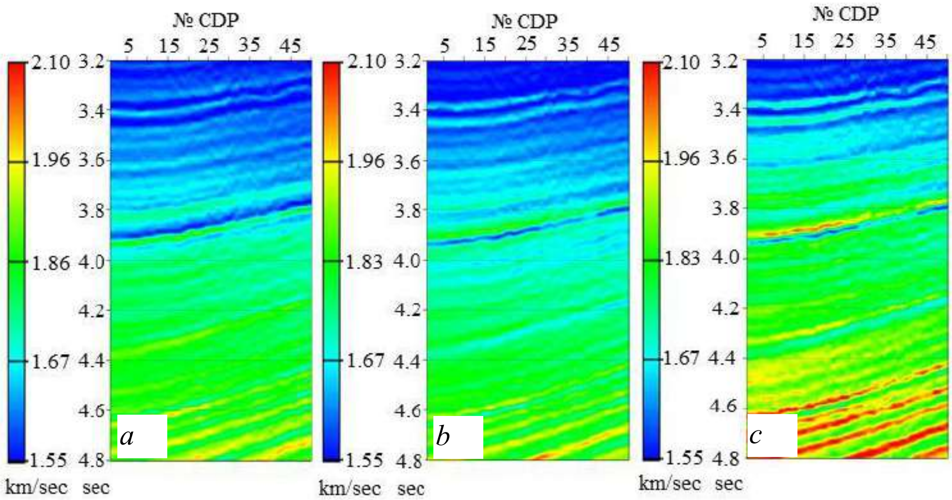


Fig. 4. Fragments of time sections of layer velocities of shear wave predicted according to "option 1" (a), "option 2" (b) and "option 3" (c)

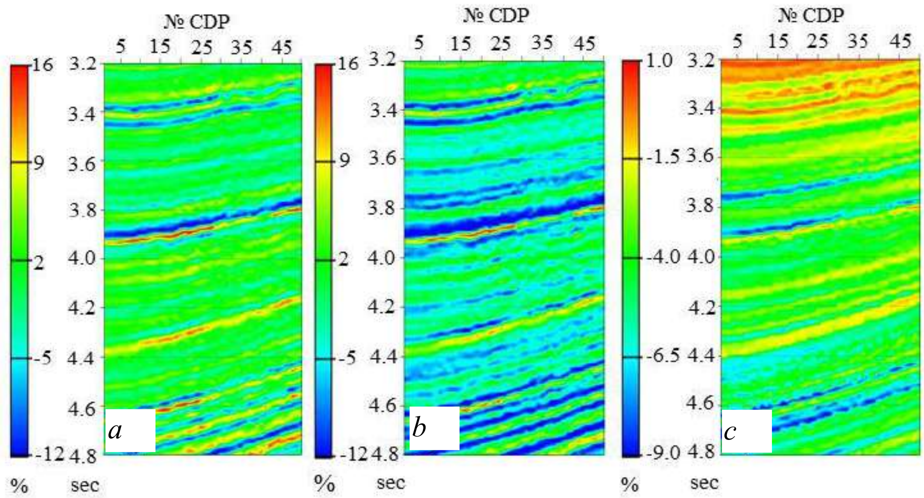


Fig. 5. Different sections of layer velocity of shear wave calculated according to the first (a), second (b), and third (c) combinations of deductible sections

Different sections are also presented in the form of time sections, where the values of differences are indicated in percent (Fig. 5). It follows from figures that the difference between the values of velocities on the first and second combinations varies from –12 % from +16 % (Fig. 5, *a*, Fig. 5, *b*). That is, there are significant differences between the values of velocities predicted by empirical dependence and applying $ANN$. The difference between the values of velocitioes on the third combination varies from -9 % to +1 % (Fig. 5, *c*). Thus, there are noticeable differences while predicting the velocities on $ANN$ in cases without, and using additional data. Based on the results of the estimation of the velocity error on the well (Fig. 3) for the case of a remote section of the profile from the well (Fig. 4, Fig. 5), we can assume:

- the application of $ANN$ provides a higher accuracy of the predicted values of velocities than predicted by polynomial;
- application of $ANN$ using additional data improves the accuracy of prediction of velocity which is reflected in Fig. 5.

