Some benefits of the neural approach in porosity prediction (Case study from Beničanci field)

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PRELIMINARY COMMUNICATION

The Beničanci oil field, located in the eastern part of the Drava depression is still one of five main hydrocarbon reservoirs in Croatia. That makes it 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. Three seismic attributes were interpreted – amplitude, phase and frequencies making the 3D seismic cube. These attributes were interpolated at 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 10 000 iterations, searching for the lowest value of correlation between attribute(s) and porosities and minimal convergence. The best training was reached using all three attributes together, which indicated the tendency that neural networks like numerous inputs. The obtained results were compared by previously interpolated geostatistical porosity maps (done by the Kriging and Cokriging approaches). The Cokriging approach, interestingly included only reflection strength (derivation of amplitude) as the 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.

Key words: Seismic attributes, neural network, porosity, alluvial fan, Beničanci field, Drava depression

1. INTRODUCTION

The Beničanci oil field is located in the eastern part of Drava Depression. The reservoir is of massive type, lithologically represented by dolomitic and limestone breccias. The top of the structure trap is at 1 699 m bsl. Average porosity was 7.33 %, initial water saturation 28.13 %, and oil gravity 875.0 kg/m^3. Production started in 1972 and waterflooding in 1975. The field is today in mature production stage, explored and developed by a total of 106 wells with 25 wells still in the production stage. The following analysis was performed on data collected from 14 wells. In the analysis, new porosity averages were calculated for reservoir interval as well as seismic attributes[1] calculated from recently performed 3D seismic survey. This oil field is still one of the five most productive hydrocarbon fields in Croatia. It makes this area a favourable target for additionally geological reinterpretation and model improvements.

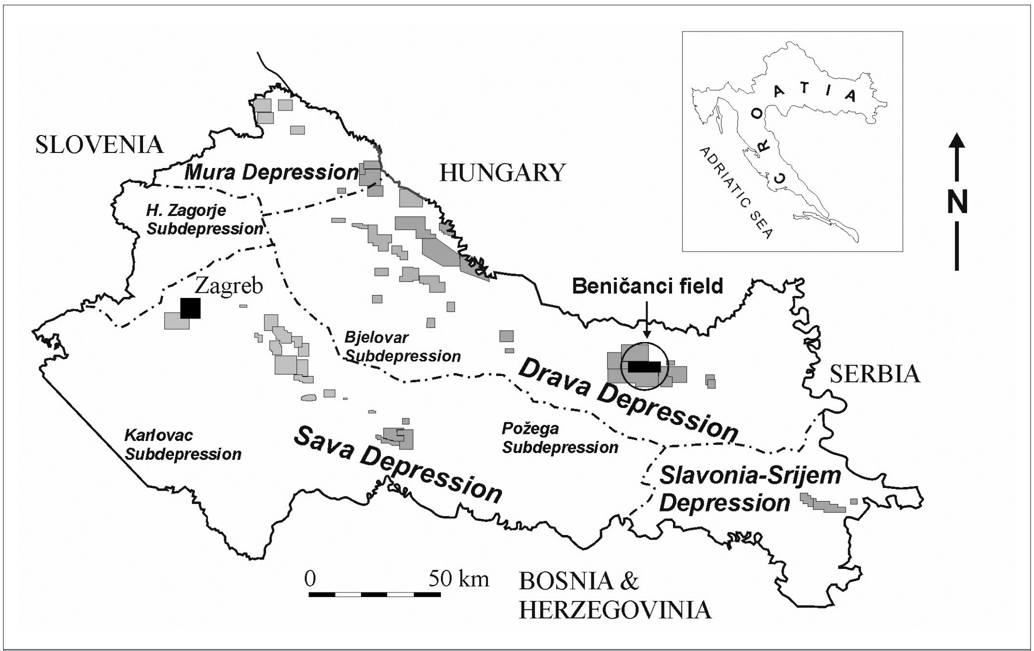

Fig. 1 Regional map of the Croatian part of the Pannonian Basin
Sl. 1. Regionalna karta hrvatskog dijela Panonskog bazena

The neural network approach is a well known developing tool within the last couple of decades. Supervised trainable networks are used in many different fields. In this case, the user provides some examples for the neural network to learn, and then the network is tested with another data set to check the success of training. One important point to remember is that the network, if trained properly, will recognize and correctly classify only those cases included in the training set. Any new conditions not included in the training set will be misclassified or not recognized. Feed forward, fully connected perceptron artificial neural networks (ANN), Learning Vector Quantization (LVQ), Probabilistic Neural Networks (PNN), and Radial Basis Function Networks (RBF) are some of the available networks.[2] Each of the methods has its advantages and limitations.

