

Using of neural network in porosity prediction (Beničanci field)

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Abstract

The Benicanci oil field, located in the eastern part of the Drava depression is still one of five main hydrocarbon reservoirs in Croatia. That makes very meaningful to plan and perform a whole new set of geological reinterpretations and improvements of field geological model. The application of the neural network approach in seismic attribute processing and finally reservoir porosity prediction is presented in the paper. The three seismic attributes were interpreted – amplitude, phase and frequencies making 3D seismic cube. This attributes were extrapolated at the 14 well locations, averaged and compared by the mean porosities. It made the network training. The network was of the backpropagation type. It was fitted through 10000 iterations, searching for the lowest value of correlation between attribute(s) and porosities and the minimal convergence. The best training was reached using all three attributes together, what indicated on tendency that neural networks like numerous inputs. Moreover, the previously interpolated porosity map was done using geostatistics, both Kriging and Cokriging approaches. The Cokriging approach, very interesting, included only reflection strength (derivation of amplitude) as secondary seismic source of information (compared by neural inputs of three attributes). It very clearly indicated on position of carefully and geologically meaningful selection of the network inputs for any reservoir analysis. Relatively smooth map, and rarely reaching of measured porosity minimum and maximum, strongly indicates on conclusion that neural estimation is more precisely than previously interpolations.

Keywords: *Seismic attributes, neural network, porosity, Drava depression.*

1. INTRODUCTION

The Benicanci oil field is located in the eastern part of the Drava Depression. It is still one of the five most productive hydrocarbon fields in Croatia. The reservoir is of massive type, lithologically represented by dolomitic and limestone breccias. The top of the structure trap is on 1699 m absolute Average porosity was 7.33%, initial water saturation 28.13%, and oil gravity 875.0 kg/m³. Production started in 1972 and waterflooding in 1975. The field is today in mature production stage, explored and developed by totally 106 wells with 25 wells still in production stage. Following analysis was performed on data collected in 14 wells. In the analysis new porosity averages were calculated for reservoir interval as well as seismic attributes calculated from recently performed 3D seismic survey.

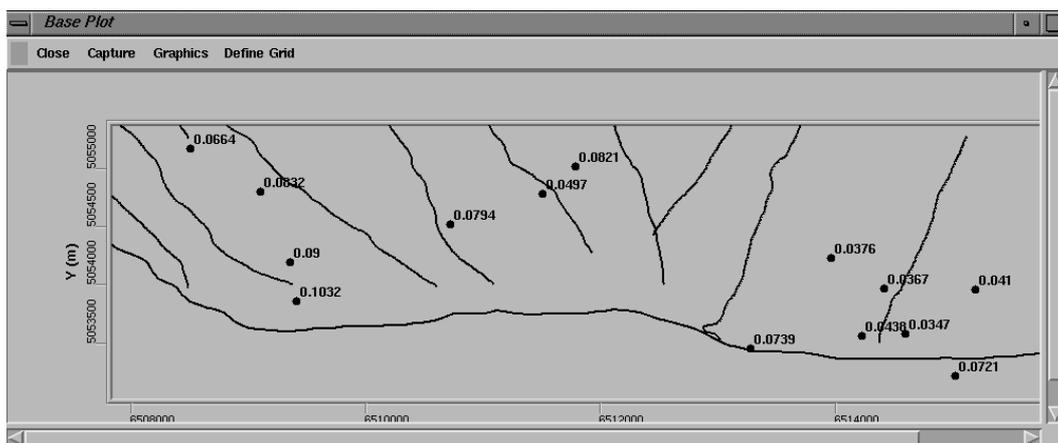


Fig. 1. Index map

Porosity is selected as the important reservoir variable with high influence on reservoir volume, OGIP and finally production. The analysed reservoir belongs to the coarse clastic sediments of Badenian age (lithostratigraphically Mosti member). Seismic interpretation was performed for interval that begins at 20 m from the member seal and spreads to the member base or the well bottom has been monitored as reservoir (**Futivić and Pleić, 2003**). Seismic attribute analysis was applied on 3D seismic data and extracted amplitude, frequency and phase were used for reservoir porosity mapping performed backpropagation neural network.

2. SEISMIC BACKGROUND

Seismic waves are reflected from layer borders and can be distinguished by receiving time, amplitudes, phases, frequencies and polarities. Every change in acoustic impedances on both layer planes will change the above parameters. Detail analysis of these changes would allow determination of structure, lithology or fluid saturation in reservoir layers (Taner, 1992).