The reliability of values of velocities for the profile section away from the well is indirectly estimated from the time section of the Poisson's ratio. The section is calculated using velocity of two-dimensional models of pressure and shear waves. The values of the coefficient in the section have real limits of change along the profile and in depth. The results on evaluation the accuracy of predicting the velocity away from the well are a priori. Naturally, it is necessary to use as much data as possible using the results of terrestrial geophysical studies to increase the accuracy of predicting the velocity away from the well.

### *Conclusions*

A method of predicting a velocity model of complexly structured medium on shear wave has been developed using an artificial neural network. Unlike existing methods, the use of a large number of different types of additional geophysical and geological data on the considered medium is provided in it. According to the method, the neural network is trained on a set of $1D$ models based on data of geophysical studies of wells. A velocity model of shear wave is predicted using complexes of various $2D/3D$ models on the physical properties of the rocks. The method has been tested to predict $2D$ velocity model of shear wave of complexly structured geological medium of a certain section of the South Caspian Basin. The use of additional data made it possible to increase the accuracy of prediction the velocities by 1.64 times and the detail of illumination of the geological medium. A thin-layered two-dimensional velocity model has been predicted on a section of the profile that is 13.7 km away from a deep well. The results show high accuracy in predicting $2D/3D$ velocity model of shear wave. It is necessary to use a larger type of data from ground-based geophysical methods to increase the accuracy of velocity prediction.

Creating the possibility of predicting shear wave velocities with acceptable accuracy allows using the data on pressure, shear wave velocities and rock density, determining the signs of oil and gas saturation, elastic properties, parameters of the current geodynamic state and other properties of the rocks of the geological medium. The method can also be used to predict other physical properties of complexly structured geological medium.

The present work had been performed within the grant project No. 6284 of the Science and Technology Center in Ukraine.

### *References*

Aghayev, Kh. B. (2012). Prediction of the shear waves velocities model accoding to the data of Geophysical researches of wells and seismic-survey using neural networks. *Geoinformatika*, 4(44), 46–52. (in Russian).

Aghayev, Kh. B. (2013). The use of cluster analysis for disassembling a geological section accoding to well logging data. *Karotajnik*. Tver. 5, 3–11. (in Russian).

Bouska, J., & Johnston, R. (2005). The first 3D/4-C ocean bottom seismic surveys in the Caspian Sea: Acquisition design and processing strategy. *The Leading Edge*, *24*(9), 910–921. http://dx.doi.org/10.1190/1.2056392.

Burger, H. R., Sheehan, A. F., and Jones, C. H. (2006). Introduction to Applied Geophysics: Exploring the shallow subsurface W.W. Norton & Co., New York, 554 pp.

Castagna, J., Backus, M. (1993). Offset-dependent reflectivity: theory and practice of AVO analysis. *Investigations in Geophysics Series, Soc. Expl. Geophysics*, January, vol. 8, 348 p.

Castagna, J. P., Batzle, M. L. and Eastwood, R. L. (1985). Relationships between compressional-wave and shear-wave velocity in clastic silicate rocks. *Geophysics*, Vol. 50(4), 571–581. http://dx.doi.org/10.1190/1.1441933.

Chashkov, A. V. and Valery, V. M. (2011). Use of the Cluster Analysis and Artificial Neural Network Technology for Log Data Interpretation. Journal of Siberian Federal University. *Engineering & Technologies,* 4(4), 453–462. http://elib.sfu-kras.ru/handle/2311/2485.

Eberhart, P. D., Han, D. H., Zoback, M. D. (1989). Empirical relationships among seismic velocity, effective pressure, porosity, and clay content in sandstone, *Geophysics*, 54, 1, pp. 82–89. https://doi.org/10.1190/1.1442580.