Also, the neural approach is not as expensive a process as some other development tasks like seismic acquisitions or drilling costs. The tool is very useful in prediction of reservoir properties, and searching for improvements of existing geological modeling results.

2. GEOLOGY

The Beničanci oil field is the largest hydrocarbon reservoir in the Beničanci oil zone. It comprises a total of four oilfields (Bizovac, Crnac, Števkovica, Obod-Lacići), three oil and gas fields (Beničanci, Bokšić, Obod), one gas field (Obradovci) and one geothermal field (Bizovac). The total geological oil reserves in the Beničanci reservoir are 34 x 10^6 m^3 and oil recovery 52.5 %.

Gas reservoirs of the Beničanci field are structurally shallower and represent a minor (secondary) production target. Proven reserves are about 2 700 x 10^6 m^3 and total recovery about 58 %.

The remaining recoverable reserves are small, but the field is still in production that could be assumed higher than expected from mathematical balance and some older history matches. Also, the precise prediction of total recoverable reserves is very difficult. It is the result of relatively complex Neogene clastic depositional model, especially of Middle Miocene breccia.

Generally, Neogene depositional environments in the Drava depression can be classified into two groups. One group comprises the local alluvial fans, which were active during the Middle Miocene (Badenian) extension throughout the entire Pannonian Basin. The second group comprises the continuous Pannonian and Pontian sedimentation starting with lacustrine environment of partly deepwater and partly prodelta (turbidity) fans and terminating at the delta plain sedimentation.

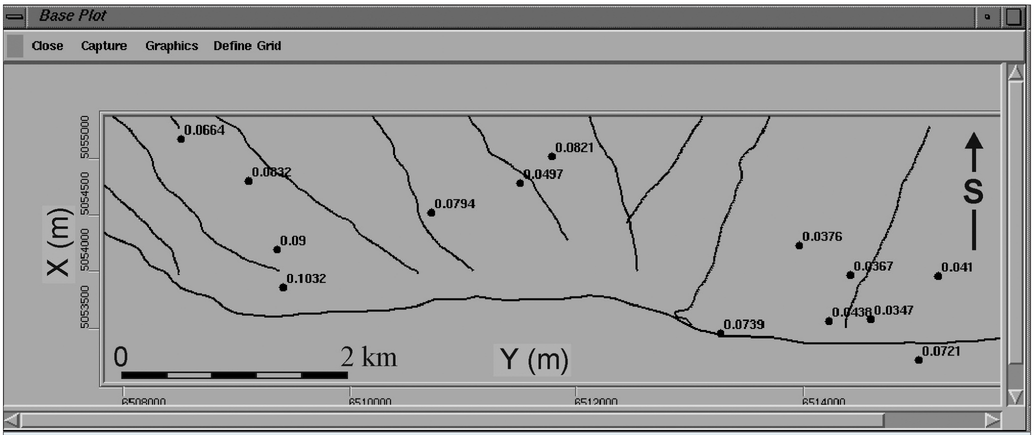

Fig. 2. Porosity index map
Sl. 2. Indeks karta poroznosti

The coarse-grained sediments of alluvial fans have great hydrocarbon potential. The Beničanci field is a major Croatian field with oil reservoir of such age and lithology.

Moreover, such reservoirs are mostly overlain by pelitic seal deposits sometimes including organic-rich source facies. This characterizes the Middle Miocene sequences (mostly of Badenian age) as complete petroleum systems.

Alluvial environments are characterized by frequent changes of petrophysical properties, due to the local character of the depositional mechanism and material sources. This renders any prediction very difficult and requires geological knowledge of depositional history and tectonics. Recently, the detailed analysis of the relation between alluvial facies and porosity prediction was published for the Stari Gradac-Barcs Nyugat field, located about 100 km north-west, also in the Drava depression.[2] The gradually decreasing porosity toward south-east was proven to be caused by alluvial fan activity. The same trend can be observed at the Beničanci field (Fig. 2), which can be observed on the field's porosity index map. This trend was a very important feature for mapping applications, and was also modeled by geostatistical maps.