Seismic trace is complex record of subsurface seismic wave arrivals presented as real trace on **Fig.2**. The associated complementary imaginary trace is calculated by Hilbert's transformations. The sum of amplitudes of real and imaginary trace is always equal to amplitude of complex trace. Such complex trace is used in further analysis and calculation of amplitudes, phases and frequencies, applying relevant mathematical operations in order to achieve reliable seismic trace analysis. It is important that input seismic traces are of good quality and containing minimal noise.

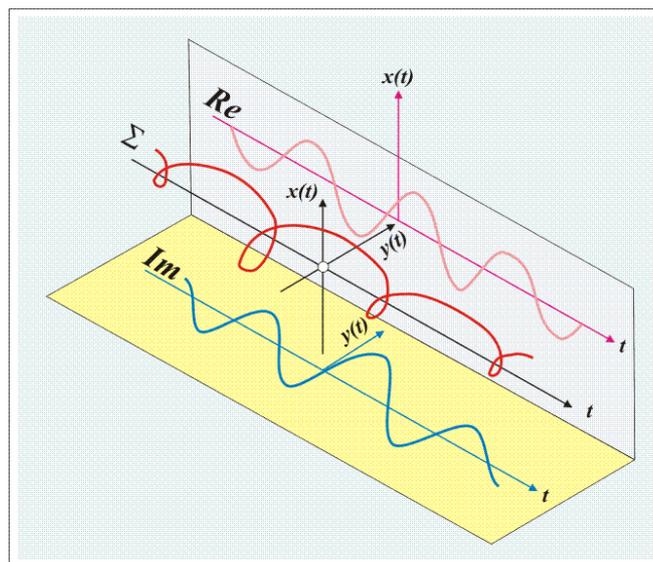


Fig. 2. Real (Re), imaginary (Im) and complex seismic trace (Σ)

Hilbert's transformation resulted in moving of all frequencies components of input – positive for -90° and negative for $+90^\circ$. Assuming that $x(t)$ is input signal, $y(t)$ output signal, $G(w)$ Hilbert's transformation in coordinate axes based on frequencies. Equation (1) describing Hilbert's transformation of input signal $H(x(t))$ in time-coordinate axes as:

$$x(t) \rightarrow G(w) = -j \operatorname{sgn}(w) \rightarrow y(t) = H(x(t)) \quad (1)$$

Where are:

$$j = \sqrt{-1}, \text{ and}$$

$$\operatorname{sgn}(w) = +1 \quad \text{for} \quad w > 0$$

$$\operatorname{sgn}(w) = -1 \quad \text{for} \quad w < 0$$

$$\operatorname{sgn}(w) = 0 \quad \text{for} \quad w = 0$$

If the amplitudes of complex function $\mathbf{z}(t)$, obtained from (1), there is possible to calculate values of instantaneous amplitudes $\mathbf{a}(t)$, phases $\mathbf{f}(t)$ and frequencies $\mathbf{w}(t)$ of the complex trace using:

$$a(t) = \sqrt{x^2(t) + y^2(t)} \quad (2)$$

$$\phi(t) = \operatorname{arctg} \left(\frac{y(t)}{x(t)} \right) \quad (3)$$

$$w(t) = \frac{d\phi(t)}{dt} \quad (4)$$

Every acoustic impedance change in layers directly influences their seismic reflection character and the detail analysis of such changes is the basis to study of reservoir status. Even small amplitude and phase anomalies can indicate on changes in lithology, thickness and fluid saturation. The changes in amplitudes, phases and frequencies became already reliable tool in rock physics study determination in oil reservoir, as schematically presented on **Fig. 3**.

Interpreted **amplitudes** can be used for determination of reservoir properties like porosity, gas accumulation, fluid contacts, lithological continuity and detection of over-pressured zones. It could be also detected very precise detection of unconformities, fault planes, stratigraphic barriers, water of CO₂ front progress etc.

The main advantage of **instantaneous phase** is simple observing of phase changes, without regard on amplitude values. Such phase transitions can be especially useful in interpretation of facies changes, unconformities, faults and stratigraphic relations.