Ellis, D. V., & Singer, J. M. (2007). *Well logging for earth scientists* (Vol. 692). Dordrecht: Springer. https://doi.org/10.1007/978-1-4020-4602-5.

Eskandari, H., Rezaee, R. and Mohammadnia, M. (2004). Application of Multiple Regression and Artificial Neural Network Techniques to Predict Shear Wave Velocity from Well Log Data for a Carbonate Reservoir, South-West Iran. Cseg Recorder, 42–48.

Garotta, R. J. (2000). Transverse waves: from registration to interpretation. Short Course of Lectures for Higher Education Institutions, Society of Geophysicists-Scouts (SEG), 226 p.

Gholami, R., Moradzadeh, A., Rasouli, V., and Hanachi, J. (2014). Shear Wave Velocity Prediction Using Seismic Attributes and Well Log Data, *Acta Geophys*. Vol. 62, 818–848. doi: 10.2478/s11600-013-0200-7.

Guliev, H. H., and Aghaev, Kh. B. (2010). The seismic sections modeling accounting the stressed state of the medium. *Geodynamics*, No. 1 (9), p. 81–86. (in Russian).

Guliyev, H., Aghayev, Kh., Mehraliyev, F. and Ahmadova, E. (2019). Determination of the physical properties of complexly constructed media using near-surface crosswell method. *Visnyk of Taras Shevchenko National University of Kyiv: Geology*. 3(86). 13–20. http://doi.org/10.17721/1728-2713.86.02

Guliyev, H. H., Aghayev, Kh. B. and Shirinov, N. M. (2010). The Research of the Influence of the Pressure to the Values of Elastic Parameters of Geological Medium on the Basis of Seismic and Well Data. *Visnyk of Taras Shevchenko National University of Kyiv: Geology*, 50. 10–16.

Guliyev, H. H., Aghayev, Kh. B. and Sultanova G. A. (2019). Determination of stress in the geological medium on the basis of well data using acoustoelastic correlations. International *Journal of Geophysics* 41(6):173–182.

Habib Akhundi, Mohammad Ghafoori, and Gholam-Reza Lashkaripour. (2014). Prediction of Shear Wave Velocity Using Artificial Neural Network Technique, Multiple Regression and Petrophysical Data: A Case Study in Asmari Reservoir (SW Iran) *Open Journal of Geology*, 4, 303–313.

Krief, M., Garat, J., Stellingwerff, J., and Ventre J. (1990). A petrophysical interpretation using the velocities of P and S waves (full-waveform sonic), The Log Analyst 31, 8, 355–369.

Meltem, Akan. (2016). Processing and Interpretation of Three-Component Vertical Seismic Profile Data, Ross Sea, Antarctica. Graduate Theses & Non-Theses, 64, 90 p. https://digitalcommons. mtech.edu › viewcontent.

Poulton, M.M. (2002). Neural networks as an intelligence amplification tool: A review of applications. Geophysics 67(3), 979–993. doi: 10.1190/1.1484539.

Puzyrev N. N., Trigubov A. V., Brodov L. Yu., Vedernikov G. V., Lebedev K. A. (1985). Seismic exploration by the method of transverse and converted waves / M.: Nedra, 277 p. (in Russian).

Robert, R. Stewart, James E. Gaiser, R. James Brown, and Don C. Lawton. (2002). Converted-wave seismic exploration: applications. Geophysics 68(1): 40–57. doi: 10.1190/1.1543193.

Saeed Parvizi, Riyaz Rharrat, Mohammad R. ASEF, Bijan Janangiry and Abdolnabi Hashemi. (2015). Prediction of the Shear Wave Velocity from Compressional Wave Velocity for Gachsaran Formation. Acta Geophysicavol. 63(5), 1231–1243. doi: 10.1515/acgeo-2015-0048.