In this analysis, porosity is selected as the important reservoir variable with high influence on reservoir volume, OGIP (Original Gas In Place) and finally production. The analyzed reservoir is also described in detail by seismic attribute analysis as the result of 3D seismic cube interpretation. Attribute analysis was targeted precisely for the interval beginning at 20 m from the reservoir seal and continued to the reservoir base or the well bottom.[1] Seismic attribute analysis included amplitude, frequency and phase analysis.

These values, including averaged porosity for the same reservoir interval were used for reservoir porosity mapping performed by backpropagation neural network. There are a total of 14 such wells (Fig. 2). These 14 values, derived from 106 wells, were selected based on the quality and reliability of log-curves analysis, quality of interpretation software and their relatively regular distribution across the reservoir zone.

3. SEISMIC BACKGROUND

Seismic waves reflect 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. Detailed analysis of these changes would allow determination of structure, lithology or fluid saturation in reservoir layers.[3]

Seismic trace is a complex record of subsurface seismic wave arrivals presented as real trace in Fig. 3. The associated complementary imaginary trace is calculated by Hilbert's transformations. The sum of real and imaginary trace amplitudes is always equal to the complex trace amplitude. 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 contain minimal noise.

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

$$x(t) \rightarrow G(w) = -j\,\mathrm{sgn}(w) \rightarrow y(t) = H(x(t)) \qquad (1)$$

Where:

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

$sgn\ (w) = +1$ for $w > 0$

$sgn\ (w) = -1$ for $w < 0$

$sgn\ (w) = 0$ for $w = 0$

With the amplitudes of complex function $z(t)$, obtained from (1), it is possible to calculate values of instantaneous amplitudes $a(t)$, phases $\phi(t)$ and frequencies $w(t)$ of the complex trace using:

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

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

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

Every acoustic impedance change in layers directly influences their seismic reflection character and the detail analysis of such changes is the basis to study reservoir status. Even small amplitude and phase anomalies can indicate changes in lithology, thickness and fluid saturation. The changes in amplitudes, phases and frequencies have already become a reliable tool in rock physics study determination in oil reservoir, as schematically presented in Fig. 4.

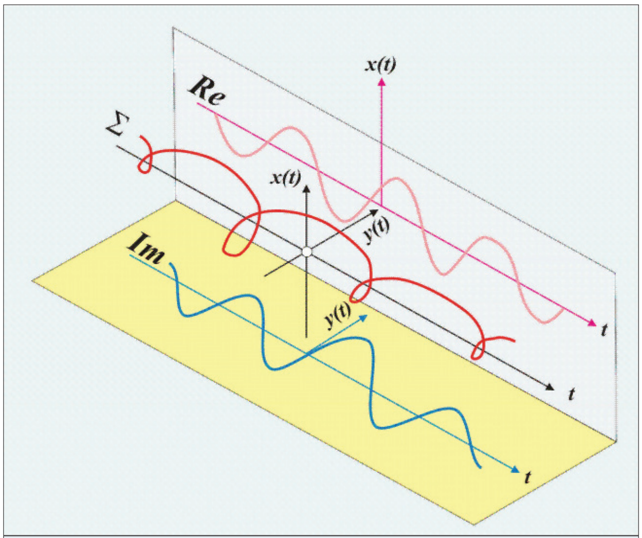

Fig. 3. Real (Re), imaginary (Im) and complex seismic trace (Σ)[4]
Sl. 3. Stvarni (Re), imaginarni (Im) i složeni seizmički trag (Σ)[4]

Interpreted amplitudes can be used to determine reservoir properties like porosity, gas accumulation, fluid contacts, lithological continuity and detection of overpressured zones. They could also be used in detection of unconformities, fault planes, stratigraphic barriers, water or CO_2 front progress etc.