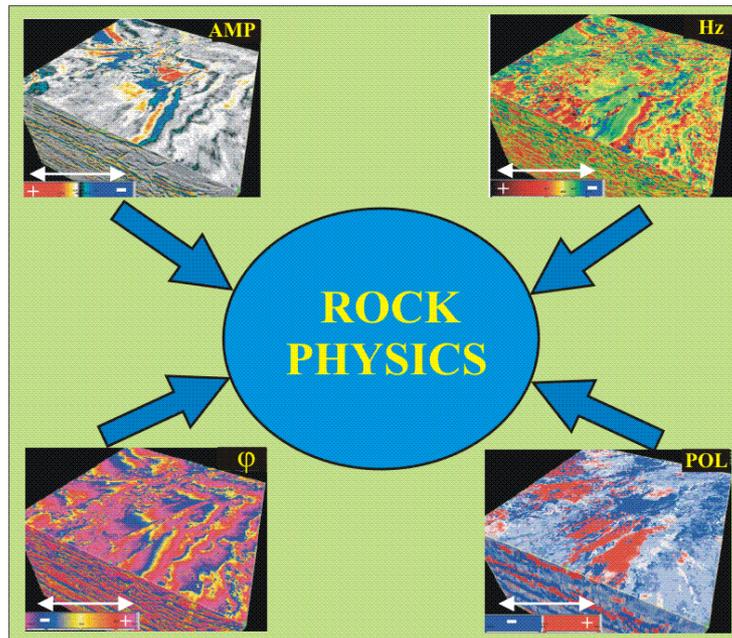


Fig. 3. Seismic attributes analysis enables rock physics determination

Frequencies can be calculated using correlations among sinusoidal and co-sinusoidal functions of different frequencies. Such correlation coefficients can be measure of frequency content in relative wide time interval. But *instantaneous frequencies* indicate on changes between particular time samples. This data can be used for lateral correlation of reflected seismic signals, detection of thin layers of small acoustic impedances, finding fractures characterised by extremely low frequencies, and sand/shale ratio calculation.

The combined and improved application of the several seismic attributes can make possible to select different facies zones in heterogeneous reservoirs, such it is Beničanci field reservoir of Badenian age. Moreover, such facies analysis can be indirectly performed, searching for the more appropriate spatial analysis of important reservoir parameter like porosity.

3. BACKPROPAGATION NETWORK

Generally, neural networks are modern tools with numerous purposes (**Anderson and Rosenfeld, 1989**). In the early days of artificial intelligence ROSENBLATT, employed at the *Cornell Aeronautical Laboratory*, was developed in the 1957 the machine called *perceptron*, based on memorizing pattern of human mind (**Rosenblatt, 1957, 1958**). Such machine could “learn” and represented prototype of neural network. Perceptron scheme included connections like that in associative memory.

The basic structure of the network is based on artificial neuron model. Such neuron is assembled from several inputs and single output. Each input is associated with related *weight* added to input value. Depending on result, the neuron could stay inactive or be activated. The values and conditions for activation are determined by *activation function*.

The way how specific number of neurons define network is described through *layers*. The set of selected neurons make *input layer*. Such inputs are modified through *hidden layers* and result is given in *output layer*. Hidden layers are not connected with information outside network, like inputs or output channels.

In general, *input layer* collect and distribute data loaded in network, and *hidden layer(s)* process such data, using activation function. Expression (5) represents set of operation performed on neuron, and equation (6) detects activation of neuron.

$$U_j = \sum (X_i \times w_{ij}) \quad (5)$$

Where are:

- j - Number of neuron ;
- i - Number of inputs ;
- X_i - Value of input “ i ” ;
- w_{ij} - Previously determined weight coefficient for input “ i ” ;
- U_j - Value of output in neuron “ j ”

$$Y_j = F (U_j + t_j) \quad (6)$$

Where are:

F - Activation function ;

t_j - Target value for neuron "j" ;

Y_j - Layer output (or total output if it is last layer)

The value of output (U_j) is compared with conditions necessary for hypothesis acceptance (t_j). Activation function (F) is eventually started based on this value.

Equitation (5) implied that previously are determined weighting coefficients, value of hypothesis acceptance, number of layers and number of neurons in each layer. It makes possible to get result of a neural network. The values of weighting coefficients and hypothesis acceptance are changed and modified in the period of network training (or learning).

Recognition of samples that only could be separated using linearity represents limits of a network based only on perceptrons. This limitation is prevailed by introducing of *back error propagation* paradigm (abbr. *backprop*). This algorithm extends the perceptron effect, using of large number of hidden layers. It is why term *the multiple layer perceptron* (abbr. *MPL*) is used.