Schön, J. H. (2015). *Physical properties of rocks: Fundamentals and principles of petrophysics*. Elsevier. https://trove.nla.gov.au/work/9281433

Shahoo Maleki, Ali Moradzadeh, Reza Ghavami Riabi, Raoof Gholami, and Farhad Sadeghzadeh. (2014). Prediction of shear wave velocity using empirical correlations and artificial intelligence methods. *NRIAG Journal of Astronomy and Geophysics* 3, 70–81. doi:10.316/j.nrjag.2014.05.001.

Veeken, P. C. H., and Silva, Da M. (2004). Seismic inversion methods and some of their constraints: First Break, 22, 47–70. doi: 10.3997/1365-2397.2004011.

Volarovich, M. P., Bayuk, E. I., Levykin A. I., and Tomashevskaya, I. S. (1974). Physico-mechanical properties of rocks and minerals at high pressures. Publishing House "Science", 1–123 p. (in Russian).

Voskresensky, Yu. N. (2001). The study of changes in the amplitudes of seismic reflections for the search and exploration of hydrocarbon deposits. Russian State University of Oil and Gas named after THEM. Gubkin. Moscow: Ministry of Education of the Russian Federation. 69 p. (in Russian).

Yilmaz, Oz. (2001). *Seismic data analysis: processing, inversion and interpretation of seismic data.* Society of Exploration Geopysicists. Investigations in geophysics, 2, Tulsa, SEG, 2027

Х. Б. АГАЄВ*, Р. Г. КУЛІЄВ, Ш. З. ЯКУБОВА

Інститут геології та геофізики АНА, пр. Х. Джавіда, 119, Баку, AZ1143, Азербайджан, тел.: (+994 12) 5105617, e-mail: khagayev@yahoo.com

## ПОБУДОВА ШВИДКІСНОЇ МОДЕЛІ ПОПЕРЕЧНОЇ ХВИЛІ ДЛЯ СКЛАДНОСТРУКТУРНОГО ГЕОЛОГІЧНОГО СЕРЕДОВИЩА З ВИКОРИСТАННЯМ НЕЙРОННОЇ МЕРЕЖІ (НА ПРИКЛАДІ ДАНИХ ПІВДЕННО-КАСПІЙСЬКОГО БАСЕЙНУ)

**Мета.** Розроблення методу прогнозування дво(три)вимірної швидкісної моделі середовища поперечної хвилі. Досліджено складноструктурне геологічне середовище на основі геофізичних і геологічних даних із застосуванням штучної нейронної мережі. **Метод** передбачає побудову та використання моделей середовища за даними геофізичних досліджень свердловин, сейсморозвідки та інших наземних геофізичних методів. На відміну від існуючих методів, у пропонованому використовують також додаткові дані про середовище: про термодинамічний стан середовища, стратиграфічну приуроченість відкладень, літологію порід, розподіл кластерів даних, фізичні властивості середовища тощо. Згідно з методом, спочатку будують одновимірні моделі за різними властивостями середовища на основі даних комплексу геофізичних досліджень свердловин. Потім за сукупністю моделей нейронну мережу вивчають для прогнозування швидкості поперечної хвилі, відтак будують дво(три)вимірні моделі середовища за результатами наземних геофізичних досліджень. З використанням сукупності цих моделей прогнозують дво(три)вимірну швидкісну модель поперечної хвилі. **Результати.** Із застосуванням методу спрогнозовано швидкісну модель поперечної хвилі для складноструктурного геологічного середовища Південно-Каспійського басейну. **Наукова новизна.** Збільшенням кількості типів використаних даних забезпечується підвищення точності прогнозування моделі середовища. **Практична цінність.** Підвищення ефективності сейсморозвідки під час визначення нафтогазонасиченості, пружного геодинамічного стану та інших фізичних властивостей геологічного середовища.

*Ключові слова*: сейсмічна розвідка; хвиля тиску і зсуву; сейсмічна швидкість; середня модель; передбачення; нейронна мережа.

Received 10.02.2020