The main advantage of the **instantaneous phase** is simple observing of phase changes, regardless of amplitude values. Such phase transitions can be especially

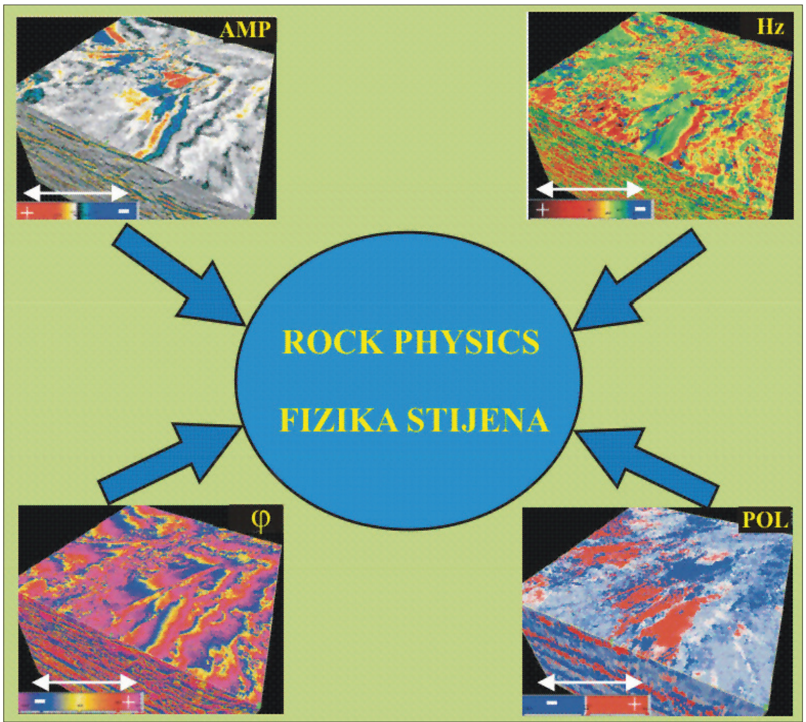

Fig. 4. Seismic attributes analysis enables rock physics determination
Sl. 4. Seizmička atributna analiza omogućava određivanje fizikalnih svojstava stijena

useful in interpretation of facies changes, unconformities, faults and stratigraphic relations.

Frequencies can be calculated using correlations among sinusoidal and co-sinusoidal functions of different frequencies. Such correlation coefficients can be the measure of frequency content in a relatively wide time interval. However, *instantaneous frequencies* indicate 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 characterized by extremely low frequencies, and sand/shale ratio calculation.

The combined and improved application of several seismic attributes may enable selection of different facies zones in heterogeneous reservoirs, such as the Beničanci field reservoir of Badenian age. Moreover, such facies analysis can be performed indirectly, in search of more appropriate spatial analysis of an important reservoir parameter like porosity.

4. BACKpropagation network

Generally, neural networks are modern tools with numerous purposes.[5] In the early days of artificial intelligence ROSENBLATT, employed at the *Cornell Aeronautical Laboratory*, in the 1957 the machine called *perceptron* was developed, based on memorizing patterns of the human mind.[6,7] This machine could "learn" and represented a prototype of the neural network. The *Perceptron* scheme included connections like those in the associative memory.

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

How a specific number of neurons defines a network is described through *layers*. The set of selected neurons make an *input layer* that collects and distributes data loaded into network. Such inputs are modified (Eq. 5) through *hidden layers* using the activation function (Eq. 6), and the result is given in the *output layer*. Hidden layers are not connected only inside the network and do not communicate by outside information.

$$U_j = \left(X_i \cdot w_{ij}\right) \tag{5}$$

Where:

j - Number of neurons

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"*

$$Y_j = F\left(U_j + t_j\right) \tag{6}$$

Where:

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 the conditions necessary for hypothesis acceptance (t_j). Activation function (F) is eventually started based on this value. Equation (5) implies that previously determined are the weighting coefficients, value of hypothesis acceptance, number of layers and number of neurons in each layer. This enables us to obtain a result from 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 could only be separated using linearity, represents limits of a network based only on perceptrons. This limitation is overcome by introducing the *back error propagation* paradigm (abbr. *backprop*). This algorithm extends the perceptron effect, using of large number of hidden layers, which is why the term *multiple layer perceptron (*abbr. *MPL)* is used.