Backpropagation algorithm means that network training includes determination of difference between true and wanted network response, i.e. means calculation of *error* that is backed in network in purpose of obtaining the optimal training. Such error is determined for each neuron and used for adoption of existing weighting coefficient and activation value. This corrective procedure is called *the backpropagation network* that describes the process of network learning and validation. It is repeated so many times while particular or total error is not decreased below the limit. After that, the training is over and the network could be applied for processing of new inputs. *The backprop* algorithm first processes inputs, checks output error and finally going backs on the same inputs. It is the most popular paradigm that is applied for neural network at all. Backprop of information in network always starts from output to inputs. Backprop is used in the multilayer networks, but often could be characterised with long lasting training. It is why the backprop using is limited for calculation without inquires for fast outputs. Such shortages in learning rate resulted from *the gradient descent* method that is used in the backprop algorithm. The backprop equitation is shown in Equations (7):

$$[w_i]_{new} = [w_i]_{old} + [LR] \cdot [transfer_function] [correction_term] + [momentum_coefficient] [previous_Δw] \quad (7)$$

Where are:

w_{new} - weighting coefficient of input (seismic attribute) in “*i-th*” iteration

w_{old} - weighting coefficient of previous iteration

$Δw$ - difference between these two weighting coefficient

$LR (\eta)$ - *learning rate*, indicates on level of using of transformation function (momentum coefficient) in each iteration. If $LR=0$ transformation function is not used and entire network is based only on applying of *momentum coefficient*.

Momentum coefficient (α) – this parameter defines how large is influence of result of previous iteration in instantaneous calculation.

Correction term – this value depends on differences between true (measured) and trained (by network) value.

Transfer function – there is several, and we used sigmoid shape expressed as $f(x) = \frac{1}{1 + e^{-x}}$

In performed training the large influence have the values of *momentum coefficient* and *correction term*. Momentum coefficient defined the size of previous iteration influence on new estimation. Let us to explain geological meaning on the following example. Imagine the set of 1D porosity values 7.2, 7.0, 6.3, 5.7, 6.2, 6.5, 5.5, 5.2%. Generally, this array tends to minimum at the end. But there is also one local minimum 5.7% at 4th place. This network will recognize these local minima if network parameters are set very sensitive. In other case, the network will only detect general decreasing trend. The ***momentum coefficient*** is extremely sensitive for detection of *local minima*, and ***learning rate*** for detection of *general trend*. The third important parameter is ***correction term*** that represents differences between true and modelled values. It is calculated for each *hidden layer*, and the network tries to decrease this differences through each the next iteration.

4. BENIČANCI FIELD NETWORK (POROSITY PREDICTION)

There were two datasets for the Benicanci field reservoir. The first one included 13 seismic (amplitude, frequency, phase) and porosity values averaged at the well locations. The second set encompassed the seismic raw data from seismic grid (16384 values in total).

The first dataset was used as training set for the neural network of the backpropagation type. Transformation function was of log-sigmoid type. There was selected the best network iteration, by the most appropriate weighting coefficient. Such network was used for porosity estimation from the second, exhaustive, seismic dataset. The final goal was to reach the **estimated porosity map**, which could be considered as improvement for any previously interpolated reservoir porosity map. The last interpolated porosity maps on the Benicanci field were obtained by geostatistics.

4.1. Insensitive network parameters fitting

The number of hidden layers in the network was 5. We tried to increase this number, e.g. up to 25, but such increasing did not improve obtained correlation between attribute and porosity (only for 0.001-0.01), but made the network very slow. The *learning rate* value was left on recommended 0.9, the *momentum coefficient* also on recommended 0.6. The network output was very similar for ranging these parameters from 0 to 1. The number of *iterations* was 10,000, but the output was not significantly differing even for 30,000 iterations.

4.2. Sensitive network parameters fitting

The most sensitive parameter was number of included seismic attribute in analysis in the same time. We tried to feed the network by single and multiple seismic attributes in the same training. The use of 2 or 3 attributes could be questionable procedure regarding physical meaning of such new "attribute". But obtained correlations are highly connected by number of included attributes. It is why we varied number of nodes in input layer between 1 and 3, combining amplitude, frequency and phase in new "complex" attribute.

The selected transfer function was log-sigmoid type. The second important value was *convergence criteria* ($\Sigma \varepsilon^2$). It played a role of the network stopping criteria. If the network calculated convergence value lower than selected value, the simulation will stop although iteration no. 10,000 was not reached. This value was set on 1 and only one the network reached lower value.

4.3. The network results

The quality of network training was expressed through correlation between porosity and included attribute(s), and the network's convergences criteria as the minimum reached by the backpropagation algorithm. Looking by different number of input network's nodes, the following results were obtained:

- Amplitude + frequency + phase = porosity - $R^2=0.987$; $\Sigma \varepsilon^2=0,329$;
- Amplitude + frequency = porosity - $R^2=0.496$; $\Sigma \varepsilon^2=1,935$;
- Amplitude + phase = porosity - $R^2=0.603$; $\Sigma \varepsilon^2=1,740$;
- Phase + frequency = porosity - $R^2=0.820$; $\Sigma \varepsilon^2=1,090$;
- Amplitude = porosity - $R^2=0.250$; $\Sigma \varepsilon^2=2,730$.

The presented results showed that porosity prediction can be done with any number of attributes. But, it is interesting that the highest correlation was reached using all three attributes together. Porosity inputs were in range 5.27-11.06%, but the estimation by the neural network had a tendency to make this variation narrower (remaining the limits). This is also often characteristics of geostatistics and regression.

Using only one or two attributes the estimation was artificially too high, e.g. pair amplitude-frequency led to average porosity close to upper limit. The problem with one-parametric estimation can be explained on amplitude. Physically, amplitude is the most "geological" attribute that could lead to good estimation of porosities in clastites. In our case, correlation of the pair amplitude-porosity is very low (0.25) and the network is poorly trained ($\Sigma \varepsilon^2=2.73$). The lower amplitude led to lower porosities, but the problem was *the differences* between these estimations. For example, amplitude value 1200 is paired by porosity of 5.27%, then 1472=7.3%, 1669=8.15%, 1842=8.16%, 1990=8.17% and 2107=8.16%. The change is not a linear.

The best porosity estimation was obtained using all three attributes. The estimated porosity varied in wide range, respecting the limits of input (5.27-11.06). Unfortunately, the input dataset was too small to interpret if the estimated porosities also respect input distribution.

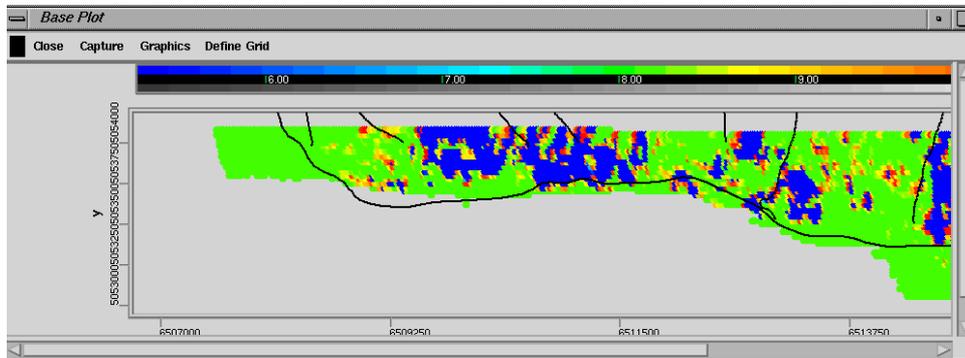


Fig. 4. The neural network porosity map at the Benicanci field (range 5-10%)

Graphically, the results are presented by the map obtained by the SigmaView™ program (Landmark application). The problem was encountered by importing the network results and there was only possibility to interpolated new one neural map at the southern part of the field (**Fig. 4**). It could be compared also by geostatistical porosity maps interpolated in 2003 at the same field (**Malvić and Đureković, 2003**) and shown at **Figs 5 and 6**.