Backpropagation algorithm means that network training includes determination of the difference between true and wanted network response, i.e. calculation of *error* that is backed in the network for the purpose of optimal training. Such an error is determined for each neuron and used for adopting the 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, until a particular or total error is decreased below the limit. After that, the training is over and the network may be applied for processing new inputs. *The backprop* algorithm first processes inputs, checks the output error, and finally goes back to the same inputs. It is the most popular paradigm that is applied for neural network at all. Backprop of information in a network always starts from the output to the inputs. Backprop is used in multilayer networks, but often could be characterized with long lasting training. This is why the application of backprop is limited for calculation without inquires for fast outputs. Such shortages in the learning rate resulted from *the gradient descent* method that is used in improving the backprop algorithm. The backprop equation is shown below (7):

$$[w_i]_{new} = [w_i]_{old} + [LR]\cdot[TF]\cdot[CT] + [MC]\cdot[previous\ \Delta w] \tag{7}$$

Where:

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

w_{old} weighting coefficient of previous iteration

Dw difference between the two weighting coefficients above

LR Learning Rate, which indicates in each iteration the use level of the transformation function and momentum coefficient. If LR=0 the transformation function is not used and entire network is based only on applying the Momentum Coefficient

TR Transfer Function can be selected among several types. Here we used the sigmoid shape expressed as

$$f(x) = \frac{1}{1+e^x}$$

CT Correction Term value depends on differences between true (measured) and trained (by network) value

MC Momentum Coefficient defines how large the influence is of the result of previous iteration in instantaneous calculation.

Training is largely influenced by the values of *momentum coefficient* and *correction term*. The momentum coefficient defines the size of previous iteration's influence on the new estimation. Let us explain the geological meaning by 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 a minimum at the end. However, there is also one local minimum 5.7 % in 4th place. The network will recognize these local minima if the network parameters are set very sensitive. In other cases, the network will only detect a 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 the *correction term* that represents the differences between true and modeled values. It is calculated for each *hidden layer*, and the network tries to decrease these differences through each next iteration.

5. BENIČANCI FIELD NETWORK (POROSITY PREDICTION)

There were two datasets for the Beničanci field reservoir. The first included 14 seismic (amplitude, frequency, phase) and porosity values averaged at the well locations. The second set encompassed the seismic raw data from seismic grid (16 384 values in total), which were averaged at the locations of the first dataset.

The best network iteration was selected by the most appropriate weighting coefficient. Such a network was used for porosity estimation from the second exhaustive seismic dataset (seismic grid). The final goal was to reach the estimated porosity map, which could be considered an improvement for any previously interpolated reservoir porosity map (obtained by geostatistics). Transformation function was of log-sigmoid type.

5.1. Insensitive network parameters fitting

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

5.2. Sensitive network parameters fitting

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

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

5.3. The results of prediction by neural network

The quality of network training was expressed through correlation between porosity and included attribute(s), while a convergence criterion was considered as the error minimum reached by the network. According to different numbers of input network 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 show that porosity can be predicted with any number of attributes. However, it is interesting that the highest correlation was reached using all three attributes together. Moreover, porosity in the input dataset ranged from 5.27-11.06 %, but the estimation by the neural network had a tendency to narrow this variation (remaining within limits). This is also often characteristic 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 the upper limit.

The problem with one-parametric estimation can be explained by amplitude. Physically, amplitude is the most "geological" attribute that could lead to good estimation of porosities in clastics. 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 difference* between these estimations. For example, amplitude value 1 200 is paired by porosity of 5.27 %, then 1 472 = 7.3 %, 1 669 = 8.15 %, 1 842 = 8.16 %, 1 990 = 8.17 % and 2 107 = 8.16 %. The change is not linear, i.e. it artificially favors porosity closer to the lower limit.

The best porosity estimation was obtained using all three attributes (Fig. 5). The estimated porosity varied widely, respecting the limits of input (5.27 - 11.06 %). Unfortunately, the input dataset was too small to interpret whether the estimated porosities also respect input distribution.

Graphically, the results are presented by the map obtained using the SigmaView™ program (Landmark application). A problem was encountered by importing the network results and there was only the possibility of interpolating one new neural map at the southern part of the field (Fig. 5). However, such a solution can be compared with the same area (bordered by a white line in southwest area) at geostatistical porosity maps interpolated in 2003 at the same field using the same software.[8]

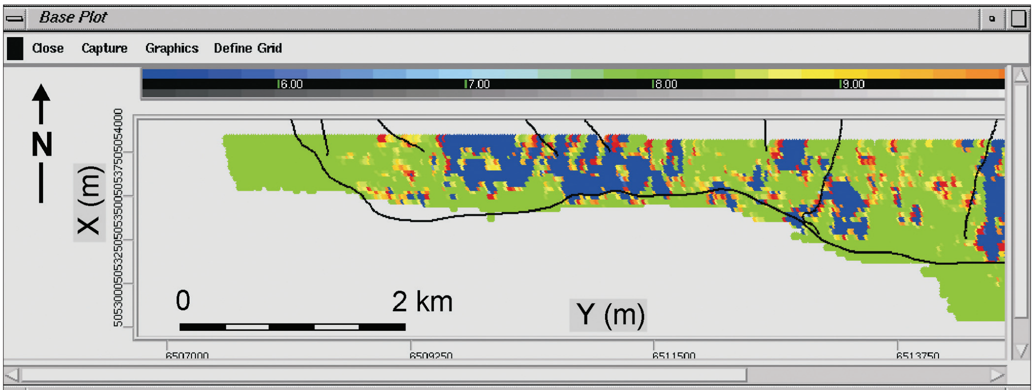

Fig. 5. The neural network porosity map of the Beničanci field (color scale 5-10 %)
Sl. 5. Poroznosti procjenjene neuronskom mrežom na polju Beničanci (kolor skala 5-10 %)

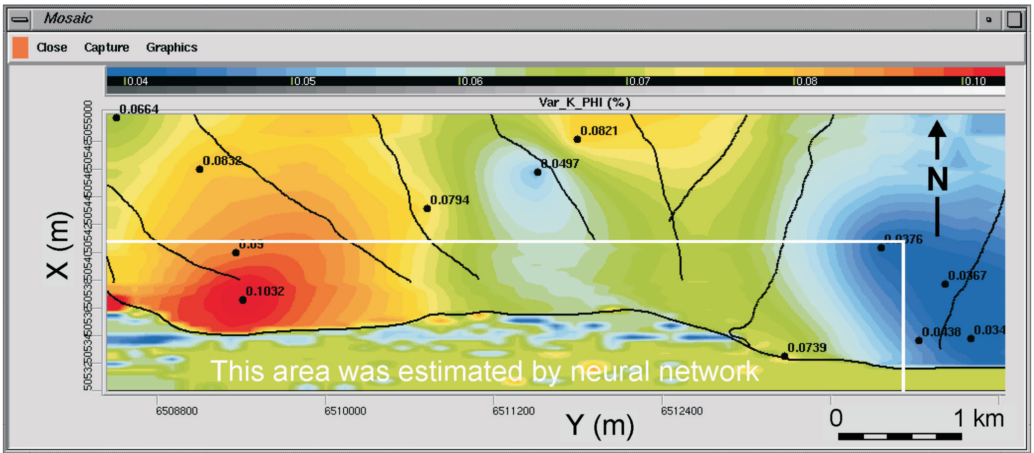

Fig. 6. The Kriging porosity map of the Beničanci field (color scale 4-10 %)
Sl. 6. Karta poroznosti dobivena krigingom na polju Beničanci (kolor skala 4 - 10 %)

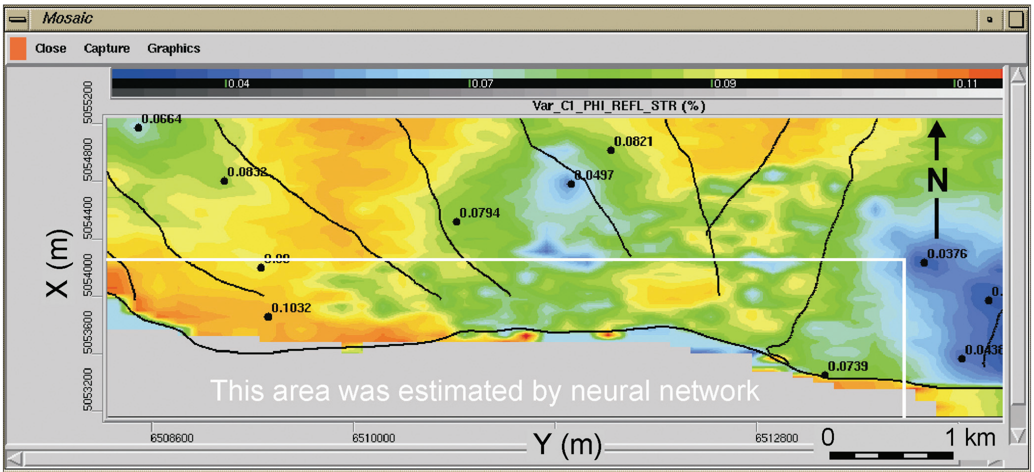

Fig. 7. The Cokriging porosity map at the Beničanci field (range 3-11 %)
Sl. 7. Karta poroznosti dobivena kokrigingom na polju Beničanci (kolor skala 3 - 11 %)