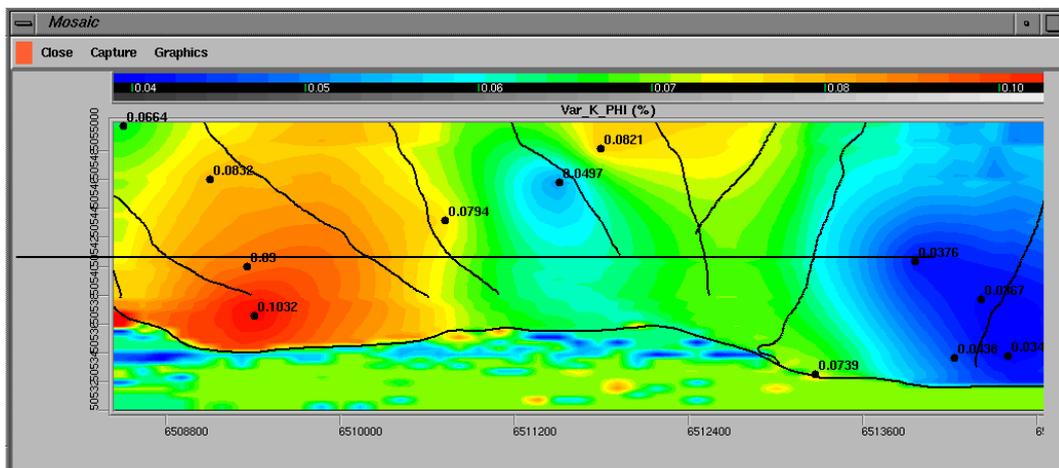


Fig. 5. The Kriging porosity map at the Benicanci field (range 4-10%)

Moreover, it was interesting that in Cokriging application as the secondary attribute was selected only single attribute. It was reflection strength, derived from amplitude. The correlation was calculated using Spearman rank coefficient with value $r'=-0,64$. Even so, it was improvements

compared with Ordinary Kriging results (compared via cross-validation). It means that neural approach “likes” more variables, and sometimes can combine physical measurements that are very slightly connected through their nature. It needs to be carefully used.

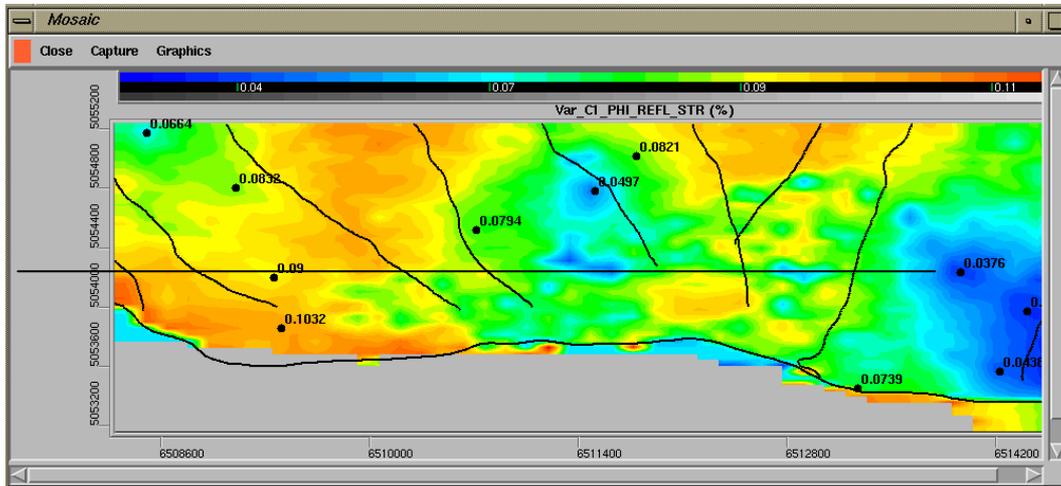


Fig. 6. The Cokriging porosity map at the Benicanci field (range 3-11%)

5. DISCUSSION AND CONCLUSIONS

Obtained results show that seismic attributes could be valuable additional source of information that could feed the neural network. Seismic could be base for reservoir parameters prediction, especially for porosity what is shown in this study.

The quality of the network could be estimated from two parameters – correlation coefficient (R) and convergence criteria and the reached minimum ($\Sigma\varepsilon^2$). The better network will be characterised by higher coefficient and lower convergence.

Based on the results presented, the following conclusions can be drawn:

- The best training results are obtained when all three seismic attributes (amplitude, frequency, phase) were used;
- The reached correlation is $R^2=0.987$ and convergence criteria; $\Sigma\varepsilon^2=0,329$;
- These values can slightly (a few percent) differs in every new training, what is consequence of stochastic (random sampling) is some process of the network fitting;
- It could be geological tricky to explain, because amplitude is often correlative by porosities, but frequency and phase much harder can describe rock pore system;
- It also indicates that neural network very favour the numerous inputs, and it need to be carefully evaluated which variable can be meaningful neural input;

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