5.4. Comparison with geostatistical maps

The quality of interpolation of the same input dataset was tested using Inverse Distance Weighting, Ordinary Kriging and Collocated Cokriging methods. The results[8] obtained by Inverse Distance Weighting and Ordinary Kriging differ very little and both maps were also characterized by the unfavorable bulls-eye effect (Fig. 6).

It was very interesting that in Cokriging application, only a single attribute was selected as the secondary attribute. This was reflection strength, derived from amplitude. The correlation between reflection strength and porosity was calculated using Spearman rank coefficient with value $r'=-0.64$. The Cokriging approach, using seismic attribute, led to significant improvements (Fig. 7). The bulls-eye effects were eliminated and the numerical quality check (mean square error) was the lowest (2.19 vs. 2.78 vs. 2.97, retrospectively for Cokriging vs. Inverse Distance vs. Kriging).

The success of Cokriging means that a seismic attribute represents an important source of additional information regarding porosity. In addition, the network results showed that the neural approach "likes" more variables, i.e. several seismic attributes may be combined to gain a very good porosity prediction.

This strongly emphasizes the importance of selecting and combining more attributes based on the geological knowledge about a reservoir, and the physical meaning and relations among such attributes.

6. DISCUSSION AND CONCLUSIONS

The results show that seismic attributes could be a valuable additional source of information feeding the neural network. Seismic data could be the basis for predicting reservoir parameters, especially porosity, which is shown in this study.

The quality of the network could be estimated from two parameters. The first is the correlation coefficient. In this paper the symbol "R" *is used for Pearson correlation coefficient*, "R^2" for coefficient of determination and "r" for Spearman correlation coefficient. The second parameter is the convergence criteria and the reached minimum ($\Sigma\varepsilon^2$). The better network will be characterized by higher coefficient and lower convergence.

A better neural output is obtained with the use of more attributes. On the other hand, the exclusive use of amplitude led to poor network training. The amplitude values very often can include uncertainties, although this is generally the most applied attribute in porosity prediction. The first reason could be addressed to seismic signal quality, due to oscillation caused by weak calibration of geophones. In that case, the observed amplitude values can be different for the same displacement in a certain time, but frequencies and phases will mostly remain the same at all geophones. The second factor of uncertainty can be gas in the reservoir or in shallower beds. This gas can masked or even hide seismic reflections from deeper strata. The main reservoir of the Beničanci field (Badenian age) includes significant quantities of gas dissolved in oil. There are also several smaller, stratigraphically younger gas reservoirs of Early Pontian age. Three of them are in production, and all together contain about 30 % additional recoverable reserves of gas. These gas reservoirs, due to their stratigraphy, can attenuate and disperse the seismic signal, reflected from deeper reservoir of Badenian age. This ultimately results in increased uncertainties and variations in amplitude measurements, which can also partially be decreased by the use of additional attributes as frequency and phase.

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

- Reservoir space is always characterized by uncertainties. The neural network was selected as a tool for handling uncertainties of porosity distribution in a breccia-conglomerate carbonate reservoir of the Badenian age;
- The lateral changes in averaged reservoir porosities are influenced by the Middle Miocene depositional environments, i.e. alluvial subfacies. The proximal part of alluvial fan was active in the NW part, and the distal in the SE part of the field;
- The best porosity training results were 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) differ in every new training, which is the consequence of stochastic (random sampling) in some process of network fitting;
- The result indicates that neural networks favor numerous inputs, and careful evaluation of which variable can be a meaningful neural input is required.

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The neural analysis was performed using Neuro3 – Neural Network Software. This is a freeware E&P Tool published by the National Energy Technology Laboratory (NETL), owned and operated by the U.S. Department of Energy (DOE) national laboratory system. The system demonstrates the ability to learn, recall, and generalize from training patterns or data.

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